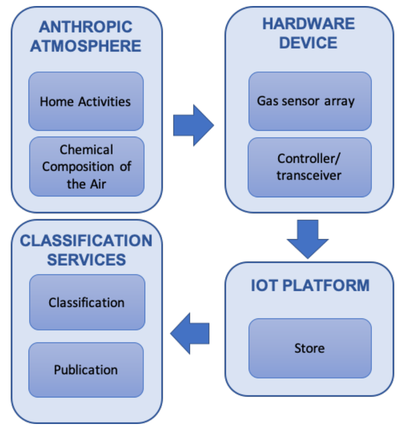
ADL recognition through machine learning algorithms on IoT air quality sensor dataset

(Article begins on next page)

ADL recognition through machine learning algorithms on IoT air quality sensor dataset

Ennio Gambi, *Senior Member, IEEE*, Giulia Temperini, Rossana Galassi, Linda Senigagliesi, *Member, IEEE*, and Adelmo De Santis

***Abstract*—The Human Activity Recognition is a focal point for Ambient Assisted Living, and may be implemented in several ways usually involving the use of different technologies, as wearable, video, environmental or radio frequency sensors, which can be used alone or in combination among them. Recently, the approaches based on machine learning have attracted a lot of interest, especially in order to create recognition systems that do not require a high detection capacity by the single sensor, as they base their decision on the processing of the information acquired from multiple sensors simultaneously. The aim of the present work is to derive information about the activities that are carried out inside the house on the basis of the data acquired by a set of sensors analyzing the air components. The Human Activity Recognition is then the result of a machine learning classification of the output of an array of low cost "commercial off-the-shelf" air quality sensors. The considered recognition system exploits electrochemical sensing, Wi-Fi technology, cloud computing, machine learning and application services. The obtained results evidence that a good accuracy in the recognition of "activities of daily living" is reached, even if a not calibrated sensing was performed.**



***Index Terms*—ADL, air quality sensor, HAR, machine learning.**

I. Introduction

Ambient Assisted Living (AAL) paradigm was born in the early years of 2000. It pushes the use of ICT technologies in everyday life activities both at home or at work, in order to let people remain active for a longer time, without losing social connections and independence [1], [2]. In the last ten years the interest toward AAL has increased, and it was driven by the awareness of ageing population and the wide availability of cheap yet accurate sensors. Recent studies [3] show an increase of elder people (aged over 60) on a global scale: from 382 million in 1980 up to 962 million in 2017. This number is going to double by 2050, thus reaching 2.1 billion. It has been foreseen that in 2030 the number of elder people will be greater than that of youngster (age between 10 and 24 years): 1.41 billion versus 1.35 billion. Life quality is a parameter which reflects the number of elder people who are living autonomously with a partner or alone. Data from 143 countries show that only 2.3% of elder people are self-sufficient in Afghanistan, while the percentage is 93.4% in the Netherlands. Independent people number has great consequences on a country health expenditure and population needs. Ensuring an easy access to home care and rehabilitation can be challenging for governments and pushes toward a new care model, which can decrease costs by using technologies and devices to build smart environments. One of the most interesting challenges in AAL is Human Activity Recognition (HAR). HAR aims to detect what kind of activity is performed by a single or a group of people, by analysing data from sensors or observations, as a function of the context in which they are collected [4]. This kind of approach is of great help to improve care actions toward elder, disabled or chronically sick people and to respond quickly to incidents or emergency situations. Day by day activity monitoring is meant to evaluate changes in monitored people capabilities. For this purpose, two specific sets of activities have been defined [5]: activities of daily living (ADL) and instrumental activities of daily living (or IADL). Actions belonging to the first group can be used to assess person's ability to take care to himself: eating, dressing, cleansing etc. The interaction level of a person with its physical and social environment falls in the IADL monitored group of actions. In order to gather data for ADL recognition, a wide range of technological aids have been developed. Among them wearable and video monitoring devices assume a particular relevance for the assessment of ADL, together with the analysis of data collected by Radio Frequency and environmental sensors [6], [7]. Wearable sensors, comprising temperature, light and SFR sensors, are usually lightweight to fit users without causing discomfort, but are limited by the coarseness of sampled data. For this reason, video monitoring

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is often used, even if it requires a higher computational cost.

The developed system here presented encompasses different technologies: sensor network, Wi-Fi technology, cloud computing, machine learning and application services. The novelty in this paper relies on the use of cheap gas sensors to gather environmental data, that makes possible the recognition of different ADLs correlated with the presence in the air of particular components, without the need of any calibration, only on the basis of the chemical compounds delivered on the air as a consequence of the performed actions. The analysis of historical and current data, gathered from indoors by a hardware device realized by the authors, and processed with a suitable machine learning algorithm, allows to assert the type of performed activity. In order to cover most of domestic ADL, the paper focuses on 4 main situations: everyday room life (living room), meals preparation, room cleaning, presence of smoke. The work is organized as follows: Section II describes state-of-the-art in ADL recognition. Section III describes the developed system and application tools and focuses on system and prototype implementation. Section IV reports on system tests and results analysis. Section V draws a summary of this work.

