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Enabling Human Centric Smart Campuses via Edge Computing and Connected Objects

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I turned to look but it was gone
I cannot put my finger on it now
The child is grown,
The dream is gone.
I have become comfortably numb.
— Pink Floyd, Comfortably numb (1979)

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 50,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 40 figures.

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Acknowledgements

The PhD is a profound life experience, a real school of life that challenges not just your technical skills as a researcher, but your most in depth philosophical existence.

The PhD is a world of endless possibilities, a fascinating chaos you and only you can learn how to dominate in time. Research is for truth-seekers, for those who constantly challenge the present and move progress further.

The PhD experience is also about facing loads of constraints, from the most granular technical ones to broader concepts of social and political views. You get to face all of them, over and over again, you will end up feeling disappointed, not honest to yourself and your own values. But at some point you will learn, that a doctorate such as it is life, is a question of balance. Being able to face constraints will no longer be a disappointment, but a strength.

The PhD has been all of this to me, and I hope that my words will inspire those who enter this amazing and intricate world for the very first time.

I would like to thank everyone who has supported me during this journey, my first supervisor Prof. Paola Salomoni for her guidance and my second supervisor, Prof. Giovanni Pau for the priceless support and mentoring. I would also like to thank my tutor, Vittorio Maniezzo and the whole research group, with a special thanks to Prof. Silvia Mirri for her constant help, feedback and time. Last but not least, a huge thanks to my dear parents Oriana and Giuseppe, and my partner Oxana, for everything.

So long, and thanks for all the fish.

Abstract

The design of non-domestic buildings has been changed along the history. One century ago offices, hospitals, schools and Universities were physical structures suitable for hosting people, supporting basic services such as gas, electrical system and water. Nowadays, buildings are designed and built in a dynamic, smart and technically more complex way. The development and evolution of buildings revolve around adding value to the same, and this depends on the context and category of the building. Traditionally, the need arises from issues relating to the cost of the building (including its maintenance) during its life, the performance, satisfaction and comfort of the people who live there. Modern buildings, where people usually spend 90% of their life, are therefore designed and managed to meet the challenging environmental, business and human needs, and this forms the concept of the "Smart Building". In recent years, this term has been used to indicate a building equipped with a network of devices to improve energy efficiency, on the one hand, and to make the lives of those who live there more comfortably, on the other hand. Early definitions of Smart Building focused almost entirely on the technology aspect and did not suggest user interaction at all. Indeed, today we would attribute it more to the concept of the automated building. In this sense, control of comfort conditions inside buildings is a problem that is being well investigated, since it has a direct effect on users' productivity and an indirect effect on energy saving. Therefore, from the users' perspective, a typical environment can be considered comfortable, if it's capable of providing adequate thermal comfort, visual comfort and indoor air quality conditions and acoustic comfort.

In the last years, the scientific community has dealt with many challenges, especially from a technological point of view. For instance, smart sensing devices, the internet, and communication technologies, have enabled a new paradigm called Edge computing that brings computation and data storage closer to the location where it is needed, to improve response times and save bandwidth. This has allowed us to improve services, sustainability and decision making. Many solutions have been implemented such as smart classrooms, controlling the thermal condition of the building, monitoring HVAC data for energy-efficient of the campus and so forth. Though these projects provide to the realization of smart campus, a framework for smart campus is yet to be determined. These new technologies have also introduced new research challenges: within this thesis work, some of the principal open challenges will be faced, proposing a new conceptual framework, technologies and tools to move forward the actual implementation of smart campuses. Keeping in mind, several problems known in the literature have been investigated: the occupancy detection, noise monitoring for acoustic comfort, context awareness inside the building, wayfinding indoor, strategic deployment for air quality and books preserving.

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Chapter 1

Introduction

The design of non-domestic buildings has been changed along the history [41]. One century ago offices, hospitals, schools and Universities were physical structures suitable for hosting people, supporting basic services such as gas, electrical system and water. Nowadays, buildings are designed and built in a dynamic, smart and technically more complex way. As described in [219], the development and evolution of buildings revolve around adding the value of the same, and this depends on the context and category of the building. Traditionally, the need arises from issues relating to the cost of the building (including its maintenance) during its life, the performance, satisfaction and comfort of the people who live there [211]. Increasing awareness of the problem of climate change and increasingly stringent regulations have made the reduction of energy consumption a factor in itself [199], as well as a significant design criterion. The energy consumption within buildings represents approximately 40% of the total world energy consumption [20], moreover, they are also responsible for about 36% of the total worldwide carbon dioxide (CO2) emissions [170]. In fact, energy efficiency, the integration of renewable energies and the suitable use of energy inside buildings are topics that are being widely investigated from both scientific and technical perspectives as explained in [115]. As suggests in [62], three keys in order to keep smart and evoluted buildings are the following ones: (i) *longevity*, (ii) *energy and efficiency*, and (iii) *comfort and satisfaction*

[87, 270]. Therefore, an advanced building will have its energy consumption reduced to a minimum, constantly allowing the maximization of the performance, comfort and satisfaction of its occupants over a long life.

Modern buildings, where people usually spend 90% of their life [115], are therefore designed and managed to meet the challenging environmental, business and human needs, and this forms the concept of the *smart building* [41]. In recent years, this term has been used to indicate a building equipped with a network of devices to improve energy efficiency, on the one hand, and to make the lives of those who live there more comfortably, on the other hand. There has been a myriad of academic literature since the '80s discussing this definition, as described in the review paper [249]. Early definitions of smart building focused almost entirely on the technology aspect and did not suggest user interaction at all [96, 248, 185]. The motivation is due to the fact that the proposal was made by architects and construction engineers. Indeed, today we would attribute it more to the concept of the automated building. In this sense, control of comfort conditions inside buildings is a problem that is being well investigated, since it has a direct effect on users' productivity [216, 217, 78, 109] and an indirect effect on energy saving [253, 254, 56]. Therefore, from the users' perspective, a typical environment can be considered comfortable, if it's capable of providing adequate thermal comfort, visual comfort and indoor air quality conditions [74] and acoustic comfort [28].

