Letter

Miniaturized Pervasive Sensors for Indoor Health Monitoring in Smart Cities

Marco Carminati [1],*[ID]**, Ganesh R. Sinha** [2][ID]**, Samrudhi Mohdiwale** [3] **and Silvia L. Ullo** [4][ID]

1   Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, 20133 Milano, Italy
2   Myanmar Institute of Information Technology, Mandalay 05053, Myanmar; gr_sinha@miit.edu.mm
3   National Institute of Technology, Raipur 492010, India; smohdiwale.phd2018.it@nitrr.ac.in
4   Engineering Department, Università degli Studi del Sannio, 82100 Benevento, Italy; ullo@unisannio.it
*   Correspondence: marco1.carminati@polimi.it; Tel.: +39-02-2399-6102

Abstract: Sensors and electronics technologies are pivotal in several fields of science and engineering, especially in automation, industry and environment monitoring. Over the years, there have been continuous changes and advancements in design and miniaturization of sensors with the growth of their application areas. Challenges have arisen in the deployment, fabrication and calibration of modern sensors. Therefore, although the usage of sensors has greatly helped improving the quality of life, especially through their employment in many IoT (Internet of Things) applications, some threats and safety issues still remain unaddressed. In this paper, a brief review focusing on pervasive sensors used for health and indoor environment monitoring is given. Examples of technology advancements in air, water and radioactivity are discussed. This bird's eye view suggests that solid-state pervasive sensors have become essential parts of all emerging applications related to monitoring of health and safety. Miniaturization, in combination with gamification approaches and machine learning techniques for processing large amounts of captured data, can successfully address and solve many issues of massive deployment. The development paradigm of Smart Cities should include both indoor and outdoor scenarios.

Keywords: pervasive sensors; health; safety; miniaturization; indoor monitoring; environment; IoT

1. Introduction

In urban contexts, and especially during the cold season, the vast majority of people spend most of the time indoors (during school, working hours, free time and, of course, sleep time). Thus, monitoring of chemo-physical parameters which relate to the quality of indoor environments can have a significant impact on improving global health. Smart Environment Monitoring systems (SEM) [1,2] are implemented to keep track of the variation in various environment parameters such as air quality [1,3–9], water quality [1,2,10,11], radioactivity levels [1,12–14], sound pollution [15], etc. The main components of the SEM are sensors, signal processing and artificial intelligence (AI) techniques, with the sensors mainly implemented in solid-state smart [1–4] and wearable [16] forms, in wireless ambience, for monitoring, for instance, different types of water, air and radioactive pollutants.

Sensors are the most essential components of automated environment monitoring systems and play a significant role in guaranteeing public health and soil health. Pervasive sensors [3,4,16,17] are modern sensors, used in health monitoring and related applications, which have got in recent years a wide use due to miniaturization [18] and machine learning tools, for processing the sensor data through signal processing tasks and classification. Figure 1 shows the potential use of pervasive sensors and the environment factors which can be monitored and controlled with the help of these sensors. The monitored environment factors, as shown in Figure 1, such as air quality, temperature quality, humidity control, acoustic control, radioactivity control, etc. are those mainly prevailing in indoor environments and directly related to public health. Networks and systems constituting the

Internet of Things (IoT) have appeared to be of great help to keep monitoring the related health parameters, due to the necessity of bringing environmental factors under control.
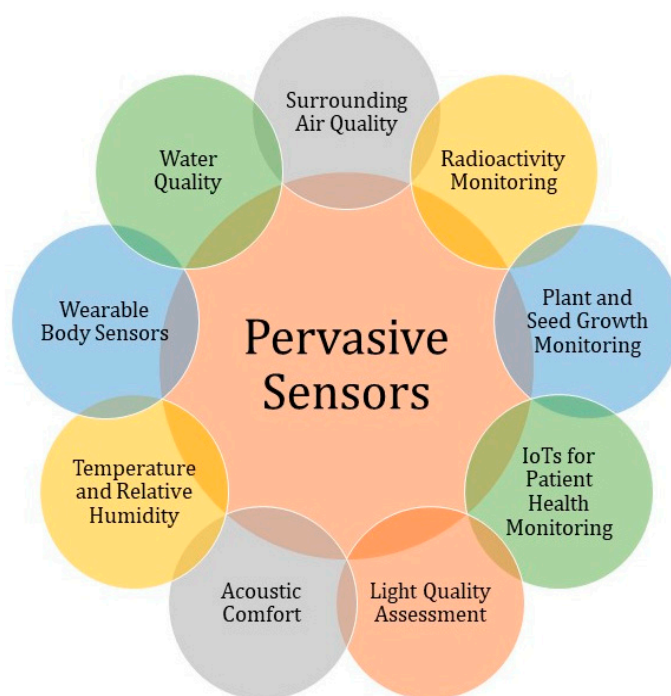
Figure 1. Map of parameters monitored in indoor urban environment by pervasive sensors for global health improvement by means of preventive medicine.