II. State of the art

Activity recognition in AAL is a well explored research field, and this reflects on the amount of scientific literature. Sensors are used to gather information about user in order to monitor his activities and improve remote care. As stated in [8] a common approach to ADL uses a 4 layers framework:

- Sensing Layer: gathering information about the environment and its inhabitants;
- Network Layer: wireless communication technologies to gather, exchange and transmit data with the highest possible efficiency;
- Data Processing Layer: data knowledge extraction by means of aggregation, processing and analysis. The biggest role in this layer is played by machine learning. The most widely used classification algorithms [9] are: Support-Vector Machine (SVM), k-Nearest Neighbour (KNN), Random Forest (RF), Hidden Markov Model (HMM), Naïve Bayes (NB) and Decision Tree (DT);
- Application layer: services to the end-users.

At the sensing level we can identify two main categories [10]: vision-based systems and sensors-based systems. The first one relies on the use of video and photo cameras which gather information on human activities. Video streams and vision data are digitized and processed using artificial vision algorithms. In spite of the ease of this approach, there are some questions about user privacy and computational workload that need to be addressed. In a sensor-based system we can monitor users by mean of a wearable device, or using objects that are in the user's environment. Data gathered are time-value series which describe state changes or sensors collected data. Such a big dataset is usually processed using data fusion and statistic. Wearable sensors (magnetometers, gyro, temperature, pressure etc.) can gather a lot of data very close to the user but their effectiveness relies on the user accepting the sensor and remembering to wear it or to charge its batteries. All these aspects lead to dimensional constraints which may limit battery and memory size and processing power. Moreover, sensor position change during the day can lead to difficulties in data analysis. On the other side, sensors that are distributed in the habitation are focused on environmental data acquisition, RFID [5] or gas. In [11] the results of an interesting work are presented. ADL were monitored in a house by using more than 900 sensors: reed switches on drawers and wardrobe, AC current, temperature, humidity, light and gas sensors. Interaction with objects was monitored using wireless systems, and many RFIDs were integrated in the environment as well. The study focused on the impact of type of sensor used on ADL. The outcome from the work shows that infrared sensors are the best choice to monitor the great amount of activities, the actions of "reading" and "using smartphone" were poorly detected regardless from the type of sensor used. The action "eating" was very well detected by wearable accelerometers. The great result obtained using IR detectors, can be explained by noticing that a dedicated sensor is used to track a single activity: "watching TV" is an action triggered by an IR sensors detecting a person sited on the sofa. Results from this paper allow us to state that there is a strong correlation between the "action" and the place in the house where it is performed.

In the following the state of the art of IoT architectures for ADL is analysed, which incorporate sensors for data acquisition and technologies for data transmission and classification. Processed data can sometimes be accessed using web and mobile applications. In [12] an ADL approach for AAL is analysed which relies on the use of accelerometers and gyro in a smartphone, thus being cheap and easy to be implemented. Six activities are monitored: walking, ascending and descending the stairs, sitting, standing and laying. The user wears the smartphone on its belt, data are processed and classified using SVM, ANN and SVM-HMM algorithms. [13] proposes a little, lightweight and cheap prototype in which air pressure sensors and an IMU are integrated. Data collected are sent by wireless network connection. 11 classes of daily activity are monitored: sitting, standing, lying, walking, running, going upstairs, going downstairs, from sitting to standing, from standing to sitting, from sitting to lying and from lying to sitting. Data processing is performed using five different classification algorithms: k-NN, DT, NB, SVM and RF. In [14] a BioHarness 3 module is used, to monitor vital signs by means of heart, breathing and accelerometer sensors. Two different classification algorithms are tested: C4.5 and Naïve Bayes. Activities are classified into four main categories: laying, sitting, walking, running. From a software point of view there are two main realms: Android mobile apps are used to collect data from hardware device via Bluetooth, pre-process information and send the results to a cloud using MQTT o HTTP protocols. Cloud service is a core element to display data using graphical elements and to configure warnings. The platform chosen for implementation in [14] is Ubidots. None of the mentioned works, however, considers the use of gas sensors for ADL, thus affecting the type of activities that can be monitored. Strongly related to our current work is the contribution in [15], where authors propose a smart monitoring system which exploits indoor air quality sensors. In this way it is possible to detect factors affecting air quality and classify them in five different categories: ambient air, chemical presence, fragrance presence, foods and beverages presence and human activity. Gathered data are analysed using artificial neural networks, and the user can access real-time data using a GUI. The use of gas, particle and thermal sensors is considered. Differently from [15], the system proposed in our work is specifically designed for ADL and it is implemented using an IoT platform supporting a large number of protocols. Moreover, only gas sensors are considered, and our system proves to achieve an excellent precision even without an accurate sensors calibration, especially when data coming from different sensors are combined together; we are in fact interested in sensors detection over time, as will be specified in the following.