Since their foundation, Smart Buildings have played an important role in both public and private sectors, allowing employees to return to work, and for shops and public buildings to open their doors once more. At the time of writing this thesis, the spread of SARS-CoV-2 and consequently the global emergency to contain the virus and safeguard people has created the need for further expansion and convergence of Smart Building technologies. It has almost drawn a new meaning to the security role of Smart Buildings, now able to make adjustments to HVAC systems, monitor social distancing, and manage building occupancy levels. The current pandemic that has hit us has shown that the Smart Building industry can help in more ways than simply through security and energy management, but also providing occupants' comfort definitely changing the way we interact with the buildings.

People live in a social context, they have emotions, opinions and behaviors. The pain experience, pleasure satisfaction, comfort and discomfort, and the environments can affect their health and performance [180]. As is well known in literature, the positive effects of a comfortable *thermal* and *visual* environment, high *air quality* and *noise nuisance reduction* on the occupants' health, comfort, and performance have been largely documented [31, 32, 143, 145]. In this sense, users' comfort will be defined, categorized and described below in accordance with the literature [74].

Acoustic Comfort

The absence of acoustic comfort as well known as noise nuisance or noise pollution. It is excessive noise or disturbance that may have a negative effect on health or the quality of life. The causes of noise pollution are attributable to population growth, urbanization and the growth associated with the use of increasingly more powerful and varied noise sources, including motorway, rail and air traffic, which are considered as one of the main sources of environmental noise [221, 222]. In particular, given the increasing spread of urbanization and road, rail and air traffic, the problem of noise pollution is constantly expanding [8], producing negative effects from different points of view, affecting social, economic and work aspects [218, 106], thus entailing a wide range of extra-auditory disturbances. However, greater awareness in planning and improved standards of construction can help mitigate potential noise problems. The noise profile of an area should be considered when designing and constructing buildings. The local topography, the location of buildings, their orientation and construction should be planned strategically to minimise the potential impact of noise disturbance, either on the development, between different parts of the development or caused by the development. Research has shown that well-designed sound environments in offices or schools help to improve concentration and enable better communication [263, 108]. Learning is more effective and less tiring when students can comfortably hear and understand their teacher. In hospitals, reducing the stress and sleeplessness created by high noise levels helps patients recover faster and facilitates the work of the staff. In our own homes, protection from noises contributes to a sense of security and privacy. Moreover, researchers found that there is a direct relationship between acoustic comfort and occupant productivity in commercial buildings [118] and with growth in open-plan offices, issues of acoustic comfort and privacy have been identified as significant issues impacting on occupant productivity [225].

Some standards to address the problem at the government level have been implemented, as in the case of The *National Planning Policy Framework (NPSE)* in UK, that incorporates provisions on noise, demanding that local planning policies should protect against noise giving rise to "significant adverse impacts on health and quality of life," and recognizing that planning policies should adequately identify and protect existing quite environments.

According to Sundstrom [225], that demonstrates how acoustic comfort brings the following benefits to the occupants:

- to improve the environment and job satisfaction of occupants;
- to facilitate the performance and the productivity of people inside the building;
- in general, to ensure better healthcare.

Air quality

Air quality is defined as a function of the degree to which human necessities are satisfied. In essence, the occupants of a building demand first of all (i) to perceive fresh air, instead of a vitiated, and (ii) to know that the health risk which could be derived from breathing that air is depreciate [70]. Therefore, the concept of poor air quality, could be defined as the possible appearance of health problems and lack of comfort for the users as expressed in [24]. Generally, particulate matter (PM), CO_2, carbon dioxide and so on are the main water from human respiration and the number of pollutants inside the building will vary depending on the load and number of occupants. Therefore, the building needs to have a mechanism to accurately assess the indoor pollutants and vary the rate of introducing outdoor air accordingly. As described in [247], air quality is an important argument that has both short term and long term impacts on the health of occupants. There are two common approaches in building design that are employed in order to give out air quality inside a building. The first one is by reducing the source of pollution within and outside the building to make fewer pollutants in the indoor air. The second one is to use and increase the ventilation rate which in turn reduces air pollutants [65]. One of the areas of research in literature wonders about nature ventilation. In fact, researchers demonstrate how using a designed natural ventilation system has the potential to provide considerable energy savings from cooling needs [35]. The air quality is really important for people and the researchers found that there is a relatively new concept in the framework of building use and construction, the so called *Sick Building Symptom*. It describes a medical condition where people in a building feel unwell for no apparent reason. The symptoms tend to increase with the time people spend in an uncomfortable indoor environment, and tend to disappear when the person leaves the building. Such a syndrome results in a substantial disruption of people's work performance and personal relationships, and considerable loss of productivity. It has been shown in the literature that the causes can be both psychological and largely due to inadequate air quality [68]

Moreover, in reference to European standards, such as *prEN13779 2007* [5] that was born with the aim of standardizing the design and implementation of ventilation systems for buildings subject to human occupation. Another European standard is the *prEN15251 2007* [4], which specifies the indoor environmental parameters which have an impact on the energy performance of buildings. So, air quality could be classified by CO2 concentration since it's the main chemical compounds that are emitted from human respiration (bio-effluent) and can be classified into four categories as shown in Table 1.1.

Category	Description	range (ppm)	value (ppm)
IDA 1	high indoor air quality	<= 400	350
IDA 2	Medium indoor air quality	400-600	500
IDA 3	moderate indoor air quality	600-1000	800
IDA 4	low indoor air quality	>1000	1200

Table 1.1 Indoor air quality (IDA) expressed in Table A.10 — CO2-level in the tech paper [5].

According to the literature cited above, air quality should take on these responsibilities:

- to improve the healthcare of the building's occupants;
- to prepare methodologies and techniques for energy saving;
- to avoid the sick building syndrome.

Thermal Comfort

The international standard ISO7730-2005 [104] and the American national standard ASHRAE55-2010 present methods for predicting the general thermal sensation and degree of discomfort (thermal dissatisfaction) of people exposed to moderate thermal environments. In accordance with these, thermal comfort can be defined as *perceived level of well-being* or *A condition of mind which expresses satisfaction with the thermal environment* [77]. However, this definition can be considered ambiguous, in fact, terms such as *perceived level* and satisfaction emphasizes that comfort is a subjective process determined by several kinds of mechanisms such as physical and psychological. Prediction of the range of temperatures for this comfort condition is complicated and apart from cultural influences it depends on environmental, exogenous factors such as the season of the year and personal factors. However, several studies in this area confirm that people choose similar temperatures under similar conditions of physical activity, humidity air velocity and clothing (the American national standard

ASHRAE-2009). Many authors have investigated the issues of the thermal comfort condition [239, 95, 253, 76]. Starting from the study developed by Professor Ole Fanger based on research undertaken at Kansas State University and the Technical University of Denmark, suggests thermal comfort can be expressed in terms of *Predicted Mean Vote* (PMV) and *Percentage People Dissatisfied* (PPD). The research was carried out to find out if people felt comfortable in different conditions and this was used to develop equations that would predict comfort. After that, during years different adaptive thermal comfort models and standards had been implemented such as the American ASHRAE 55-2010 standard, the European EN15251 standard, and the Dutch ATG guideline. Today, these standards are increasingly used in research and in practice within the field of thermal comfort.