In addition, the advances in sensor design and technology are happening so fast and thus the compact and miniature IoT [1,10] products are developing in the useful direction for applications to indoor environment monitoring. Figure 2 shows the advances of the sensors in the last 25 years and we can see that the most recent and modern sensors are becoming robust and secure, which means that these IoT devices can merge the functionalities of many sensors in a robust way and can assist monitoring multiple environmental and health-related factors as never before.
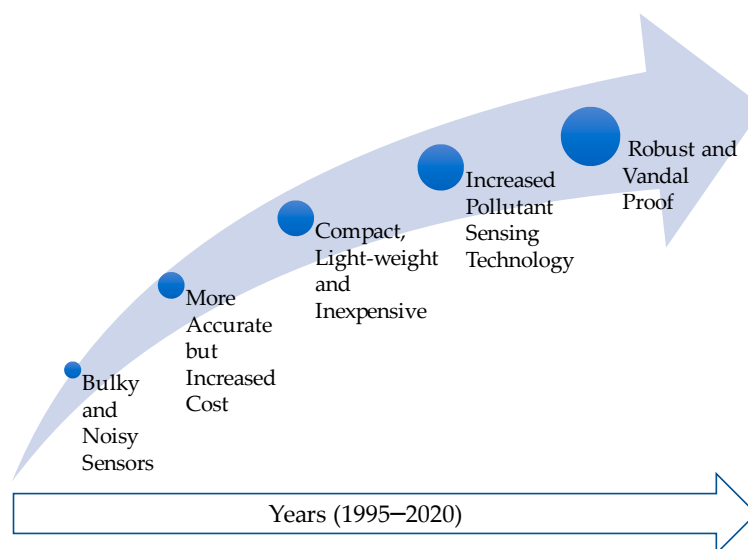
Figure 2. Evolution of trends in the development of sensors.

In this paper, studies and research on pervasive sensors have been briefly reviewed, with their advances, miniaturization achieved, use of machine learning and signal processing for augmented performance of sensor technologies, so that an effective health monitoring system can be developed in practice to ensure an improved control of health parameters in indoor environments.

2. Peculiar Aspects of Indoor Sensors Networks

The goal of this paper is to highlight the relevance, in particular for health and preventive medicine, of the application of IoT and wireless sensors networks (WSN) technologies to domestic indoor monitoring, while most WSN efforts are currently devoted to wide area networks (WAN) and street-level urban applications (traffic, mobility, pollution, waste management etc.). Although in this review we focus on domestic environments, similar considerations are valid also for industrial ones (developed within the industrial IoT and Industry 4.0 paradigms).

The main differences between indoor and outdoor sensing concern the properties of the network. Indoor sensing nodes are typically placed at shorter distance (thus adopting short-range radio protocols such as Zigbee and Bluetooth) and a radio infrastructure, such as Wi-Fi, is often already present in the apartment. While the latter aspects relax the challenges of wireless communication, indoor sensors are typically battery powered anyway, to avoid excessive cabling, and the daily data rate is on average higher than in outdoor SEM. Thus, despite the proximity to the grid, indoor sensors share similar low-power challenges with outdoor ones. Energy harvesting indoors can be more difficult than outdoors, since, for instance, the kinetic energy of water flowing in domestic pipes is smaller than in external pipelines or the power of lamps is clearly lower than the solar one.

The most common type of installation of indoor sensors is static. Domestic moving sensors can be embedded in portable and wearable devices, as well as on-board of moving robot such as autonomous vacuum cleaners. Participatory sensing and, in particular, gamification, i.e., the stimulation of the user to perform a mapping task by means of a ludic reward in a videogame, already successfully adopted for outdoor sensing, can also be adopted at building and apartment level to improve, for instance, the mapping of uncovered areas (such as common areas or basements) or to promote healthy habits.

