Evaluation of Suitability of Low-Cost Gas Sensors for Monitoring Indoor and Outdoor Urban Areas

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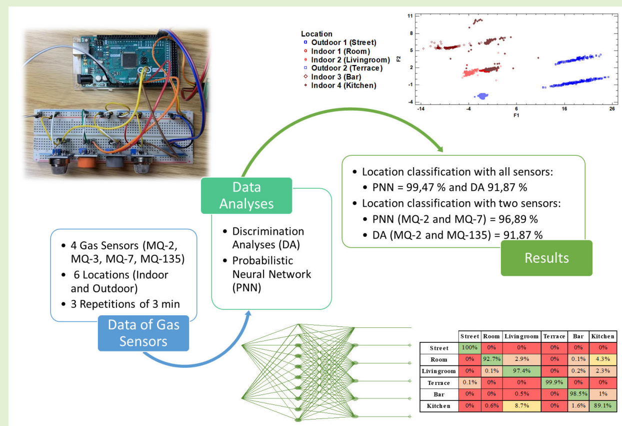
***Abstract*—Air pollution is a significant environmental risk to health; reducing pollution levels could help minimize related diseases, such as cancer, asthma, and stroke. Gas sensors, such as the MQ family, can be used to establish security measures for detecting environmental problems and improving air quality. The aim of this article is to develop a low-cost system using MQ sensors and an Arduino Mega to monitor air quality in different indoor and outdoor scenarios and identify the origin of the data using different approaches such as discriminant analysis (DA) and probabilistic neural network (PNN). The system is composed of an Arduino Mega and four MQ gas sensors. The response of four different MQ sensors (MQ-2, MQ-3, MQ-7, and MQ-135) to different indoor and outdoor environments is analyzed. The results indicate that the living room and kitchen have a stable response for all sensors, while the bar and the terrace have higher variability in their response. This article presents the results of using DA and PNN to identify indoor and outdoor areas using different combinations of MQ sensors, achieving up to 99.47% correctly classified cases with all sensors using PNN. This article's results show that their proposed system outperforms existing applications in correctly classifying cases, with well-classified cases with two sensors and the PNN reaching 98.22%.**



***Index Terms*—Air pollution, Arduino Mega, discriminant analysis (DA), eHealth, MQ sensor, probabilistic neural network (PNN).**

I. Introduction

According to the World Health Organization, poor ambient and domestic air quality causes approximately 6.7 million premature deaths. Air pollution implies a significant environmental risk to health. Nonetheless, a decrease in pollution levels could help to reduce the number of patients whose diseases are related to air quality, such as cancer, asthma, and stroke [1].

One of the foremost problems is that, in some cases, the human being does not give enough importance to environmental problems and how these could affect health [2], [3]. Environmental problems are situations that cause an alteration in the parameters. Those changes might be harmful to human beings. Some examples of these environmental problems are deforestation [4], drought [5], excessive use of limited resources, alterations in the cycles of living beings [6], and, above all, air pollution by chemical compounds [7].

Therefore, detecting these problems and applying solutions to improve them becomes essential. In this way, reducing environmental issues and minimizing the consequences of poor air quality on health worldwide will be possible. In order to reduce air pollution, it is required to decrease human activities' environmental impact [8].

Currently, air quality is mainly measured in the center of cities or concrete spaces, monitoring particulate matter (PM), volatile organic compounds (VOCs), biological

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pollutants, and aerosols, among others [9]. It is possible to find some gas sensors used for VOCs measurement for different applications [10]. In addition, some compounds can interact with other air elements, producing highly dangerous elements [11].

Hence, using gas sensors is of particular interest to establish security measures. Among the best-known gas sensors are the sensors of the MQ family. These types of sensors are based on the change in resistance depending on the presence of certain gases. There is another family of sensors, which is the TSG. Some articles indicated that the MQ family presents better results [10], [12]. According to a recent survey, MQ sensors are the most used ones and provide reliable and cost-effective performance despite the calibration problems [13].

The air quality in indoor and outdoor scenarios changes. Saini et al. [13] have focused on analyzing air quality differences in indoor and outdoor scenarios. Nonetheless, no clear differences among average values of CO_2 or PM were identified between studied indoor rooms. Most evident differences were found between outdoor and indoor scenarios. The air quality might impact human health, as described before. Thus, identifying where a person is located might help interpret their vital signs in e-health applications. In order to reduce the dependence on human–computer interaction, such as indications about the location, and to prevent the violation of their privacy, sensors can be used to identify in which ambient the person is. Gas sensors might be a possible solution since the air quality varies along different locations.