Research in thermal comfort integrates several sciences in a horizontal and interdisciplinary way. In fact, a collection of proficiencies, researchers and various professional figures such as engineers, psychologists, architects and designers collaborate with each other. According to Raw and Oseland [191] there are six reasons for developing knowledge in the field of thermal comfort:

- control over the indoor environment by people;
- affecting the work efficiency of the building occupants discussed in [119];
- improving indoor air quality discussed in [57, 178];
- achieving energy savings;
- reducing the harm on the environment by reducing pollution production;
- reasonable recommendation for improving or changing standards.

Visual Comfort

In general, humans receive the most information through sight and light is an essential element in order to discriminate colours, shape and perspective of different objects. Therefore visual comfort is also an important factor that involves the provision of natural light, external views, reduction of glare and so on. Built-environment, are often not tailored to meet individual visual comfort needs. Therefore, meeting the need for personalized visual comfort whilst achieving energy efficiency in the open-plan office environment has been an open challenge. Within the smart building, the preferences of occupants vary dynamically over time, and several factors attribute to this dynamic change in visual preferences [84] such as indoor lighting conditions, outdoor climate, the psychological and physical condition of individuals. In this sense, visual comfort can be defined as a subjective condition of visual well-being induced by the visual environment as defined in [3]. Even if the definition assumes a physicological side, some properties of the visual environment can be used to estimate it in an objective way [84]. Luminance distribution, illuminance, colour of light, colour rendering, glare, flicker rate and amount of daylight are some of these properties. The international standard UNE EN 12464-1 makes reference to the lighting of indoor workplaces [81]. Moreover, visual comfort permits to improve the awareness inside the buildings facilitating visual tasks.

According to the international professional engineering association CIBSE 2002 [3], visual comfort should satisfy the following main tasks:

- to ensure the safety of people in the environment;
- to facilitate the performance of a visual task;
- to aid in the creation of an appropriate visual environment.

This chapter is organised as follows: an introduction that includes the definition of users' comfort from several orientations and attitudes. Open issues and research questions are presented in section 1.1 and then, contributions and thesis outline and the list of publications are exposed in section 1.2 and 1.3 respectively.

1.1 Open issues and research questions

The section above documented how occupant comfort and well-being are affected by Indoor environmental quality (thermal, visual, acoustic and air quality). The literature has highlighted that the relationship between IEQ and the well-being and comfort of occupants and how complex this relationship is. However, people spend more than 90% of our life indoors, it is important to understand it and act accordingly. Based on the literature, it is important that designers and engineers need to take into account a range of factors such as sick building syndrome, thermal, visual and acoustic comfort. Literature suggests that smart building designs don't automatically guarantee that the building designed will be comfortable and ensure occupant well-being. More specific and in-depth consideration of occupant well-being is required along with the impact on building efficiency and sustainability. Just designing a potentially comfortable building is not enough. One also needs to monitor building and occupant performance during its operations. In this context, it's necessary to take into account that smart building could have specific roles and goals, hence their occupants would have some distinctive needs and related comfort conditions. One of these interesting cases is represented by the University campuses.

The *smart campus* topic has been widely explored in the last 30 years, both from Academia and the industry. As described above, state-of-the-art has discussed whether or how the so called *Ubiquitous Computing* has become accessible every day and how the advancements in this discipline would translate the smart campuses into reality. In the last years, the scientific community has dealt with many challenges, especially from a technological point of view (low power sensors design, software interfaces design, communication protocols, etc.). This has allowed us to improve services, sustainability and decision making. Many solutions have been implemented such as smart classrooms, controlling the thermal condition of the building, monitoring HVAC data for energy-efficient of the campus and so forth. Though these projects provide to the realization of the smart campus, a framework for the smart campus is yet to be determined.

These new technologies have also introduced new research challenges: within this thesis work, some of the principal open challenges will be faced, proposing a new conceptual framework, technologies and tools to move forward the actual implementation of smart campuses. After three decades of works in this context, there are several interesting issues that have still to be faced to have smart campuses parts of our daily life. Keeping in mind, several problems known in the literature have been investigated: the occupancy detection, noise monitoring for acoustic comfort, context awareness inside the building, wayfinding indoor, strategic deployment for air quality and books' preservation. All the works presented in this thesis refer to a conceptual framework that will be exposed in the next chapter.

In order to overcome the aforementioned research challenges, the following research questions (RQs) are explained, with the goals of achieving a human-centric comfort-oriented smart campus. Then, there will be the main research question and other research question associated with it as explained below:

RQ-MAIN. *How to define a conceptual framework for building a comfort-oriented smart campus?*

RQ-1a. *How to recognize human occupancy inside a smart campus in order to improve human comfort and energy saving?*

RQ-1b. *how to perform transfer learning to predict the utilization of another room with limited training data?*

RQ-2. *How to monitor acoustic noise with low-end devices in order to improve the acoustic comfort within a smart campus?*

RQ-3. *Which are the Human-Smart Building-Interaction methodologies in order to improve the community awareness inside a campus?*

RQ-4. *How to provide support for moving around a University Campus?*

RQ-5. *How to deploy sensors in a smart campus to collect environmental data in a more accurate and effective way?*

RQ-6. *How to find strategies to stem the problem related to the books preserving?*

1.2 Contributions and outline

Given the background concepts, ideas and theories exposed above, A detailed overview of the work done with this thesis will be provided below, highlighting the contribution to the smart building and especially the smart campus field. This thesis is organized into nine parts.

Chapter 1 in the first chapter, the context of this thesis introduces at first, and then the motivations are given. It presents the definition of users' comfort and open issues and research questions are summarised. Lastly, the list of publications done during my Ph.D. is listed.