Indoor sensors demand for integration with domestic ecosystems (such as Google Nest and Amazon Alexa) as well as safety devices, such as gas and smoke detectors, emergency monitors for elderly people and other wearable medical devices. Such an integration with "consumer" devices can bring the production volumes of these sensors into very large ranges (millions per month), thus making silicon foundry fabrication and application specific integrated circuits (ASIC) very attractive, not only for the miniaturization, but also from the cost point of view.
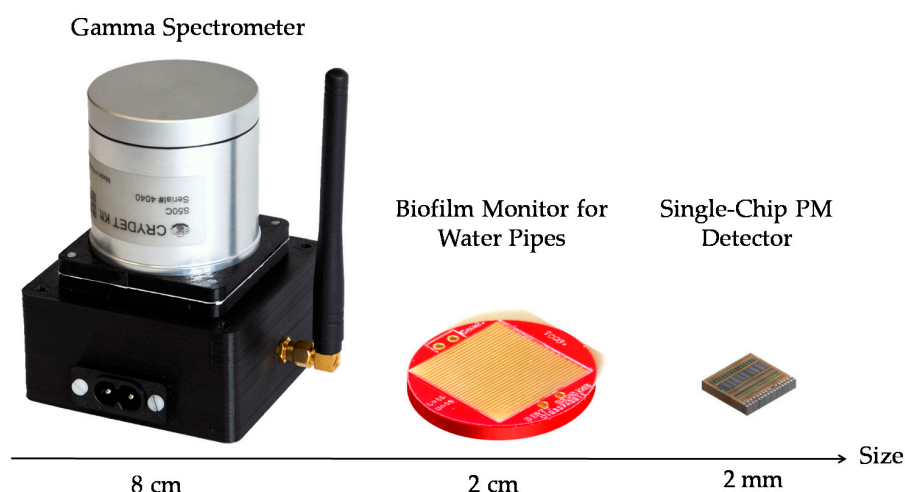
3. Water, Air and Radioactivity Monitoring

We begin the survey with three examples, showing a clear miniaturization trend. As is well known, a direct effect on human health is produced by the quality of drinking water and indoor air, especially in terms of the particulate matter (PM) and radioactive material concentrations. The general goal here is reducing the risks and increasing the safety of people in drinking and breathing through controlling these elements. As regards water, monitoring its quality at the tap is crucial to check the impact of the last section of pipes in the buildings, which might suffer aging and degradation over time. A miniaturized impedance sensor has been developed to track the status of the inner surfaces of pipes for the distribution of drinking water, based on the utilization of WSN [2]. Extensive data were collected in real time, in an experimental campaign carried out for a few months in the field (a pilot network of three nodes) in North Italy [2]. The same sensor, originally fabricated on rigid substrates [19], has later also been fabricated on flexible Kapton substrates, enabling its installation in pipes of small diameter (a few centimeters), typical of domestic networks and appliances [20].