It is important to note that our aim is not to accurately monitor the concentration of gases or evaluate the air quality in the studied areas. Thus, the MQ sensors, which are characterized by a low cost and are widely used for multiple purposes, are evaluated. The main purpose of this article is to evaluate whether it is possible to recognize the area in which data are gathered by analyzing the response of different MQ sensors. Thus, we will assess the possibility of creating a response pattern for each area using an array of sensors.

The aim of this article is to develop a low-cost system using MQ sensors to identify in which location the air quality data were gathered. The selected scenarios to monitor air include both indoor (bedroom, living room, kitchen, and bar) and outdoor (street and terrace). An Arduino Mega is used to program the sensors and collect data. The air quality, according to MQ sensors, in selected locations is monitored in different time slots, including three repetitions. Different approaches are used to identify the origin of data. We included discriminant analysis (DA) and probabilistic neural network (PNN) among tested approaches. Our objectives, and the main novelties of the article, are the following.

1) Monitor the air quality differences in indoor and outdoor scenarios with low-cost sensors.
2) Evaluate the suitability of MQ-based sensors for gathering data to characterize the studied area.
3) Determine the position of elderly people within the home without needing image cameras and without invading their privacy.
4) Identify the best approach to differentiate the environments in which data were gathered.
5) Minimize the number of gas sensors used as much as possible to reduce the system's cost.

The rest of this article is organized as follows. Section II outlines the related work. Section III describes the materials and methods employed in implementing the work. The test bench is fully defined in Section IV. Results are presented and discussed in Section V. Finally, the conclusion and future work are presented in Section VII.

II. Related Work

In this section, different studies in which gas sensors have been implemented are summarized. These sensors can be used to monitor air quality. Nonetheless, they might be used for other types of applications. First, we outline the main contributions of sensors for monitoring indoor and outdoor air quality in urban scenarios. Then, the use of MQ-family sensors for other issues is mentioned.

A. Sensors for Air Quality in Indoor and Outdoor Urban Scenarios

This section provides an overview of the most relevant research in which gas sensors that are used to monitor environmental gases are summarized.

In 2019, Moreno-Rangel et al. [14] developed a gas sensor system using the Arduino nano as a microprocessor. The sensors used were MQ-2, frequency identifier, 16 × 2 liquid-crystal display and inter-integrated circuits, buzzers, and SIM800L modules. The objective of this research was to detect gas leaks. The wireless connection was through a short message service. They concluded that gas leaks could be detected from levels of 52%.

In later years, other authors developed studies based on gas sensors. Moreover, they used alarm systems to warn of danger due to a gas leak. This is the case of the Mluyati and Sadi [15] study in 2021, which, using the MQ-7 and MQ-135 sensors, developed a mobile alert system to improve safety in the car. The system detected carbon dioxide and carbon monoxide gases. As a microcontroller, they used ESP32. When the gas exceeded the appropriate ppm levels, an alarm gave notice to the mobile phone. In the same year, Seow and Ali [16] proposed an alarm system for detecting dangerous gases in laboratories, factories, and chemical product warehouses. They based their design on gas sensors and the Internet of Things (IoT). The sensors used were SGP40 and BME680. A WeMos D1 Mini IoT microcontroller was used to process the data obtained. These data were transmitted through the wireless fidelity (Wi-Fi) network. These data could be viewed directly on a computer, smartphone, or tablet. They concluded that these sensors could detect small leaks and spills in the laboratory.

Finally, these sensors have also been implemented in work areas. On the one hand, AI-Okby et al. [17] developed a dangerous gas detection system. The system is intended for workers in coal mines, gas industries, and sewage cleaning. For that purpose, they used MQ sensors. They were based on three steps. First, they prepared the data set. Second, they created the neural network model and finally trained the system on the data set. The values were processed using an industry-standard

IoT device, the national instrument-compact reconfigurable input–output industry standards, to the different values of the gases obtained from the implemented sensors. These data could also be updated in the cloud. They used Python for the creation of the neural network model. That same year, Anitha et al. [18] displayed an air quality monitoring system in a laboratory environment. They used a set of MQ sensors, a Wi-Fi module, and an Arduino microcontroller. This system was connected to a smartphone, where you could view the data obtained from the MQ sensors. Besides, by using ThingSpeak, the data were sent to a web page. Finally, the system consisted of a set of signals to notify the user of changes in air quality

Khadim et al. [19] used the MQ-2 sensor to detect smoke and combustion gas inside homes. For instance, they used burning paper, cigarettes, and gases such as the ones from lighter and stoves. They concluded that the MQ-2 sensor, together with the use of other sensors, could improve current smoke detectors.