Chapter 2 many solutions have been implemented such as smart classrooms, controlling the thermal condition of the building, monitoring HVAC data for energy-efficient of the campus and so forth. Though these projects provide to the realization of the smart campus, a framework for the smart campus is yet to be determined. So, the second chapter of this thesis therefore focuses on preparing a conceptual framework and therefore on the concept of Human-Centric Comfort-oriented Smart Campus, aiming to answer the research question *RQ-MAIN*.

Chapter 3 this chapter focuses on the problem called the occupancy detection problem, in fact, knowing the position of people in a building is an important information, since it enables smart behaviours like understand the best distribution of classrooms based on the number of students or lighting on the room when someone is inside or shutting the lights off when nobody is. Nowadays, a good occupancy detection technology, cheap but accurate at the same time, is still missing, making this one of the most relevant topics in smart campus conferences. With respect to this topic, this thesis experiments the usage of RGB and depth cameras on the edge in order to have a cheap, accurate and GDPR compliant device for human comfort. This chapter aims to answer the research question *RQ-1a* and *RQ-1b*.

Chapter 4 Noise pollution is one of the most serious and underestimated environmental problems. According to the World Health Organization, noise pollution from traffic and other human-activities, negatively impacting the population health and life quality. In this chapter, machine learning models are used to obtain data from low-cost devices as close as possible in terms of accuracy to calibrated phonometer. The goal of this chapter is to answer the research question *RQ-2*.

Chapter 5 such a system acts as a proof of concept of the importance of considering the community members as key players of a smart campus, not only as passive beneficiaries but also as active contributors. In this chapter, in order to prove our concept we deployed an IoT infrastructure to gather data about different environmental conditions, concerning both indoor and outdoor phenomena, and we designed and put available with a public installation a rich web-based interface, to let students interact with hyperlocal data. This chapter aims to answer the research question *RQ-3*.

Chapter 6 moving across a University campus (outdoor, among the buildings, and indoor, among classrooms and offices) could represent a barrier for students with disabilities, affecting their independence while they conduct their daily activities. In this chapter is presented a system based on beacon technology, design and develop to equip student with and indoor navigation system that support campus' occupants in finding classes, lab, libraries and other significant places. This chapter aims to answer the research question *RQ-4*.

Chapter 7 according to the literature, a building needs to have a mechanism to accurately assess the indoor pollutants and vary the rate of introducing outdoor air accordingly so as not to have health problems and lack of comfort for users. In this chapter we present a preliminary experiment based on a single line of sensors, showing interesting insights into the actual open challenge of air pollution modeling techniques validation, taking into account the effects of air pollutant emissions sources, meteorology, atmospheric concentrations and urban vegetation. This chapter aims to answer the research question *RQ-5*.

Chapter 8 monitoring environmental conditions can provide great benefits, allowing users to be aware of ambient parameters, such as temperature, humidity, pressure, lights, pollution, etc. Collecting and measuring such kind of information means that, after adequate analyses, specific actions can be decided and applied by policymakers in urban scenarios and in public smart buildings, with the aim of improving humans' comfort. Hence, in this chapter we exploit IoT and smart objects that can play a strategic role in equipping smart buildings with systems devoted to such monitoring activities. This chapter aims to answer the research question *RQ-6*.

- **Chapter 9** draws conclusions and paves the way for future contributions.

1.3 List of publications

The list of publications are the following:

- S Mirri, C Prandi, P Salomoni, L Monti, *"Social location awareness: A prototype of altruistic IoT"*, in 8th IFIP International Conference on New Technologies, Mobility and Security (NTMS 2016);
- S. Mirri, C. Prandi, P. Salomoni, L. Monti, *"Fitting like a GlovePi: A wearable device for deaf-blind people"* in 14th IEEE Annual Consumer Communications & Networking Conference (CCNC 2017);
- D. Aguiari, C. Contoli, G. Delnevo, L. Monti, *"Smart Mobility and Sensing: Case Studies Based on a Bike Information Gathering Architecture"* in International Conference on Smart Objects and Technologies for Social Good (GoodTechs 2017);

- L. Monti, G. Delnevo, S. Mirri, P. Salomoni, F. Callegati, *"Digital Invasions Within Cultural Heritage: Social Media and Crowdsourcing"* in International Conference on Smart Objects and Technologies for Social Good (GoodTechs 2017);
- G. Delnevo, A. Melis, S. Mirri, L. Monti, M. Prandini, *"Discovering the City: Crowdsourcing and Personalized Urban Paths Across Cultural Heritage"* in International Conference on Smart Objects and Technologies for Social Good (GoodTechs 2017);
- R. Tse, L. Monti, C. Prandi, D. Aguiari, G. Pau, P. Salomoni, *"On assessing the accuracy of air pollution models exploiting a strategic sensors deployment"* in International Conference on Smart Objects and Technologies for Social Good (GoodTechs 2018);
- L. Monti, S. Mirri, C. Prandi, P. Salomoni, *"Smart Sensing Supporting Energy-Efficient Buildings: On Comparing Prototypes for People Counting"* in International Conference on Smart Objects and Technologies for Social Good (GoodTechs 2018);
- L. Monti, C. Prandi, S. Mirri, *"Iot and data visualization to enhance hyperlocal data in a smart campus context"* in International Conference on Smart Objects and Technologies for Social Good (GoodTechs 2018);
- G. Delnevo, L. Monti, F. Vignola, P. Salomoni, S. Mirri, *"AlmaWhere: A prototype of accessible indoor wayfinding and navigation system"* in 15th IEEE Annual Consumer Communications & Networking Conference (CCNC 2018);
- L. Monti, G. Delnevo, *"On improving GlovePi: Towards a many-to-many communication among deaf-blind users"* in 15th IEEE Annual Consumer Communications & Networking Conference (CCNC 2018);
- D. Aguiari, G. Delnevo, L. Monti, V. Ghini, S. Mirri, P. Salomoni, G. Pau, M. Im, R. Tse, M. Ekpanyapong, R. Battistini *"Canarin II: Designing a*

smart e-bike eco-system" in 15th IEEE Annual Consumer Communications & Networking Conference (CCNC 2018);