As regards air monitoring, the different gases must be first identified, since its concentration impacts on the final air quality. Generally, this is affected by the combination of some gases such as NO_x and VOC, for instance, and the amount of PM, which is divided into different granulometric classes (PM_{10}, $PM_{2.5}$, etc.). Most efforts are carried out on the measurement of air quality in urban environments, and by means of networks based on the employment of compact solid-state instruments [3,4], and the same trend in the development of miniaturized sensors is benefitting also indoor monitoring (Figure 3).
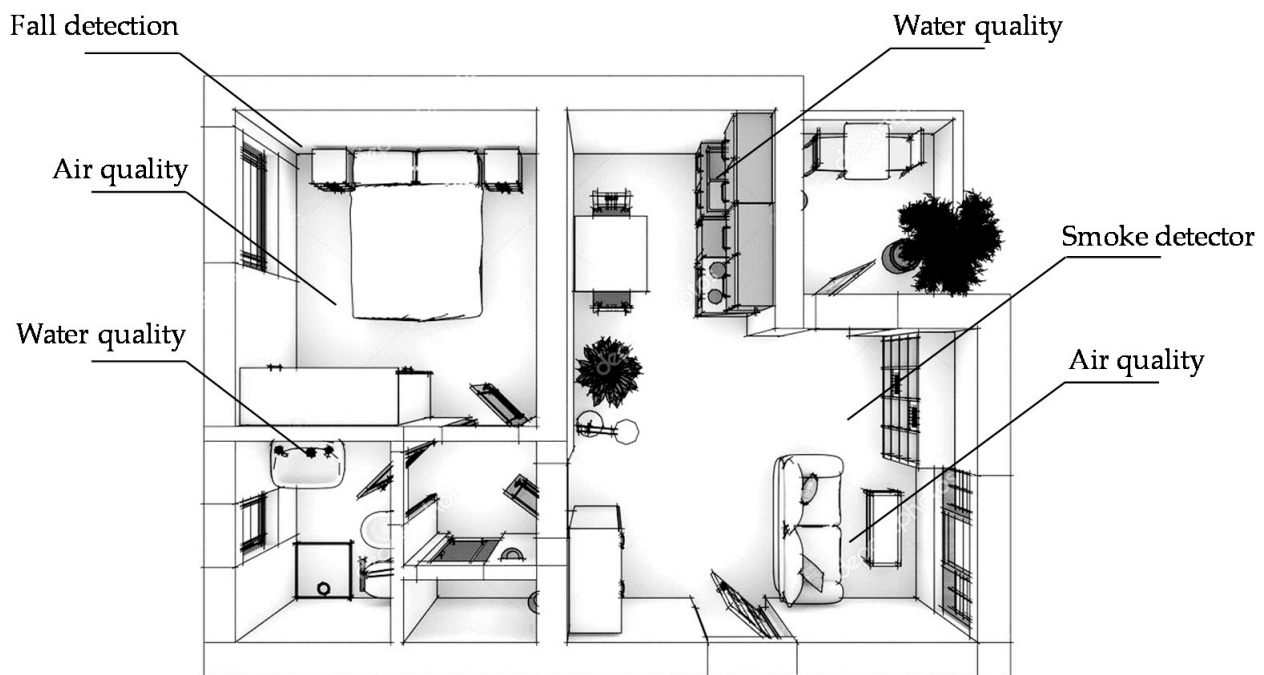
Figure 3. Indoor monitoring of health-relevant parameters such as air and water quality.

In indoor spaces, another factor affecting air quality is the presence of radioactive material which can stem from multiples sources, both of natural and anthropogenic nature. One of the most dangerous elements is Radon, a radioactive gas that, being heavy, tends to accumulate, especially in ground levels and basements of buildings. One way to measure Radon is to quantify the concentration of the solid elements in which it decays such as ^{214}Pb and ^{214}Bi. They emit gamma rays with different energies, the most relevant one around ~600 keV. It is possible to capture this particulate by means of a filter. Circulation of air through the filter is forced by a pump (with a few L/min flow rate). Then the filter is analyzed by means of a gamma spectrometer. Additionally, in this case, miniaturization is steadily advancing. In particular, the miniaturization of scintillator-based gamma spectrometers is enabled by the replacement of bulky and delicate photo-multiplier tubes (PMT) with silicon photo-multipliers (SiPM). Nowadays, very compact, USB-powered, self-contained spectrometers are available: when using a few SiPM pixels, the performance, cost and volume of the unit are dominated by the scintillation crystal (typically a 2" NaI) [21]. Such detectors (Figure 4) are so compact that can be either embarked on drones (for outdoor mapping) or carried around by hand (for indoor mapping) to scan rooms and basements (and thus install air ventilation systems where needed to reduce the accumulation of Radon).

Figure 4. Examples of miniaturized sensors for radioactivity [21], water [2] and air quality [3] monitoring of decreasing dimensions and increasing integration.

4. Literature Review: Trends and Impact

As discussed in the previous sections, smart and wearable sensors are of significant importance for environment monitoring and assessment of health-hazard parameters. These sensors belong to numerous application categories, which are developed as per the requirement and the factors to be controlled. Smoke detectors, fall detectors, noise control by means of microphones, motion/ambience control in a room are also important sensors that help in monitoring the health of persons, especially disabled and elderly persons, as the control can be achieved without any movement, by using portable, smart and IoT devices. In this paper, we have focused on pervasive sensors and their usage for health monitoring and studied the relevant literature consequently. The research on general purpose sensors is vast, but when referring in particular to indoor sensors, it is less extended, especially for health applications. Table 1 presents a summary of major and relevant contributions in the area of pervasive sensors used for monitoring different parameters and methods at this end.

Table 1. Advances in pervasive sensors for indoor health monitoring.