Even though the proposed monitoring systems have been tested in different places and the results are promising, existing proposals are limited. Their main limitations are the reduced number of used sensors and the lack of classification methodologies to differentiate between different locations based on data from air quality sensors.

B. Other Uses of MQ-Family Sensors

Previously, the use of gas sensors for monitoring the environment has been discussed. Nevertheless, research related to gas sensors and other application types is featured in this section.

Stančić et al. [20] 2021 developed an electronic nose system to monitor the smelly air of poultry farms. This system was capable of detecting hydrogen sulfide, ammonia, and ethanol. In addition, they considered the humidity values that could affect the sensors. The humidity in these farms increased from 15% to 67%. Nevertheless, this study displayed that the effect of humidity remained below 0.6%. Moreover, the database was processed by DA and support vector machines (SVMs), obtaining a sample recognition success rate of 89% and 41%, respectively. In the same year, Moufid et al. [21] used the gas sensors ME3-C2H4, H2S-B4, and MQ-3 to determine the durian's maturity state (a type of fruit) based on its aroma. A neural network was trained to distinguish different stages of maturation. It was established when the fruit was overripe, when it was immature, and when it was ripe. Finally, the performance evaluation values were higher than 91%.

Another application is to determine the amount of alcohol in a drink. In 2021, Rivai et al. [22] used the MQ-2, MQ-3, MQ-4, and MQ-135 sensors to establish the degree of alcohol in beer and wine. As a microcontroller, they used the 32-bit ESP32 WROOM. As a result, they obtained that with the developed electronic nose, they could determine the degree of alcohol with an accuracy of 92%. Being the MQ-3 sensor, it is the most stable for taking measurements. They have also been used to determine the state of a drink. Montoya et al. [23] obtained a 90% success rate in legen/palm wine classification. For it, they implemented the MQ-3 gas sensor. ATmega2560 was used as the microcontroller. The Arduino sent the data to a personal computer for further processing. The system could differentiate between three different wine conditions (good, fairly good, and dangerous). The entire system was connected simultaneously via IoT, which allowed real-time monitoring of the state of the wine.

Finally, these sensors were applied to different areas that same year. Viruses such as COVID-19 were also detected. Rahmawati et al. [24] implemented an electronic nose to detect diseases such as COVID-19. They used a breath sample containing acetone, a mixture of carbon monoxide, COVID-19, and alcohol. The MQ-2 and MQ-135 sensors were exposed to the model. As a result, they obtained that the MQ-2 sensor takes longer to normalize the baseline than the MQ-135 sensor because other gases can cause interference. The data obtained were compared with breath data in COVID patients in Edinburgh and Dortmund. The results demonstrated that the developed method provides a noninvasive and rapid detection of viruses. In 2022, Miller et al. [25] carried out a low-cost system for rescue situations. This report monitors the air quality of the lifeguard's environment and their vital signs. An external agent was used to monitor vital signs through IP access, a web monitor, and a mobile application, an app monitor so that the lifeguard can be warned; the smartwatch includes a vibration signal, different light-emitting diodes (LEDs), and a screen to warn him of danger.

The aforementioned papers used different classification methodologies to differentiate the state of fruits, products, or even the presence of diseases. Nevertheless, no papers used these methodologies to identify the location based on the origin of data, indoor or outdoor scenarios.

III. Proposal

This section presents the proposed system. First, selected gas sensors are described. Then, the used node is identified. Finally, the proposed system's architecture is used for identifying a person's location.

A. Gas Sensors

One of the main objectives of this project is to develop a low-cost system capable of detecting the presence of gases in different zones and times throughout the day. For this, a set of MQ sensors has been used. Regarding the operation of MQ sensors, they have an internal heater (usually SnO_2) that heats the resistance. This resistance varies its temperature depending on the gas that is present. These are electrochemical sensors. The heater is protected by a stainless steel mesh that protects the sensor and prevents environmental damage due to the internal heater. Fig. 1 represents the diagram of both the MQ sensor and the circuit.

As shown in Fig. 1, the circuit is composed, on the one hand, of the MQ sensor itself and, on the other hand, of two types of circuits. The first (orange) can be seen inside the sensor, the heater. The heater is part of the heating circuit (1). Second, the circuit that allows measuring the resistance change when the sensor is exposed to different gases is shown (blue; 2). In this case, the resistance is 10 K (3), and the supply voltage is 5 V (5). The signal voltage of the circuit

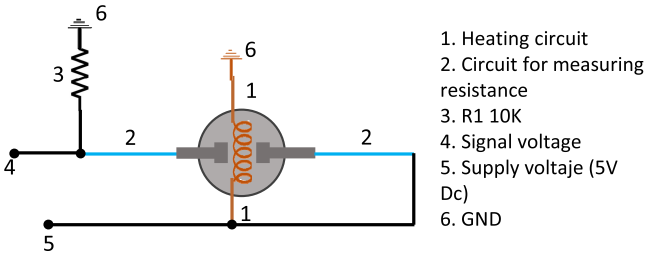

Fig. 1. MQ sensor diagram and circuit.