III. System Architecture

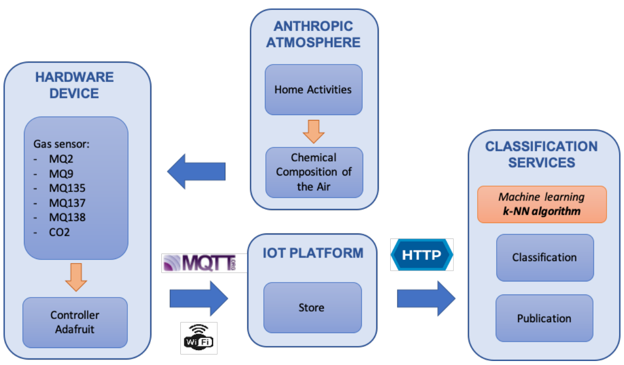

Fig. 1. System Description.

The present work aims to monitor real-time people activity on the basis of the chemical composition of the air, related to the home activities, in order to let a care giver have an easy access to data, to better tailor assistance and allow quick response to critical situations. The main blocks of the system, shown in Fig. 1, are:

- Anthropic Atmosphere;
- Hardware device;
- IoT platform;
- Classification services.

The working principle is as follows. Due to the home activities, a variation of the chemical composition of the air is evidenced, that is called Anthropic Atmosphere. The core of hardware device is a microcontroller, connected to a series of different gas sensors able to detect carbon monoxide, formaldehyde, alcohol, ammonia and carbon dioxide. Data are collected by the microcontroller, processed and sent to IoT platform ThingSpeak using MQTT protocol and WiFi connection for data storage. Classification is performed using a k-NN approach, a non-parametric, instance driven algorithm. End users can monitor events by using an Android app and, in case of a critical situation, a warning can be raised with an email.

A. Hardware device

Hardware is composed of two main sections: gas sensors and controller module (Adafruit Feather M0 Wi-Fi with ATWINC1500). The MCU plays an important role as it gathers data from sensors using GPIO interfaces, pre-processes and sends information to ThingSpeak platform. Powering the prototype requires a 12V power supply. Further switching voltage regulators are used to get 3.3V and 5V to power the MCU and sensors boards. The Controller Module is based on Adafruit Feather M0 module, and is the core of the system. It performs many tasks:

- WiFi network connection;
- Sensor data acquisition;
- Data processing;
- Data storage on ThingSpeak platform.

The module is based on ATSAMD21G18 ARM cortex M0 processor, which is tailored for embedded applications. Its main features are 20 GPIO pins, 3.3V operating voltage, 48MHz lock, one ADC and one DAC both with 10-bit resolution. The board on which the processor lies, is equipped with other I/O connectors, to make the integration of this device easier: I2C, UART, USB and SPI. The added value of this MCU implementation lies in the presence of an integrated Wi-Fi module based on ATWINC1500 and able to support 802.11b,g,n standards. The entire MCU board is not energy hungry as the max current consumption is 22mA. Arduino IDE can be used to program the processor, thus giving access to the big number of libraries that have been developed so far for this platform. Moreover the IDE is really easy to use and allows for a very fast start-up.

TABLE I
List of Air Sensors

Sensor	Gas
MQ2	Molecular hydrogen, LPG, natural gas, carbon monoxide alcohol, propane
MQ9	Natural gas, LPG, carbon monoxide
MQ135	Ammonia, carbon mono- and dioxide, ethanol, toluene, acetone
MQ137	Ammonia, carbon monoxide, ethanol, dimethyl ether
MQ138	n-hexane, benzene, natural gas, carbon monoxide alcohol, propane
MG-811	CO_2

The aim of the work was to use cheap and "easy to use" sensors. According to this principle we selected some electrochemical gas sensors among the plethora of commercially available modules. The rational has been to select a relatively small finite number of sensors, fixed as six, featured by the same sensing material, SnO_2, but with the ability to detect a wide range of volatiles and with a declared high sensitivity to classes of compounds, that may be roughly classified as polar or not polar gases. The underpinnings of this sorting is based on the fact that the first step in the electrochemical detection process is a surface chemical phenomenon, hence, the polarity of the molecule determines the nature of the intermolecular interactions between the gas and the surface of the sensing material [16]. According to these foundations, the different detection's abilities of these sensors are described in data sheets and summarized in Tab. I.

The CO_2 gas sensor, MG-811, is the only one having a different sensing material consisting of a NASICON/carbonate redox active couple; it exhibits a very good sensitivity to carbon dioxide being poorly influenced by air temperature and humidity. Leaving apart this latter, the detection of gas by these sensors is based on the redox reaction between the gas and the oxygen of the SnO_2 surface but, as indicated in the technical sheets, they show different responses to gases. In fact, the gas detection is significantly affected by the phase and the particle size of the nanometer-scale thickness of the electron depletion SnO_2 layer and, therefore, sensors apparently of the same type result in quite different outputs [17].

In general, the choice of this kind of sensors was made on the basis of their main features: fast response, high sensitivity, overall robustness and relative longevity, small size and lower power consumption.