- G. Delnevo, L. Monti, F. Foschini, L. Santonastasi, *"On enhancing accessible smart buildings using IoT"* in 15th IEEE Annual Consumer Communications & Networking Conference (CCNC 2018);
- G. Delnevo, S. Mirri, L. Monti, C. Prandi, M. Putra, M. Roccetti, P. Salomoni, R. J Sokol, *"Patients reactions to non-invasive and invasive prenatal tests: a machine-based analysis from reddit posts"* in IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2018);
- C. Prandi, A. Melis, M Prandini, G. Delnevo, L. Monti, S. Mirri, P. Salomoni,*"Gamifying cultural experiences across the urban environment"* in Journal of Multimedia Tools and Applications, 2019;
- L. Casini, G. Delnevo, S. Mirri, L. Monti, C. Prandi, M. Roccetti, P. Salomoni, *"What Do Patients Tell Doctors on the Internet? Ask AI How to Valorize Online Medical Conversations"* in 28th International Conference on Computer Communication and Networks (ICCCN 2019);
- C. Prandi, L. Monti, C. Ceccarini, P. Salomoni, *"Smart campus: Fostering the community awareness through an intelligent environment"* in jorunal of Mobile Networks and Applications, 2019;
- L. Monti, S. Mirri, C. Prandi, P. Salomoni, *"Preservation in Smart Libraries: An Experiment Involving IoT and Indoor Environmental Sensing"* in IEEE Global Communications Conference (GLOBECOM 2019);
- R. Tse, L. Monti, M. Im, S. Mirri, G. Pau, P. Salomoni, *"DeepClass: edge based class occupancy detection aided by deep learning and image cropping"* in Twelfth International Conference on Digital Image Processing (ICDIP 2020);

- *RaveGuard: A Noise Monitoring Platform Using Low-End Microphones and Machine Learning* in Sensors 2020, 20(19), 5583;
- L. Monti, R. Tse, M. Im, S. Mirri, G. Pau, P. Salomoni, *Edge based transfer learning for class occupancy detection in a smart campus context* (under review).

Chapter 2

A conceptual framework for a Human-centric Comfort-oriented Smart Campus

How to define a conceptual framework for building a comfort-oriented smart campus?

— **RQ-MAIN**

The smart campus has emerged as an important concept of embedding technology in education and the related emerging technologies have improved the living standards of individuals and enhance the quality of their lives in many aspects. In recent years, it has gained an enormous amount of attention from professionals, academics, and researchers from multiple disciplines. It can be defined as *living environments able to self-organize themselves given some policies*. Defining the smart campus is a fundamental step since this term does not have a shared meaning for all the different interested occupants. For example, for a final user, the smart campus it's an environment where there are technologies focused on education, such as apps to find classrooms. For researchers and IT experts a campus is smart when it's responsive to its occupants and it's able to fit autonomously in elegant ways such as machine learning algorithms to predict occupants occupancy and as a consequence controls the HVAC system. Instead, in this thesis, a smart campus is intended as a distributed control system, in which several kinds of distributed computation, sensing and actuator modules, are exploited to increase the comfort of the occupants while managing the building energy efficiency at the same time.

The smart campus is an integral part of what is called smart cities. Both fall into a similar socio-economic, environmental and geographical context and consequently share similar infrastructures, services, challenges and even needs. Smart campuses have a partial intersection with some other contexts of smart cities for universally required applications. Energy management, efficiency and environmental sustainability are some examples. However, a campus is a place to provide education services to different types of users such as *students*, *professors*, *staff (tech/administrative)* and *governance*. Consequently, the performances of these subjects are the focal point, so, one of the most important considerations when designing a building is the extent to which it provides an environment that is comfortable for its occupants. In fact, a considerable amount of research paper about environmental design shows the positive effect *comfort* can have on learning, human productivity, and creativity [93, 189] and confirm the close relationships between indoor environmental quality (IEQ) and performance of the school building occupants [244]. Moreover, it would be more sensible to bring these subjects into the design phase and focus on the development and growth of comfort quality. In this sense, the vision of the educational transition should be based on human needs and the comfort of them in order to improve their performance and institutions. Therefore, in this chapter it will present the Human-centric Comfort-oriented Smart Campus (HCSC), defining the design criteria 2.1, system architecture and a framework, and finally the main characteristics.

2.1 Design Criteria

Based on the above, the following design criteria that should be reflected when deploying the emerging technologies on the smart campus will be presented.

2.1.1 A Human-centric Approach

A campus is a place of education, that promotes social and individual development. Therefore, the primary role of a smart campus is to have a learning-oriented environment. The educational field has benefited enormously from digital technologies and several applications have been created aiming to improve teaching and learning experiences at all levels, but the deployment of these smart devices and technologies shouldn't be the entire focus. This is a place to promote and improve learning performance thanks to advanced techniques and technologies. Based on many research studies [266, 60] we should rethink the role of technology in this context and move intelligent services towards a more human-centered approach. The smart campus is not only a space with technology on its inside, but also a new form of environment supported by new technologies, that takes care not only of people's education but also of people's comfort.

As defined in ISO 9241-210 [90], the human-centered design is an approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and the needs of the occupants. In this way, through this approach, the human experience, satisfaction and performance are highlighted improving the efficiency of the human related task and oppose possible negative health effects and performance.

Moreover, smart have different types of users it addresses. The main occupants, as explained above are *students*, *professors*, *staff (tech/administrative)* and *governance*, which all have different needs and take different roles. In this sense, the human-centric criterion means that in a smart campus is not focused solely on students, but on the needs of all occupants trying to satisfy the comfort of each of them in a coordinated way.

2.1.2 A Comfort-oriented Approach

The early concept of the smart building was mainly focused on the use of technology to improve building automation and environmental performances. An important actor was being excluded from the picture, human beings. Over time, technology started to become not just a tool only experts could handle, but an important part of everyone's life. Therefore, the need for technology to start speaking a language everyone could understand. Technology became user-friendly and focused more and more on human beings' needs. Increasingly, its goal turned into making experiences with technology easier for its users. When the smart campus concept started to embrace the new era of human-centred design, it became almost natural for technology to become an important tool for making a space comfortable.

In this sense, control of comfort conditions inside buildings is a problem that is being well investigated, since it has a direct effect on users' productivity [216, 217, 78, 109] and an indirect effect on energy saving. Therefore, from the users' perspective, a typical environment can be considered comfortable, if it's capable of providing adequate thermal comfort, visual comfort and indoor air quality conditions [74] and acoustic comfort [28].