TABLE I
DESCRIPTION OF SENSIBILITY OF USED SENSORS

Sensor name	Sensible to:
MQ-2 [26]	Methane, Butane, LPG, smoke
MQ-3 [27]	Alcohol, Ethanol, smoke
MQ-7 [28]	Carbon monoxide
MQ-135 [29]	Air Quality (CO, CO2, Ammonia, Benzene, Alcohol, smoke)

is represented by the number 4. Finally, the GND is the number 6.

Although there are many sensors of the MQ family, it is established that each presents greater sensitivity against a gaseous compound. The MQ family includes sensors such as MQ-131, which is sensitive to air quality (CO, CO_2, ammonia, benzene, alcohol, and smoke); MQ-136, sensitive to hydrogen sulfide gas; MQ-9, sensitive to carbon monoxide, liquefied petroleum Gas (LPG), and CH4; MQ-4 that is sensitive to methane, and natural gas for vehicles (CNG) gas, among others. For the development of this system, the sensors used are MQ-2, MQ-3, MQ-7, and MQ-135 (see Table I).

B. Microprocessor

As a microprocessor, the Arduino Mega [30] has been chosen. We have chosen this device for its versatility in the inputs. It has 16 analog and 54 digital inputs, allowing multiple sensors to be connected simultaneously. This allows the connection of the four sensors and the possible inclusion of more gas sensors in the future.

The sensors are connected directly to the Arduino Mega 2560 to obtain the analog values of each sensor. The digital values are output using the Arduino's own analog-to-digital converter, and the air quality is determined by analysis. The internal amplification of the microcontroller is kept at the initial value.

Finally, the proposed system is represented in Fig. 2. The system is made up of the MQ sensors (1), the breadboard (2), the Arduino Mega microcontroller (3), the screen (4), and the smartphone (5).

C. Architecture

The architecture of the proposed system is based on the use of different types of networks (see Fig. 3). First, a body area network (BAN) is used to connect the wearable devices with the sensors with the smartphone of the user. For this connection, the Bluetooth technology is selected due to the low energy consumption, which will extend the duration of batteries of both wearable devices and smartphone, and the low required bandwidth. Among the wearable devices,

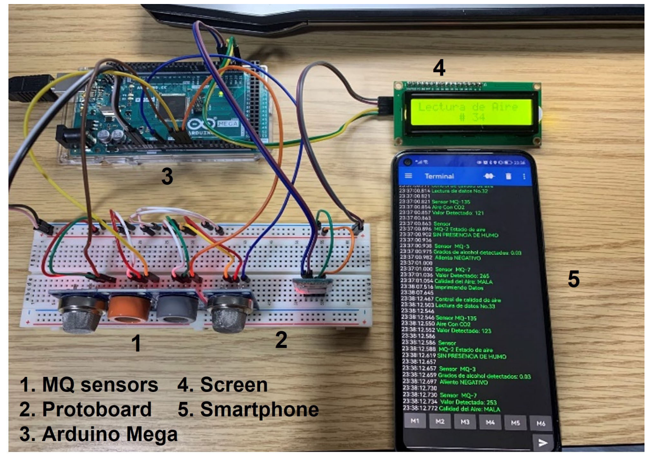

Fig. 2. Proposed wearable gas sensor device.

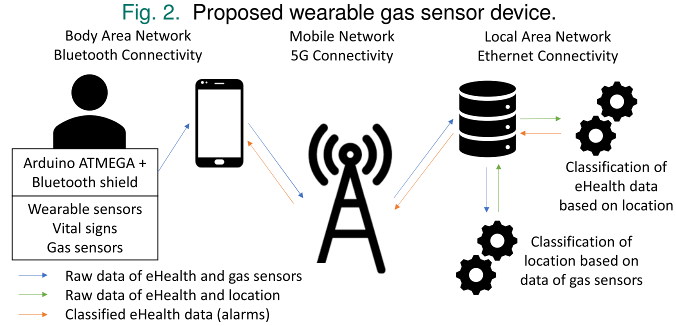

Fig. 3. Proposed architecture for eHealth system.

we will have the information from GRAS sensors, the devices presented in this article, and information from the vital signs of the person.