As concern the pool of compounds present in the air, taking in consideration the actions we want to discriminate, it is noteworthy that thousands of volatiles may be formed during complex reactions such as the Maillard's in the cooking action [18] or the oxidation reactions in the combustion of organic materials [19]. Remarkably, during the activities polar and not polar compounds are produced, differently detected by single sensors and, overall, from the set of sensors. The optimal sensor temperature is guaranteed by a heater, while a signal conditioning device is implemented too on the sensor modules. The presence of a gas results to an output voltage, ranging from 0 to 3.3 Volts: the bigger is the gas concentration, the lower is the output voltage.

In the present work we aim to track gas concentration variation over time and to use this information to assess the type of activity that is performed in the room. For this reason, we are not interested in a quantitative approach, which would require an accurate calibration of the sensors, but their detection over time. Raw data gathered from sensors are not even processed by the MCU: they are packed and sent on the IoT platform for further processing.

B. IoT platform

Hardware device and mobile app, both transfer data with cloud platform by using Wi-Fi or mobile data connection. The sensor node uses MQTT while the app HTTP protocol. In order to chose the IoT platform for data storage and processing, the evaluation criteria have been:

- Support for a wide number of protocols (MQTT, HTTP, HTTPs);
- Type of supported devices;
- Application libraries (i.e. Javascript, PHP, Python, Java);
- Device libraries (i.e. Matlab, Python, C, Java);
- Cost;
- Offered Services;
- Features (data storage, data extraction, data processing).

After analysing the features of different platforms, ThingSpeak [20] was selected as reference platform for this project, since it's an open source platform able to collect, display and process data in real time, and processed data can even trigger an action that will be performed on the platform or using external software applications. ThingSpeak was created by ioBridge in 2010 and supports both HTTP and MQTT, thus allowing a great flexibility in the device implementation. A dedicated MQTT broker can be reached at the address mqtt.thingspeak.com and it allows only QoS 0. Three main features are available on the platform:

- Data collection is performed in real-time by using "channels" and "fields", where data are stored. Each channel can store up to eight fields (or feeds), each with a different parameter. In a practical scenario, we can use a channel to store data coming from a single room, by storing temperature, humidity, light and air quality.
- Data analysis and visualization tools can integrate MATLAB code. In this way we can write a code that will be executed in real-time during data acquisition, or we can time-trigger the software execution;
- Application services are the real added-value from this platform: TimeControl, React, ThingTweet etc. allow the user to implement data triggered application behaviour, i.e. social network interaction on a particular sensor data.

C. Anthropic Atmosphere

With the aim to monitor the daily activities, 4 target situations have been identified:

- Normal situation - Activity 1: clean air, one person sleeping or studying or resting; Samples: 595.
- Meals preparation - Activity 2: cooking meat or pasta, fried vegs. One or two people in the room, forced air circulation; Samples: 515.
- Smoke presence - Activity 3: burning paper and wood for a short period of time in a room with windows and door closed; Sample: 195.
- Cleaning - Activity 4: using spray and liquid detergents with ammonia and/or alcohol. Forced air circulation can be switched on or off; Samples: 540.

We associated to the four different situations a quite different composition of the air, taking in consideration that any activity produces chemicals due, i.e., to human breathing, to metabolic processes exhalations, to the delivery of volatiles by combustion and / or oxidation, and to the evaporation of houseware cleaners. To a "normal situation" a genuine composition of the indoor air is normally referred to a mixture of nitrogen, oxygen, CO_2 and water vapor as major components [21]. Moreover, in addition to these compounds, some contaminants named as VOCs or particulate (PM) are normally present in ppm or ppb range of concentrations depending on the kind of building and on its geographic location [22], [23]. These latter, although represent a problem for human health [24], are generally present in very low concentrations and during a period of measurement without anthropic activity they remain unchanged. Therefore, the "normal situation" represents the set equal to zero of our sensors. Any of the other activity taken in exam results in an overall change of the composition of the air in a range that, once detected by the set of sensors, affords to the harvesting of the activity. Noteworthy, the technical specifications of the sensors describe the detection of a wide range of volatiles; in example, the MG-811 sensor reveals almost exclusively CO_2, attributable to burning paper and wood and cooking, MQ9 detects mainly alkanes and CO, while the other sensors MQ137, 138 and 139 are more sensitive to polar both inorganic and organic volatile compounds mainly produced in the cleaning and in the cooking activities.

D. Classification services

During data collection, a set of data to train our system was created. Each record consists of seven numerical values: six of them represent gas concentration as detected from the sensor, the last one is a label for the action performed in the room (current situation). System training was performed in an apartment by taking 5 different rooms into consideration: kitchen, bathroom, living room and two bedrooms. In this approach ADLs are recognised by environmental analysis monitoring the activities carried out by a single person who lives alone at home. The monitoring of the ADL is in fact of interest in order to allow people to live independently at home, but ensuring a certain level of assistance. Collection phase lasted 15 days and data were acquired at different times of the day. Before and after data collection, windows were opened to let fresh air in. Sensors where placed in a room where a specific activity is performed. MCU gathered sensors values and transferred them to the IoT platform with the label identifying the current situation. Data were stored on the "training-set" channel. At the end of the collection phase, 1845 samples were gathered describing the 4 target situations we want the system to be able to recognize.