2.1.3 The Multidisciplinarity Nature of a HCSC

The smart campus is an integral part of a smart city as explained above. The smart city development plan is generally multidimensional hosting multiple disciplines supporting citizens. The largely accepted taxonomy is explained in [128]. It includes smart economy, smart mobility, smart environment, smart people, smart living and smart governance. Since the development and quality of smart people in a city highly depends on the education they receive, and a smart campus can meet these needs. Therefore, a smart campus should be built with these multidisciplinary implications in mind and developed in a compatible way with other smart city dimensions. Regulatory requirements on data protection and privacy could exert pressure resulting in bureaucratic delays, but by providing innovative talent to the city, the smart campus has created an innovative environment to facilitate the self-development of other dimensions of smart cities. Ultimately, a smart campus should be built taking into consideration the multidisciplinary implications and developing solutions compatible with the other dimensions of smart cities.

2.2 Framework Design

The Human-centric Comfort-oriented Smart Campus framework is shown in 2.1 where smart campus acts as an important part in the context of the smart city in order to provide smart services comfort-oriented for the occupants of the campus. It's also connected to other domains with a smart city, such as society, economy, politics, environment, etc. As explained in 2.1.3, the multidisciplinary nature is reflected in a smart campus. The main idea of a smart campus is provided by three layers surrounding the occupants. *Infrastructure layer*, *Processing layer* and *Application layer*. The first layer deals with managing the hardware part and the network between them while the last is the one that interacts directly with the occupants. All of the layers in this framework take the campus occupants at the center, and even if some of these are not directly connected to the occupants, should be centric on their interests. Therefore, all the necessary components that make up the framework design will be described below.

2.2.1 HCSC System architecture

Moving forward from this vision, in order to be able of managing the problems cited above and to correctly manage the complexity of a modern smart campus, this thesis proposes a layered system architecture composed of three different layers as following explained and shown in Figure 2.2:

- **Infrastructure Layer:** good infrastructure support is essential for the development of a smart campus, in fact it is the layer that will support all the others. It should include all ICT elements to support new technologies

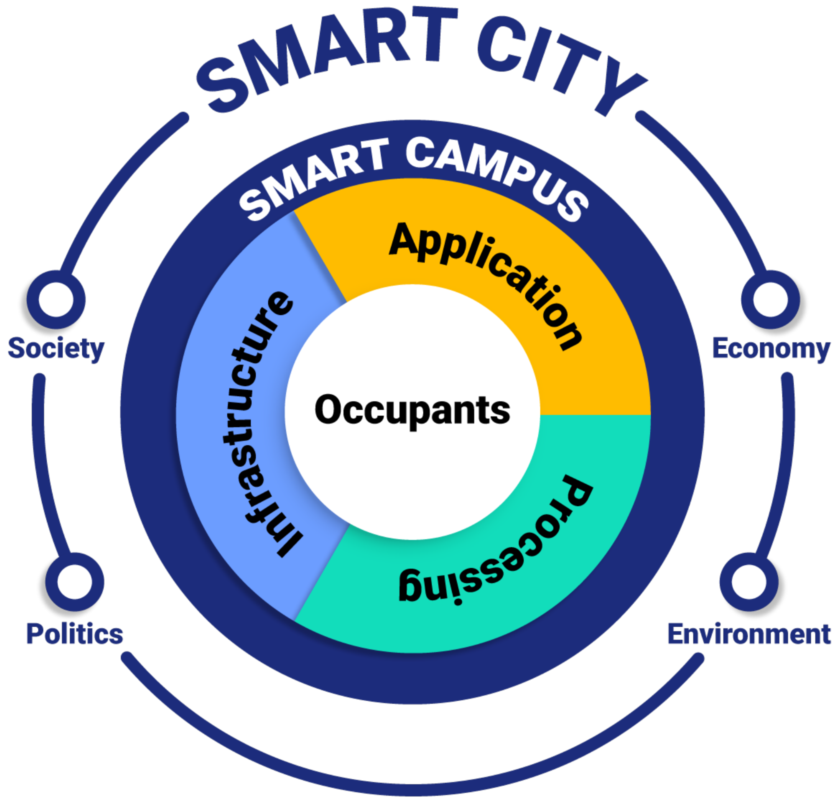

Fig. 2.1 The Human-centric Comfort-oriented framework proposed

in accordance with the smart campus concept, but also the occupants of the building as part of the infrastructure. This layer consists of two sub-layers: the first called *perception layer* should deal with sensors, actuators, sensor devices and smart objects. The second, called *network layer* should manage wired and wireless communication networks and protocols and bridge the *perception layer* and the *processing layer*.

- **Processing Layer:** processing represents the intermediate layer in the smart campus framework as shown in Figure 2.2. Although isn't connected to the occupants indirectly, this layer relies on the *infrastructure layer* in order to prepare the environment for the smart campus. The processing layer deals with processing data of various types that are retrieved to it by the underlying layer. The essential elements are therefore those of data storage (pre or post-processed) and the processing of these data which can take place on the server side or directly on the smart devices.

- **Application Layer:** this is the layer that the campus occupants access directly. In the HCSC, these provided applications that are able to meet the several occupants' needs (human-centric criterion) so as to improve their comfort and performance (comfort-oriented criterion). The human centric concept of the smart campus requires the applications provide to understand and meet the needs of different occupants. In this sense, the *application layer* is composed of web services, session analysis and data visualization components. Lastly, contributions from this thesis are indicated on top of the system architecture as depicted in Figure 2.2.