When the smartphone received the information, it sends the data using the available mobile network, such as 5G to the server. In the server, using a local area network (LAN), received raw data from the wearable sensors for gas monitoring are classified based on the proposed method. Classified data are then sent back to the served. Once the data include the predicted location and the vital signs, an additional tool classified the vital signs as normal or anormal. Then, information about classified eHealth data is forwarded to the monitored person, who received in the smartphone the generated alarms.

IV. TEST BENCH

In this section, we describe the test bench, including the measured procedure, areas in which data are collected, and data treatment.

A. Measurement Procedure

Before starting the measurement procedure, the system was used for two days in the laboratory following the manufacturer's recommendations. The node is moved from location to location, and 2 h of data are discarded in each location until stable measures are reached before collecting the data presented and analyzed in this article. This is necessary to ensure that sensors reach the required temperature and that all impurities that can be deposited over the filament are burned.

The sensor node was configured to gather data every 1 s in order to have a high temporal resolution in the generated

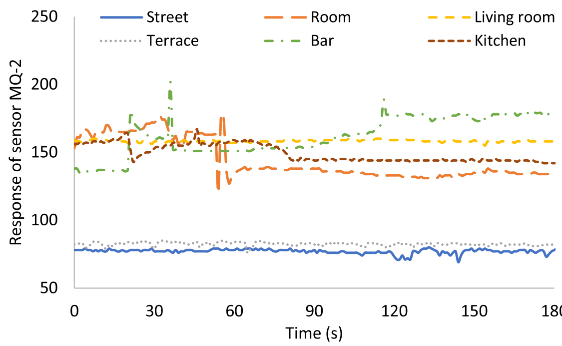

Fig. 4. Response of MQ-2 sensor in the first replica.

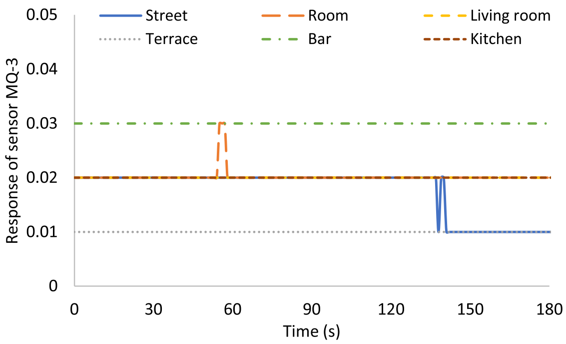

Fig. 5. Response of MQ-3- sensor in the first replica.

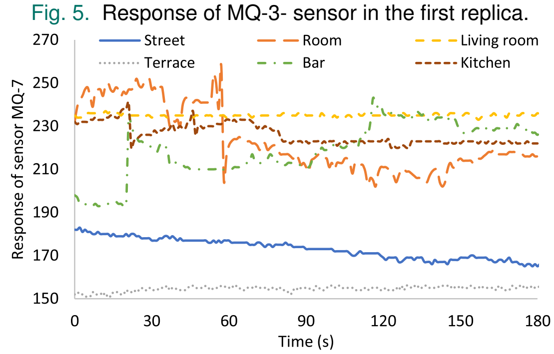

Fig. 6. Response of MQ-7- sensor in the first replica.

datasets. In each measured site, three datasets of three minutes were recorded. The recorded dataset was saved in.csv files which contain the response of each one of the MQ sensors. The system is initiated for each measurement, and after 3 min, the system is stopped. Data were recorded in monitored areas with no interference. After finishing each measurement, repetitions were performed.

B. Measured Scenarios

For this article, a total of six areas have been selected, including indoor and outdoor scenarios. The areas were selected to cover the different places in which a person can be during the day.

On the one hand, the selected scenarios of indoor areas include a room, a living room, a kitchen, and a bar. On the other hand, as outdoor scenarios, a street and a terrace were measured. The measurements were conducted Zaragoza (Spain).

C. Data Analyses

Data analyses include the individual analyses of temporal variability of each of the included sensors in every location,

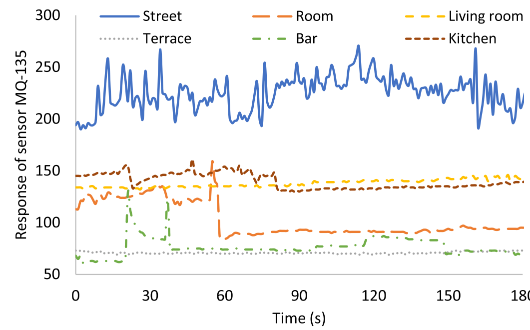

Fig. 7. Response of MQ-135- sensor in the first replica.

the evaluation of differences among conducted repetitions, and two classification methods.