Title	Usage	Method	Salient Features and Limitations
Chemical exposure monitor (6,7)	Standard gas concentration measurement in workplace	Portable DRM apparatus using a photoionization detector (PID) and real-time location system (RTLS)	Calibration against certified isobutylene; direct reading of location using laser; risk due to chemical sensor
Low cost monitoring of emissions (8)	Monitoring of temperature, humidity, $PM_{2.5}$, PM_{10}, total VOCs ($\times 3$), CO_2, CO, illuminance and sound levels in indoor environment	Low Cost Environment Monitoring using Sensors	Customization and flexibility; monitoring of parameter variations; specific event based
Environmental sound classification (9)	Environmental sound monitoring; structured noise and sound events with strong harmonic contents	Hybrid deep learning model	Accurate monitoring, applicable in real time; non-stationary signals; different levels of sound pose difficulty
Wireless water quality sensing network (7)	Thin deposits in indoor water sources	Multi-parameter sensing node embedded system with miniaturized slime monitor	Biological and chemical stability; early warning functions; predictive maintenance; efficient process management; surface fouling
Trace-gases monitoring (10)	Traces of gases in surrounding atmosphere	Blind source separation method	Easy detection; accurate with minimum dependence criterion of independent component analysis

The implementation of sensors is affected by a number of challenges related to design issues, simulation factors, variation in supplementary parameters, and most importantly to the threats on the sensor networks. The wireless sensors are deployed over a network to constitute a WSN and many of the sensors are connected with the Cloud and therefore the network threats represent a big risk and a challenge also in modern pervasive sensors. However, the technologies have also been evolving with the advent of wireless and distributed sensors in the direction of combating these threats. Table 2 shows major types of threats and the technologies used in combating them. In this table, the reasons for the different types of threats are also discussed.

Table 2. Indoor health monitoring and security threats.

| Threat	Agent	Sensing Technologies		References
Biological	Aerosol	Physical detection principles	Light scattering	Challenges in detection, identification and monitoring of indoor airborne chemical-biological agents [2]
			Laser induced fluorescence	
			Flame photometric detection	
		Biochemical detection principles	Affinity based detection	
			Nucleic acid-based techniques	
Chemical	Chemical warfare agents (CWAs) and toxic industrial chemicals (TICs).	Resistive and Capacitive Electronic Gas Sensors		[2,15]
		Flame ionization detection		
		Infrared spectrometry		
		Photo acoustic spectroscopy		
		Photo ionization detection		
		Mass spectrometry		
Security	Inefficient existing security technology for big data; attacks, software vulnerabilities	Block chain		IoT and security challenges [1,10]
		Fog computing		
		Machine learning		
		Edge computing		

We can clearly see in Tables 1 and 2 that sensors are of great importance in health monitoring since they help in improving quality of life. Yet, at the same time, a few challenges are still there, which need more and more research to address and solve. In our study, one important observation has been made regarding miniaturization, the research on it, and the role of miniaturized sensors and devices especially for indoor health monitoring. For instance, monitoring of chemical exposure [2,8] has made possible by employing miniaturized components inside direct reading method (DRM) equipment such as photo-ionization detectors that could assist in measuring the concentration of gases and their behavior in the workplace. They represent real-time location systems (RTLS), able to detect the presence of gases down to a concentration of 0.2 ppm for open areas with a spatial resolution down to 13 cm, ideal for indoor workplaces [6,7]. Proper calibration and AI solutions can help in detecting any possible risks even in complex conditions, where the risk to workers is due to a combination of multiple factors.

A similar work on low-cost monitoring of emissions was explored in [15], in which the response is event-based. The value of the IEQ (indoor environment quality index) was maintained to a very satisfactory level, up to 85.5% in all conditions. In another interesting work [22], a *k*-Nearest Neighbor (*k*-NN) and a deep neural network were employed for the classification of sounds, useful for monitoring noise pollution. The classification of sounds into desirable spectral components and noise components was made very smartly with the help of a deep architecture of neural networks. Accurate monitoring, suppression of unwanted harmonics and 95.8% of classification accuracy are among salient contributions of this work.

In another peculiar work for detecting gases-traces, a blind source method was used. Easy detection with good accuracy was achieved with minimum dependence criterion of independent component analysis. The correlation coefficient was observed as close to 0.96 for NO_2 gas and 0.91 for SO_2 gas, which indicates satisfactory performance of the method for detecting traces of gases in [23] in open environments. The method reaches a good performance and can be easily transferred to indoor environments.