2.2.2 Technologies in the Smart Campus

Being the smart campus context a multidisciplinary field and with borders common to different areas of research, the development of technologies that support this area is manifold. With the advancement in smart sensing devices, internet and communication technologies, another key trend in the smart campus domain is call *Internet of Things* (IoT). It extends the concept of connectivity to everyday physical devices. Several papers in a reading suggest this paradigm to evolve in an environment surrounded by intelligent objects [226, 11]. Based on the perceived environment (datasets), artificial intelligence (AI) algorithms should be able to extract critical information from statistical data, and apply those techniques in order to add intelligent solutions. In this sense, AI and in particular machine learning and deep learning has achieved several successes in real world applications such as customize the learning content [105], learning analytics [183], energy consumption and building efficiency [250, 210, 210]. Moreover, the fast growth of the cloud platforms in recent years, has been

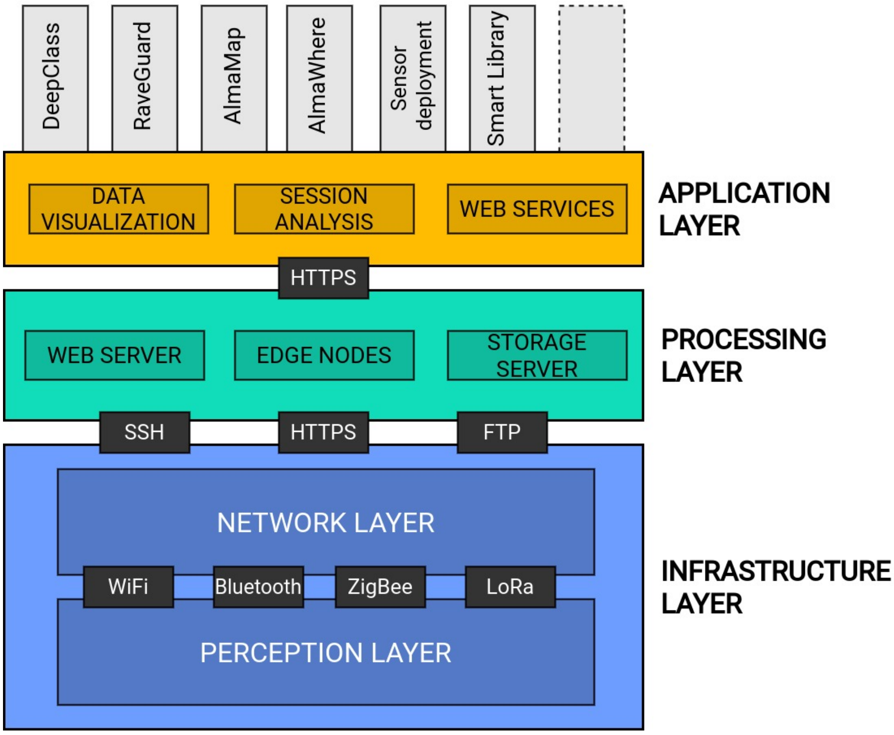

Fig. 2.2 The Human-centric Comfort-oriented architecture proposed

identified as a key trend on the smart campus domain [99, 172]. Compared to the standard computational infrastructures, *Cloud computing* helps to activate learning activities and services in unstructured environments. Moreover, the spread of the Internet of Things (IoT) and the success of rich cloud services have pushed the horizon of a new computing paradigm, *Edge computing* [214], which calls for processing the data at the edge of the network.

2.2.3 HCSC: main features

Based on the proposed framework reported in Figure 2.1, the expected features are the following:

- *Ubiquitous*: Thanks to the pervasive deployment of mobile technologies and wireless communications web services can be accessed everywhere.

The smart campus is expected to expand in a new way in order to have available services at everytime and everywhere, which promotes adaptive comfort-based services for the occupants of the campus. At the time of writing this thesis, we are well aware, due to the SARS-CoV2 virus, the concept of Ubiquitous learning has become relevant. It was possible to continue teaching exploiting the u-learning paradigm defined in [251].

- *Data-driven*: Within a smart campus, data are collected in real-time or in batches from various sources including sensing devices and occupants. Hence, a large amount of data can be stored and shared keeping in mind the importance of the privacy of each user. It's an important feature for enhancing campus smartness that is, in most cases, based on big data analytic in order to improve performances' occupants and energy saving for the building.

- *Predicting*: The huge amount of data generate from the sensing devices and users permit to learn and anticipate the needs of the occupants forecasting the future comfort conditions. Moreover, this feature also involves the decision-making in response to future events providing useful insights for different purposes, including those ones related to the management of staying quality in indoor environments.

- *Context aware*: A smart campus is often equipped with a series of smart sensing devices able to monitor most of the physical areas of the building. This promotes the concept of context awareness. Context is often defined as a series of aspects that describe the state of the campus. Context awareness mainly refers to the ability to observe and become aware of both the environmental conditions of the building and the behavior of the occupants, thus being able to provide services to meet personal needs by increasing the comfort of occupants. It's seen as essential for a smart campus to enable the implementation of personalized services and is fully supported by technologies promoted by the IoT.

Chapter 3

Human Occupancy Detection and Prediction

> How to recognize human occupancy inside a smart campus in order to improve human comfort and energy saving? and how to perform transfer learning to predict the utilization of another room with limited training data?
>
> — **RQ-1a and RQ-1b**

Monitoring people flows and presence, counting individuals in indoor environments, including means of transport, detecting if persons are present in a building or in a specific place has always been strategic goals in different contexts, providing information that could be useful and exploited with different purposes [46]. In 2020, these activities have become vital and needful, representing a means to control and guarantee the conduction of everyday life activities in so many contexts, due to the need of keeping and ensuring social distancing in most of the public places, such as schools and universities, malls and stores, offices and workplaces, etc., because of the Covid-19 pandemic we are living.

In this context, the Internet of Things paradigm, together with the diffusion of the availability of sensors and smart objects, can provide significant support in monitoring and detecting daily life activities in various situations. Moreover, advancements and specific analysis in image processing can play a strategic role in guaranteeing and improving accuracy, whenever cameras are involved in these situations, to get pictures from the monitored environments. In this chapter, we present a people counting approach we have defined and adopted with the aim of monitoring persons' presence in smart campus classrooms, which is based on the use of cameras and Raspberry Pi platforms, with the aim of answering research questions 1a and 1b, as described in chapter 1. Such an approach has been improved thanks to specific image processing strategies, so as to be generalized and adopted in different indoor environments, without the need of a specific training phase. Moreover, some evaluation tests we have conducted are presented, showing the accuracy of our approach.