Regarding the temporal variability, we will analyze one of the repetitions of the temporal variability of the different locations. This will provide information about how different are the values of each sensor in the studied locations. Moreover, the stability of the measure along the time can be visualized in these types of graphics. We will represent in each graphic the response of each sensor for all tested locations during 180 s.

Then, the means of each measurement are calculated and compared in a radial graphic. This graphic will evaluate whether different sensors have similar means in each repetition over the different locations. If means of different locations are similar, it indicates that, for this sensor, it would not be possible to differentiate the locations. The use of analyses of variance (ANOVAs) in a single way will be proposed to evaluate statistically whether the variance is different or not among measured locations. In addition, to the single-way ANOVA, multiple-range tests with the least significant difference (LSD) are conducted to identify the different groups.

Finally, the use of statistics to classify the data according to the locations is evaluated. Two different options are compared. The first one is based on the DA, which provides functions and coefficients to classify the data. This method requires low computational capacity, but it might offer inaccurate results. The other method, the PNN, tends to offer more accurate results but requires a greater computational capacity. In PNN, a series of neurons are used in different layers (input, pattern, summation, and decision layers) to classify the data. In this step, the metric used to compare the results is the percentage of correctly classified cases and the metrics calculated based on the amount of true positives (TPs), true negatives (TNs), false positives (FPs), and false negatives (FNs), described in the following equations:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$F1 = \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{3}$$

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4}$$

V. RESULTS

In this section, the results of testing the proposed system in different environments are detailed. First, we analyze the sensed data in different environments. Then, we evaluate which sensor is most useful to identify whether the data are sensed in an indoor or outdoor environment.

A. Air Quality Data in Different Environments

First, the results of the response of each MQ sensor to the different environments in the first replica can be seen in Figs. 4–7. In these graphics, the results are expressed as the response of each of the used sensors after applying the equations provided by the manufacturer. Fig. 4 shows the variation of MQ-2 data in the six sensed environments. The results indicate a higher response in indoor than outdoor environments and low differences between outdoor areas.

The response of MQ-2 sensors is very stable in the outdoor locations, characterized by standard deviations of 1.67 and 1.28 values on the sensor response for the street and the terrace, respectively. The differences in indoor areas are more relevant than in outdoor areas: the bar and the living room are the ones with a higher response, with maximum values of 202 and 160 of MQ-2 response, respectively. The room and the bar have higher variability (standard deviation above 14 in both cases) than the kitchen or the living room (the standard deviation is equal to 6.44 and 0.79 for each one), which is the most stable of the indoor environments.

The response of MQ-3 sensor, see Fig. 5, has very small variability in the first replica. Almost all sensed environments have the same response, and the response does not vary with time. It is characterized by standard deviations less than 0.005 in all the scenarios. The bar and the terrace were the environments with the higher and the lower response, 0.03 and 0.01 values in the sensor response, respectively.

The response of MQ-7, shown in Fig. 6, exhibits a similar trend to the one of MQ-2, with the outdoor areas with lower response than the outdoor areas, with values less than 175 for outdoor areas and greater than 2015 for outdoor areas. Nonetheless, the differences between areas, particularly for outdoor areas, are higher for the MQ-7 sensor. Regarding the indoor areas, the living room is the one with a higher response, with a maximum value of 258 values of the MQ-7 sensor.

Both the living room of indoor environments and the terrace, as an outdoor environment, have a very stable response for this sensor, with standard below 1.2 values of the MQ-7 sensor.

Regarding the MQ-135 sensor, its response can be seen in Fig. 7. In this case, there are no differences between indoor and outdoor locations, but the street is the environment with the highest and most variable response, characterized by a maximum value of 270 and a standard deviation of 17 units of the MQ-135 sensor. The living room and the kitchen have a similar and stable response (with maximum values of 146 and 161 and standard deviations below 7.5 units), while the bar and the room have a more variable response (with standard deviations above 9 units).

In the following, we focus on the variability of the three replicas. We have depicted the mean value of each replica and environment for each one of the tested sensors in Fig. 8. We can identify that different areas have different responses for each sensor, and the sensor with more stable lectures among replicas is the MQ-7. The MQ-3 response has been multiplied ∗1.000 to be represented in the graphic. The response of MQ-3 is similar to the response of MQ-7.