Table 2 mainly highlights various types of threats and the technologies used to combat these threats. The main reason for biological threat was reported due to aerosol, where a number of physical and biological detection principles are studied. Light scattering method, laser induced fluorescence technique, flame photometric detection method and nucleic acid-based techniques were mainly reported to address these threats [2], with a maximum possible value of correlation and correction as 80%. Then, chemical risks due to emission and flow of toxic gases and chemical substances, representing a major threat in indoor environment, can result from a number of electronic appliances such as refrigerator, air conditioner etc.; resistive and capacitive electronic gas sensors; infrared spectrometry; photo-acoustic spectroscopy; photo-ionization detection; and mass spectrometry are main technologies for addressing the threat issues due to chemicals [2,15]. Another threat for network deployment is security: it can pose a great challenge in breaching the security of individuals when the sensor network is implemented in indoor applications. In addition to hardware cryptography, block chain, edge computing, machine learning and fog computing are major technologies that enable enhanced security in WSNs.

From Figure 5, reporting the number of publications with the indicated keywords (red and blue lines), it is evident that the research on miniaturization for indoor pervasive sensors has reached limited results with respect to that for pervasive sensors in general. It is likely that the number of research contributions is increasing very year, as plotted in Figure 5. Therefore, we can see how miniaturization is taking place steadily on sensor technologies, but there are still wide margins for further exploration in this research area.
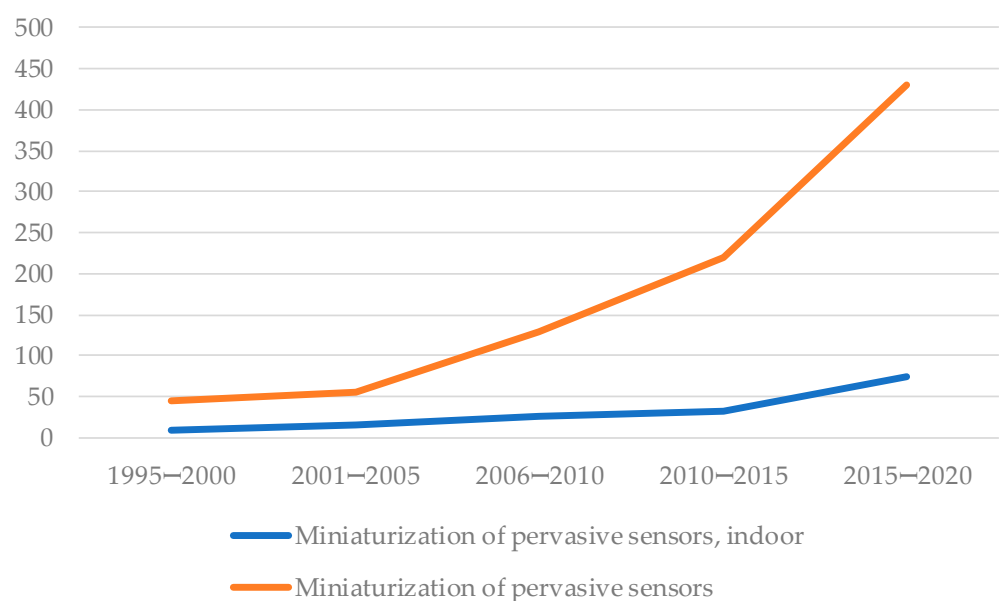

Figure 5. Recent trends in miniaturization of pervasive sensors emerging from the literature, expressed in number of publications for the specified keywords along the years.

5. Machine Learning

In recent years, the adoption of statistical techniques and in particular of machine learning (ML) has flourished in multiple fields. It has started playing a significant role in automated processing of large amounts of data collected by sensors and WSNs. Data are captured through various sensor nodes present in the WSN and proper signal processing is

employed to extract meaningful information from data and perform the appropriate tasks accordingly. Here, the role of ML techniques is of utmost importance while calibrating and interpreting acquired data. ML helps to understand the data and to extract a number of features which are subsequently used in classification and decision-making tasks that ultimately help control various parameters of health and environment.