The machine learning algorithm k-NN has been used to classify the "target situation" from sampled data. With a small training set dimension, in fact, k-NN is able to guarantee high level performance with a limited computational cost. Moreover, in the scenario examined in this paper, it allows to achieve a better accuracy than other widespread classification algorithms, such as SVMs. The parameter *k* has to be chosen in order to get the best fit to dataset. In fact, the system is subject to overfitting when the model over-adapts to a particular set of data, while underfitting occurs when the model is unable to interpret the structure underlying a data set. In addition, high values of k reduce the variance due to the noise present in the dataset, but lead to a loss of accuracy in the classification of minor patterns. Small values of k define more complex decision limits, but are more sensitive to noise. In our work k value was chosen, that minimizes validation errors. Many validation tests were performed by varying k value. Each time the leave-one-out cross-validation algorithm was used. In general, the g-fold cross-validation works as follows. Original dataset is randomly divided in g equinumerous parts. At each step the g-th part of the dataset acts as a validation set, whilst the remaining part is the training set. The g-th group will be predicted by using the remaining $g-1$ groups, thus avoiding overfitting and asymmetric sampling problems. Leave-one-out cross validation here considered represents an extreme case of g-fold cross-validation, where g is chosen equal to the training set dimension N. In this way all samples are used only one time both for training, both for validation.

Let us denote by x_i the test sample and by y_i its membership class, with $i \in [1, N]$. The following procedure has therefore been implemented:

- One single instance x_1 is used for validation, while the training set is composed by the remaining $(x_2, y_2), \cdots, (x_N, y_N)$ samples;
- Class $\widehat{y}_1$ is predicted on the basis of $N-1$ observations. Validation error is evaluated by comparing the predicted class $\widehat{y}_1$ with the true class y_1 as $Err_1 = I(y_1 \neq y_i)$, where $I(\cdot)$ is an indicator function;
- The process is iterated over every observation (x_i, y_i), thus obtaining a series of N errors: $Err_1, Err_2, \cdots, Err_N$;
- Validation error is computed as

$$CV_N = \frac{1}{N}\sum_{i=1}^{N} Err_i.$$

The algorithm is repeated for values of k between 1 and 49, using only odd numbers to avoid obtaining parity cases in classification phase. At the end of the process we choose k which minimizes the Validation Error. This algorithm is implemented in Matlab. According to Fig. 2, the best value for k is 3, which leads to a validation error of about 3%.

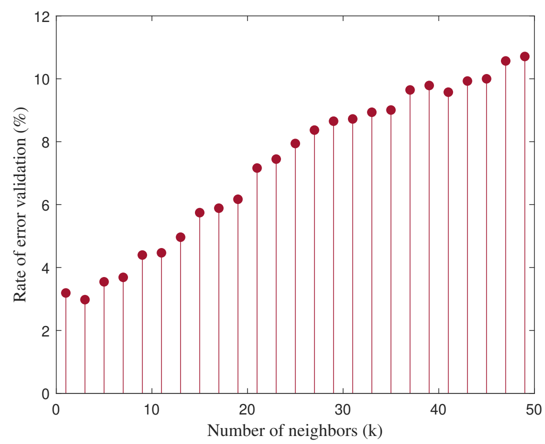

Fig. 2. Results of the leave-one-out cross validation.

The application of the classification algorithm to a generic observation x_i to obtain the relative predicted class $\widehat{y}_i$ involves the use of some features of the IoT platform, in particular MATLAB analysis and React App. The considered methodology works as follows:

- Hardware device sends dataset from sensor at a regular time interval on the Back-end classification channel of ThingSpeak platform;
- React comes into help when wanting to apply the classification algorithm to each new observation. IoT platform "reacts" to new data, by executing machine learning algorithm called Classification k-NN;
- Classification k-NN algorithm reads the last dataset, the classifier output and publishes results on the Home activity channel. Seven values are shown: six coming from sensors, the seventh is the output from the classifier.

IV. Results and Discussion

A. Experimental results

Test were executed in order to evaluate system performance in situation recognition. During this phase the whole dataset

TABLE II
MEAN VALUES OF THE SENSOR'S OUTPUTS (IN VOLTS) FOR EACH ACTIVITY

Activity \ Sensor	MQ2	MQ9	MQ135	MQ137	MQ138	CO_2
Normal situation	0,32	0,39	0,75	1,19	0,81	1,86
Meals preparation	0,44	0,50	0,95	1,30	1,00	1,80
Smoke presence	0,67	0,72	1,18	1,41	1,31	1,56
Cleaning	0,60	0,63	1,05	1,37	1,27	1,85