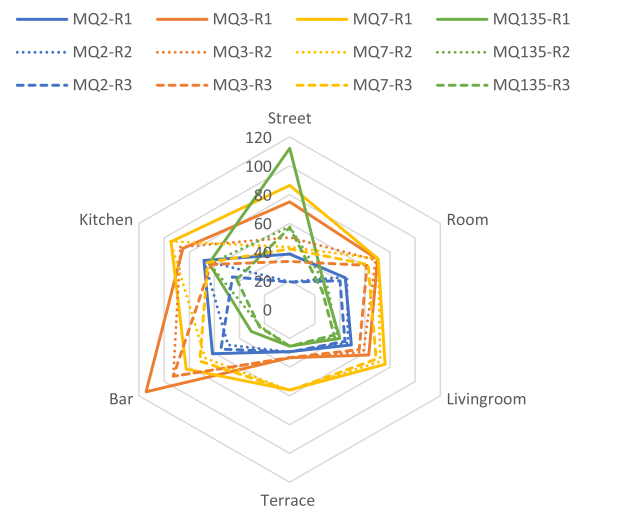

Fig. 8. Comparison of data gathered in different replicas and locations.

TABLE II
SUMMARY OF ANOVA AND MULTIPLE RANGE TESTS

Sensor	p-value	Differentiated groups (nº)	Undistinguished scenarios
MQ-2	0.000	6	-
MQ-3	0.000	5	Room and Livingroom
MQ-7	0.000	5	Terrace and Street
MQ-135	0.000	5	Terrace and Bar

B. MQ-Based Sensor as a Sensor to Distinguish Indoor and Outdoor Locations Based on Air Quality

In this section, we compare the MQ-based sensors to appraise, which are most suitable to identify the different environments. As a preliminary step, ANOVAs are calculated for each MQ-based sensor, see Table II. The results of ANOVA for MQ-2 can indicate a p-value of 0.000, which means that the differences between the data of different environments are very significant. In addition, the multiple range tests indicate that the six included environments are different. Thus, this sensor should be able to identify differences among tested environments.

For the data from the MQ-3 sensor, the p-value is 0.000. Nonetheless, the multiple range tests indicate that there are two scenarios for which there are no differences, the room and the living room. Regarding the MQ-7 sensor, the result of the ANOVA was a p-value of 0.000. As for the MQ-3, multiple range tests were not able to differentiate among all tested scenarios. It was not possible to differentiate between Street and terrace. In other words, it is not possible to differentiate between outdoor environments. Finally, for MQ-135, the

TABLE III
CLASSIFICATION ACCURACY OF DIFFERENT COMBINATIONS OF MQ-BASED SENSORS AND STATISTICAL TOOLS

Combination of MQ-based sensors	Correctly classified cases with DA	PNN
MQ-2 + MQ-3	80.55	91.60
MQ-2 + MQ-7	83.64	96.89
MQ-2 + MQ-135	91.69	98.42
MQ-3 + MQ-7	79.93	85.56
MQ-3 + MQ-135	89.49	90.70
MQ-7+MQ-135	91.14	98.22
MQ-2 + MQ-3 + MQ-7	84.44	96.13
MQ-2 + MQ-3 + MQ-135	91.54	98.57
MQ-2 + MQ-7 + MQ-135	92.83	99.10
MQ-3 + MQ-7 + MQ-135	92.13	99.45
All	91.87	99.47

TABLE IV
CONFUSION MATRIX FOR MQ-2 AND MQ-7 WITH PNN

Current / Classified Group	(1)	(2)	(3)	(4)	(5)	(6)
Street (1)	100%	0%	0%	0%	0%	0%
Room (2)	0%	94.8%	2.5%	0%	2.3%	0.5%
Livingroom (3)	0%	0.3%	99.3%	0%	0%	0.4%
Terrace (4)	0%	0%	0%	100%	0%	0%
Bar (5)	0%	4.1%	0.5%	0%	94.8%	0.6%
Kitchen (6)	0.2%	0.4%	3.4%	0%	0%	96%
Total well Classified = 98.22%						

TABLE V
CONFUSION MATRIX FOR ALL MQ-BASED SENSORS WITH PNN

Current / Classified Group	(1)	(2)	(3)	(4)	(5)	(6)
Street (1)	100%	0%	0%	0%	0%	0%
Room (2)	0.2%	99.2%	0.1%	0%	0%	0.5%
Livingroom (3)	0%	0%	99.7%	0%	0%	0.3%
Terrace (4)	0%	0%	0%	100%	0%	0%
Bar (5)	0%	0.5%	0%	0%	99.5%	0%
Kitchen (6)	0.8%	0.4%	1.6%	0%	0%	97.2%
Total well Classified = 99.47%						

p-value was 0.000, and it was not possible to distinguish between terrace and bar.