If a mathematical model of the monitored process is available, along with an estimation of uncertainties of the model and of the measurements, the optimal tool to merge data is the Kalman filter [24]. Unfortunately, very often a model is unknown and ML techniques can be adopted. As shown in Figure 6, the main goal of the ML classifier is to process the signals from the heterogeneous sensors in order to assess in real time the level of risk. Additional inputs (such as the number of persons in the house, meteorological conditions etc.) can be combined as well. In some cases, in addition to displaying quality indicators (and warnings/alarms) to the user, if actuators are also available, the algorithm can activate some counter actions (such as ventilation of the basement, cleaning of the pipes, purification of the air in the room etc.) in a closed-loop manner.
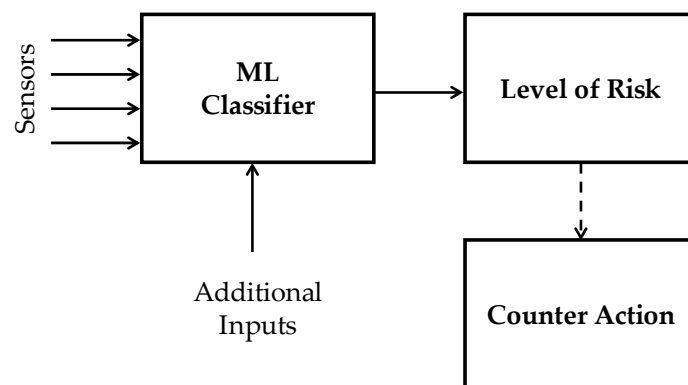
Figure 6. Role of Machine Learning (ML) in extracting features and classifying a level a risk from the sensors signals in a SEM.

Very interestingly, beyond the local use of the SEM outputs (for individual room, apartment), a hierarchical structure of classifiers can be adopted for utilities, such as drinking water, involving different apartments, at building level, thus enabling interesting functions such as predictive maintenance. Building Area Networks (BAN) are being developed to support this type of distributed sensing infrastructure [25].

ML techniques can be grouped into supervised and unsupervised algorithms according to the learning approach. Among supervised ones, Support Vector Machines (SVM), k-NN and Decision Trees (DT) are the most common ones. Although SVM can better cope with outliers, when the amount of training data is larger than the number of features, as usual in this context, k-NN is preferable. DT and k-NN offer similar performance, but the computation cost of k-NN (computing the distance between fresh data and all previous measurements) is much higher. In conclusion, DTs (also organized in Random Forests) represent the best choice for processing the signals of pervasive indoor sensors. Furthermore, DT can be efficiently implemented in low-cost digital embedded devices such as microcontrollers [26].

The most successful family of unsupervised methods are those based on neural networks [27–30], whose detailed description is beyond the scope of this review. In the context of the proposed study, miniaturization of sensors and their management over a WSN can be effectively carried on and an optimal use of resources can be achieved through ML techniques. The huge amount of data is in fact a major concern in real-time application of various pervasive sensors, despite big data tools attempting to address these issues. The contribution of deep learning using either convolutional neural networks (CNN) or any other deep neural technique, can create significant impact in handling large amount

of data and their processing. The problem of huge data may seem not to be there in an indoor environment for the limited applications, but it may arise when several units are hierarchically networked. Finally, Principal Component Analysis (PCA) is a consolidated technique for reduction in data dimensionality by simply applying a linear transformation to samples (that maximize the information conveyed by them), can be applied in this context as well.

6. Conclusions

In this short review we have discussed some technological trends, based on several case studies selected from the literature, in the development of pervasive sensors. Miniaturization of solid-state sensors for monitoring human activity and safety through the local and real-time measurement of chemo-physical parameters (such as water and air [31]) of the surrounding environment and the increasing relevance of machine learning in automatic interpretation of large amounts of acquired data from wireless sensors networks are turning out to be two key elements for the success of this paradigm.

The motivation of this work is to put in focus the relevance of the application of these technologies to indoor monitoring (as opposed to outdoor urban and rural monitoring [32]), especially in smart cities scenarios. For instance, a very recent and interesting result reports that in different cities across the world there has been a small but consistent increase in NO_2 and VOC levels indoors during lockdowns [33]. Novel concepts of smart building networks integrating eco-systems of wearable and positioning devices are emerging [34] and should be further merged with hardware advancements. Domestic safety and comfort a key factor to public health and preventive medicine. In fact, early and automated diagnostics of unsafe or unhealthy personal home conditions can enable fast and effective response and, thus, reduce the pressure on the public healthcare system. Such a relevance has also been dramatically highlighted by the health and socio-economical effect of the current COVID-19 pandemic.

Author Contributions: All authors equally contributed to conceptualization and paper writing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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