TABLE III
STANDARD DEVIATION VALUES OF THE SENSOR'S OUTPUTS (IN VOLTS) FOR EACH ACTIVITY

Activity \ Sensor	MQ2	MQ9	MQ135	MQ137	MQ138	CO_2
Normal situation	0,050	0,045	0,066	0,047	0,101	0,095
Meals preparation	0,055	0,042	0,064	0,035	0,087	0,110
Smoke presence	0,119	0,088	0,085	0,037	0,108	0,078
Cleaning	0,117	0,122	0,121	0,067	0,113	0,145

is divided into a training set of 1410 samples, and a test set of 435 samples. Each sample is a couple (x_i, y_i) of the observed data and its corresponding class. A MATLAB algorithm was developed to classify each x_i and compare the predicted class $\widehat{y}_i$ with the real class y_i. Data were analysed using a confusion matrix, that is the table layout which helps to assess an algorithm performance in the field of artificial intelligence and machine learning. This approach is used to represent the accuracy of a statistical classification. Each matrix column represents predicted values, while each row represents real values. Element on i-th row and j-th column is the number of times the classifier has been able to detect "real" event i as j. By using this matrix, the "confusion" among classes prediction is evidenced. Total accuracy is then evaluated as the number of samples correctly classified (those on the main diagonal) over the total number of samples in the training set.

Three different situations are classified:

- "Normal situation classification", identification of the Normal situation vs all the other activities;
- "Smoke presence classification", identification of the dangerous Smoke presence;
- "Single activity classification", identification of each single activity.

The location of the sensors was chosen arbitrarily inside the rooms where the activities were performed. During the data collection phase the sensors have assumed different positions within the rooms. Sensor modules were assembled inside a box located in the middle height in a flat plane; a flux of air was continuously forced to enter inside the box by an electrical fan to ensure a constant circulation of air during the events.

In order to assess the overall performance, 100 classification results are averaged, where training and test samples are randomly chosen each time.

Tables II and III show the mean values and the standard deviation values of the six sensors' outputs (in Volts) for all the considered activities. By observing both tables it is possible to infer that, although mean values for the four activities are quite different, the high values of the standard deviation make difficult to recognize activities by resorting to a single sensor.

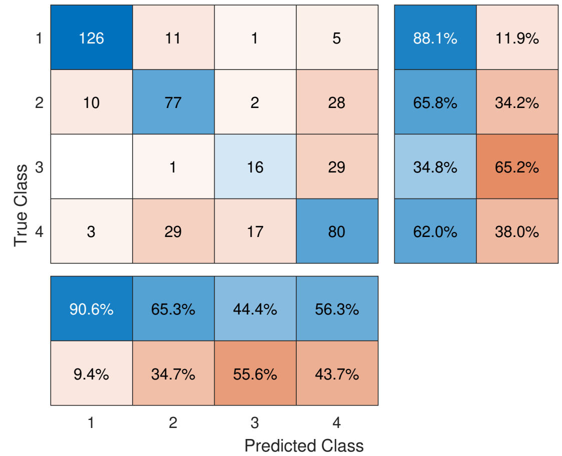

Fig. 3. Confusion matrix related to the "Single activity classification", using only data derived from MQ9 sensor. Total accuracy 68.7%.

TABLE IV
ACCURACY ACHIEVED BY SINGLE SENSORS IN THE "SINGLE ACTIVITY CLASSIFICATION".

Sensor	Accuracy
MQ9	68.74%
MQ135	66.21%
CO_2	56.6%

TABLE V
ACCURACY ACHIEVED BY DIFFERENT COUPLES OF SENSORS IN THE "SINGLE ACTIVITY CLASSIFICATION".

Sensors	Accuracy
MQ9-MQ135	86.9%
MQ9-CO_2	83.4%
MQ135-CO_2	84.1%

This is easily proved by the confusion matrix depicted in Fig. 3, where the best accuracy, achieved using the MQ9 sensor, is only 68.7%. Similar and even worse results are obtained with the MQ135 and CO_2 sensors, as shown in Tab. IV.

By combining the data acquired by couples of sensors, the higher precision was obtained with the couple MQ9-MQ135 (see Fig. 4 and Tab. V), especially when we consider the "Normal situation classification" (Fig. 5) and the "Smoke presence classification" (Fig. 6). As expected, best results are obtained considering the assembly of all the sensors. Fig. 7 displays the confusion matrix related to the "Normal situation classification". Average accuracy obtained is equal to 98.85%. The presence of activity is detected almost perfectly, with more than 99.4% of accuracy. Excellent results are achieved also for the "Smoke presence classification", as shown by the confusion matrix in Fig. 8. Results testified that the classifier can detect a critical and dangerous situation (the smoke presence) and raise the alarm with a high certainty, of more than 91%. Confusion matrix on Fig. 9 describes the results of the "Single activity classification", with an accuracy of 96.32%, while the model in general achieves an average accuracy of 96.73%. Best results are obtained, as expected, for the class "normal situation", while the worst results concern the detection of "smoke presence" (90.9%), although this is still detected with great precision, more than 9 times over

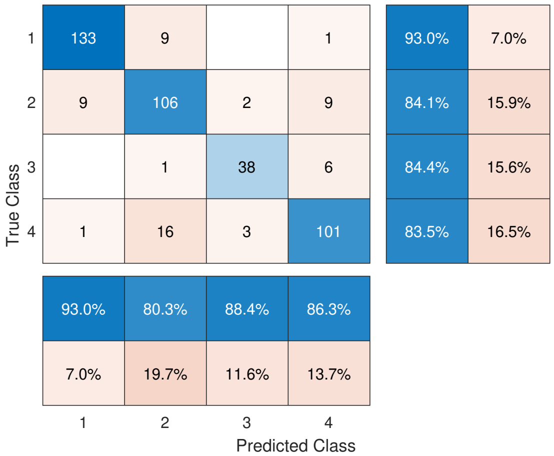

Fig. 4. Confusion matrix related to the "Single activity classification", using data derived from MQ9 and MQ135 sensors. Total accuracy 86.9%.