C. Most Suitable MQ-Based Sensor and Statistical Approach for Identifying Scenarios

In this section, we detail the results linked to selecting the most suitable sensor or sensor for identifying indoor and outdoor areas. For this purpose, two techniques are used. On the one hand, DA is performed. From the DA, we will focus on the results of the classification table. On the other hand, PNN is used as a secondary option for data classification. Again, the results of the classification table are used.

Table III summarizes for each method the percentage of correctly classified cases for DA and PNN, including different sensor combinations. When using two sensors, the best-attained classification with DA corresponds to the combination of MQ-2 and MQ-135, in which 91.69% of correctly classified cases are achieved. Regarding the PNN, with two sensors, the highest percentage of correctly classified cases is achieved with MQ-2 and MQ-135, with a 98.42% of correctly classified cases. When three sensors are used, the percentage increases. The combination of MQ-2, MQ-7, and MQ-135 offered 92.83% of correctly classified cases for DA. Meanwhile, for PNN, the best results are achieved with MQ-2, MQ-7, and MQ-135. In this case, 99.45% of cases have been correctly classified. Finally, when all sensors were used, the correctly classified cases were 91.87% and 99.47% for DA and PNN, respectively. Examples of confusion matrixes for PNN with two sensors and all sensors can be seen in Tables IV and V, respectively. In both cases, the results are similar. The major differences are found in the correctly classified cases of the living room and bar. When two sensors are used, up to 5% of cases are not correctly classified.

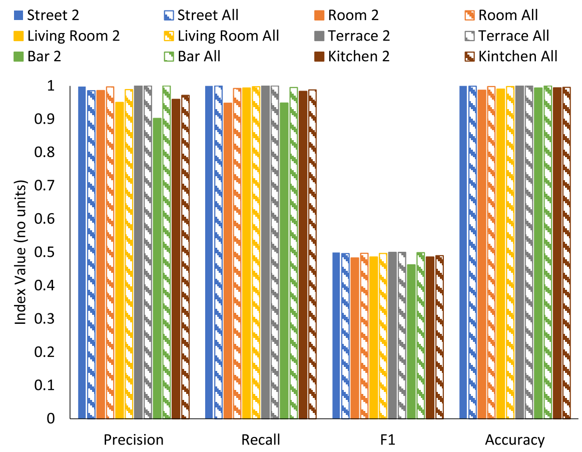

Fig. 9. Summary of precision, recall, $F1$, and accuracy.

VI. DISCUSSION

In this section, we discuss the obtained results compared with existing related work.

In Fig. 9, we display the different locations' precision, recall, $F1$, and accuracy. On the one hand, solid bars indicate the results when only two sensors are used. On the other hand, the striped bars indicate the results when all sensors are used. The most evident differences are for the living room and the bar. For the rest of the locations, the performance of the PNN is similar.

Comparing our results with existing literature, we find several examples of MQ sensors used to classify the measured samples. In most cases, the sensors are used to classify types of food or to determine the quality of the food. No examples of these sensors can be found to classify the type of areas. Thus, we will compare the results with the existing literature for other applications. Stančić et al. [20] attained a sample recognition success rate of 89% and 41% with SVM and DA. In [21], [22], and [23], the accuracy of the evaluation techniques was 91%, 92%, and 90%, respectively. Focusing on air quality monitoring, 76%–95% accuracy is obtained, classifying the quality of the air with SVM and decision trees using four sensors (MQ-5, MQ-131, MQ-135, and MQ-136) [32]. Another example in which MQ sensors are combined with additional sensors to classify the quality of air in indoor scenarios provides 99.3% of cases correctly classified with Naïve Bayes and 99.1% with J48 algorithms [33].

In this article, well-classified cases with two and four sensors and the PNN reached 98.22% and 99.47%, outperforming the previous studies. The only studies which improved the classification are [12], in which 100% of correctly classified cases were obtained. Nonetheless, it was achieved by classifying essential oil samples in a closed measuring chamber.

VII. Conclusion

In this article, data from indoor and outdoor are collected from the indoor and outdoor spaces. Our results indicate that by processing gathered data from the four sensors with PNN, 99.47% of cases are correctly classified. In addition, if the system is optimized to use only two sensors, 98.22% of cases are correctly classified.

In future work, the results obtained from the gas sensors will be combined with other sensors, such as the ambient humidity, temperature sensor, and light. The use of additional machine learning algorithms [34] will be considered. This will allow us to know where the person is without invading their privacy. The generated information will allow establishing tailored behavior patterns for elderly people to detect abnormal situations and alerting to their relatives.

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