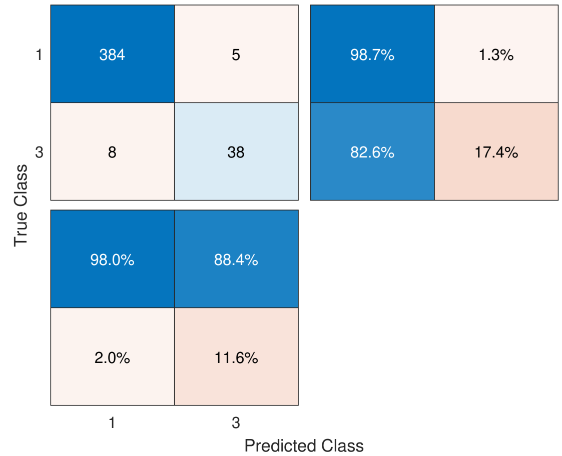

Fig. 6. Confusion matrix related to the "Smoke presence classification", using data derived from MQ9 and MQ135 sensors. Total accuracy 97%.

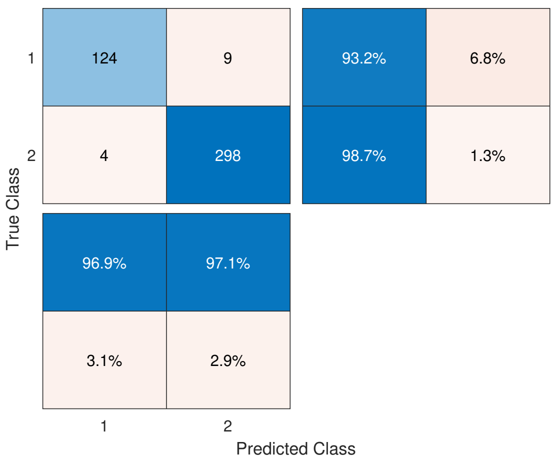

Fig. 5. Confusion matrix related to the "Normal situation classification", using data derived from MQ9 and MQ135 sensors. Total accuracy 97%.

10. Classes "cleaning" and "meal preparation" are also well distinguished from the others.

B. Discussion

The sensors used in this work are described to be sensitive to classes of compounds, but their discriminating ability is generally poor. The low specificity of the sensors' detection is confirmed by the results of the analysis. The data highlight that only the assembly of all the sensors allow the takeover of all the activities with an averaged accuracy of about 99% but when we group two of them and we process the data, a lowering of the reliability is observed. Actually, if we analyze the activity from the point of view of the air chemical composition, we can distinguish between activity producing polar (humidity, alcohols, amines, ketons, esters etc.) or not polar volatiles (alkanes, CO_2). The air composition derived from the activities taken in consideration in this paper may be classified as:

- normal situation, that corresponds to an almost constant composition of polar/nonpolar components;
- cleaning activity, corresponding to a large increase of humidity and of detergent perfumers (generally amines, alcohols, esters or ethers);
- cooking, corresponding to an increase of CO2 (in normal cooking burners), of humidity and of many volatile compounds such amines, amides, ketones (due for example to Maillard reaction) [18];
- burning, representing the most complex situation since in addition to CO2 and humidity, due to complete oxidation of the carbonic structures, also particulate matter is formed (smoke).

For an accurate discussion, a detailed description of the air composition for each activity should be performed through an elaborated chemical analysis or by using a set of expensive and specific sensors; however, the qualitative and quantitative determination of the atmosphere composition is beyond the scope of this work. The data output of this set of sensors show that MQ137 and MQ138 are described to be sensitive to hydrophilic compounds and to other similar small polar hydrophilic molecules without or with very low discrimination. Therefore, these sensors detect these activities, such as cleaning and cooking, affording to an increase of humidity and of volatile polar molecules concentrations, such as ketones, esters, alcohols, amines, etc., as resulted from the entries "meals preparation" and "cleaning" compared to "normal situation" of Tabs. II and III. The burning activity, according to the technical specifications, should be better detected by both MQ9 and MG-811 sensors, but if we compare their data on tables II and III at the entry "smoke presence" with respect to the entry "normal situation", we observe a better fit of data for the former than for the latter, whose measurements record a decay of the values of CO_2 upon burning; simultaneously, the other MQ sensors, MQ135 and 138, detect all the polar volatiles which are normally produced by a combustion confirming the activity. As a consequence, considering this preface and the confusion matrix plots, it is straightforward that one sensor is not able to discriminate with good accuracy the purposed activities (see Fig. 3), and not even a selection of two of them (Fig. 4 and Tab. V) with the best

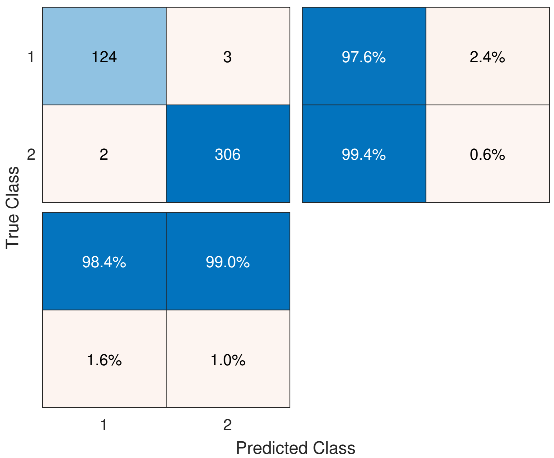

Fig. 7. Confusion matrix related to the “Normal situation classification”. Total accuracy 98.85%.

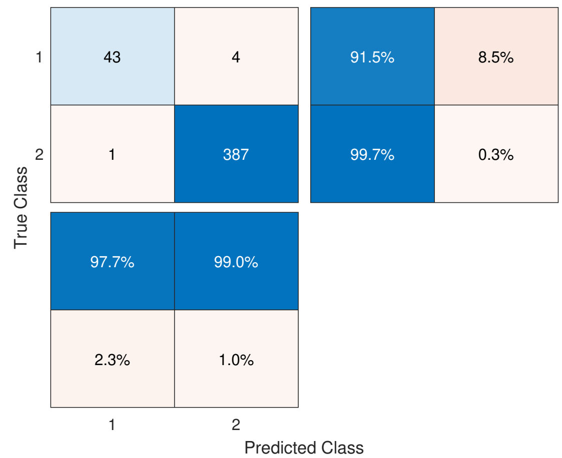

Fig. 8. Confusion matrix related to the “Smoke presence classification”. Total accuracy 98.85%.

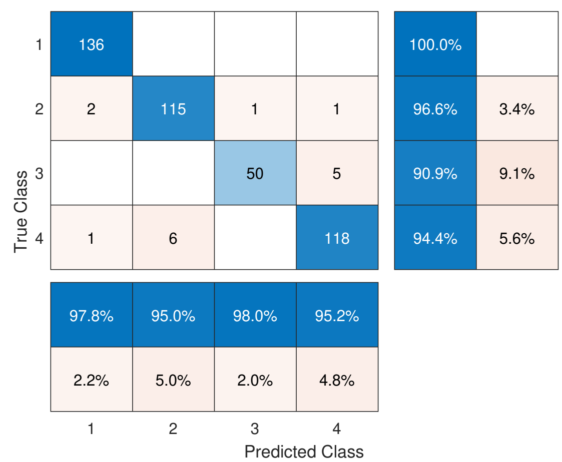

Fig. 9. Confusion matrix related to the “Single activity classification”. Total accuracy 96.32%.

performance for the match MQ9 and MQ135 (Fig. 6) whose accuracy approaches 97% for the “smoke presence” situation. The assembly of all the set of sensors allows a quite good discernment of the activities as shown in Figures 7, 8 and 9, with the worst performance in the entry “smoke presence”; however, the detection of this situation might be overcome by setting the alarm on the output of MQ9 and MQ135 sensors.

As regards an analysis of the risks associated with the use of the system proposed here, the sensors we adopted are with the lowest environmental chemical impact, as they do not deliver any substance in the air during their action or emit dangerous radiations. All of them are electrochemical sensors mainly based on sensitive material composed by metal oxides such as SnO_2, and just in a case we have a different sensing material the NASICON. They need a heater to activate sensing, but the working temperature is relatively low and electronically controlled. As concern the risk of the sensor’s damage, in the domestic contexts we evaluated activities which are not producing corrosive gases in a concentration which might be dangerous for the sensors. Moreover, the set of sensors are placed in order to avoid direct droplets or even splashing of water particularly harmful for these sensitive devices.

On conclusion, assemblies of an electrochemical sensors set, whose total cost is about 100,00 Euros, can be successfully applied in AAL systems for the detection of anthropic activities by approaching the method of implementation herein discussed.

V. Conclusion

This paper demonstrates the feasibility of the recognition of daily life activities in AAL, carried out through a system based on the classification process of the data generated by a set of economic gas sensors. The prototype allows for recognition of 4 different scenarios: normal situation, meal preparation, smoke presence, cleaning. A k-NN machine learning algorithm is applied to real-time dataset to predict current situation on the basis of historical data (classificatory knowledge). System accuracy is more than 96%, thus allowing to detect with high precision all the considered activities, including a possible dangerous situation. The proposed system is versatile and, after having properly trained the classifier, it can be applied to any environment, thanks to the combined use of air sensors and machine learning algorithms. Future work should improve system ability to detect the same activity even if it is performed in a different way or in a different room, but this implies the use of a larger training set. A further effort can be done to try to predict two or more situation that are performed in the same room at the same time. Activity recognition should guarantee people privacy by design, by using authentication and secure communication between sensors, IoT platform and end user device.

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