3.1 Introduction

Detecting people's presence, monitoring their flows and their activities, counting how many persons are in a specific place can be strategic goals in different contexts, that can provide useful insights for different purposes, such as the ones related to the control and the improvement of staying quality in indoor and outdoor environments [46]. With these aims in mind, the Internet of Things paradigm [164], together with the diffusion and availability of sensors and smart objects, can provide great support in monitoring and detecting daily life activities in various situations, such as the ones related to education and learning fields [187, 162], those ones in the health and medical fields [136, 193], those ones in the museum and cultural heritage fields [43, 231], as well as many other ones. As a preliminary study in this field presented in section 3.3, we have investigated two different approaches and hardware low-cost equipment, with the purpose of detecting and counting people who are occupying a classroom in a smart building, within a University campus [161]. In fact, having information about the occupancy of an indoor environment can provide insights for smart building management, letting it adequately configure settings like Heat, Ventilation and Air Conditioning (HVAC), the alarm, the lighting, and the building security systems, just to cite the most commonly used and important ones [158]. We have set up a prototype, for preliminary experiments, that iteratively repeats the following steps: (i) takes a picture of the people in the room by means of a camera, (ii) predicts the number of occupants on the basis of already conducted training (such a computation is based on YOLOv3 [195], and in its first version it was conducted on a Raspberry Pi 4 model B), (iii) deletes the picture. The prototype has been installed in a classroom (max capacity: 100 persons), and, after a training phase, it provided interesting and reliable results, showing a high level of accuracy. On the basis of such results, we have installed the prototype in a different classroom, with different characteristics in terms of dimensions, persons capacity, orientation and position, lighting (e.g., windows dimensions and position). The results we have got after a first monitoring experiment show that our prototype returns a low accuracy of the predictions it made, letting emerge the need of an investigation about tiny deep learning models. Specific training phase, based on that specific new classroom has been done, and in particular showing that there are some critical areas in the classroom, where the object recognition algorithm behaves worse. In order to answer to **RQ-1a**, we propose an approach we have set up and evaluated, which is based on the idea of adding a specific image processing phase. In particular, here we anticipated that we have based our proposal on the image cropping, testing different thresholds. These preliminary tests show promising results, except for some false positives, that occur whenever the crop cuts persons: in that case, the algorithm counts a person twice. Hence, we have adopted a strategy to highlight and to avoid potential false positives, focusing on the specific cropped areas. In order to answer to **RQ-1b**, we have we expanded the experiments and installed prototypes in every classroom on the University Campus in which each room have different characteristics in terms of dimensions, persons capacity, orientation and position, and lighting. The results we have got after a first monitoring experiment show that our prototypes return different percentage of predictions' accuracy. This makes us query about how to generalize our occupancy detection algorithm, making our prototype more precise, with better generalized performances in people counting,without the need of training the system with specific picture on the basis of a specific room. The machine learning techniques used fall into the hat usually defined as *transfer learning*. The remainder of the chapter is structured as follows. Section 2 briefly presents some main related work, by comparing the approaches that can be adopted so as to face similar purposes. Section 3 described our preliminary experiments and Section 4 the investigation about tiny deep learning models and image-cropping algorithms to improve the accuracy. Section 5 described a general approach exploiting transfer learning techniques. Finally, Section 6 concludes the chapter, disclosing some future works.

3.2 Background and Related Work

This section briefly presents some background and related work, focusing on the most interesting approaches used to count people in an indoor environment. In literature, there are several works devoted to track and count persons, based on different technologies and architectural solutions. Some of those works are based on the use of passive infrared sensors (PIR), a kind of electronic sensors that can measure infrared light radiating from some objects in their field of view. Some projects take advantage by the use and the combination of multiple PIR sensors [255, 192], thus they can compute the number of persons who are in an indoor environment by computing the number of persons passing through doorways to access that specific indoor environment. A different approach exploits the Radio Frequency Identification (RFID) technology. It, basically, consists of three components: (i) the readers, (ii) the tags, and (iii) the middleware software. Several solutions are based on this approach, that exploits probabilistic estimators that achieve the required accuracy and confident level [15, 114]. Other methods are based on the Wi-Fi probe-request-frame, which take advantages by the fact that smartphones and mobile devices have been designed to periodically transmit such frames with the aim of identifying when a known access-point is positioned within a specific distance and by capitalizing such a kind of Wi-Fi behavior.

Hence, monitoring and counting these Wi-Fi frames can provide support in crowd and people counting [252, 120]. A different process based on the use of a single carbon dioxide sensor (CO_2) has also been investigated. Starting from the assumption that an indoor environment is affected by human activities and the influence can be measured by various sensors from different aspects, to infer the density of the crowd, as described in [129, 121], or with the use of hybrid techniques, by combining different sensors such as video camera and CO_2 sensors, as proposed in [245].

A last kind of approaches that we have analyzed, is the one based on taking pictures by cameras: its main target is the design and the development of algorithms aiming to automatically count people. Taking into account a method based on the recognition of video segments stream, the counting process can be divided in two main steps:

1. This first step consists of detecting a moving blob on the basis of some classic algorithm for motion detection, such as background subtraction and/or a segmentation strategy (i.e., K-means).

2. The second step consists of monitoring the detected blobs, with the aim of identifying the direction of the monitor or computing the number of people that are present in case of a single frame shot from a camera. Two main categories of methods can be used in this sense:

    - The Line of Interest (LOI) counting methods can evaluate the number of people crossing a virtual Line of Interest within the monitored scene [71, 134, 103].
    - The Region of Interest (ROI) counting methods can estimate crowd, evaluating the number of people who are present within a specific Region of Interest in the monitored scene [265, 34, 80].

In particular, the ROI methods are based on images analysis and processing, and they can be structured in three main categories, on the basis of the main strategies they adopt:

1. pixel-based analysis: the methods based on this analysis are more focused on the estimation of density rather than the whole count operation. They extensively use local features, such as edge information or individual pixel analysis to count [264, 54, 55].

2. Texture-based analysis: this analysis represents an active and interesting topic in image processing, playing a significant role in many applications, such as image retrieval and face recognition. Rely on texture modelling through the analysis of image patches [55, 26], some texture-based analysis methods well-known in literature are grey-level co-occurrence matrix, Fourier analysis and fractal dimension [79].

3. Object-level analysis: the methods based on this analysis try to locate different types of objects in a scene, first determining if the objects corresponding to the right classes are present in the scene and then finding where they are placed in the scene [264, 111, 101].

For our experiments, we have adopted the last approach described in this section, as detailed in the following section, presenting the system design and the methodology that we have applied.

3.3 Preliminary Experiments

In our preliminary experiments [161], we had a common client-server architecture, in which, the computation was taken over by the server side. This case study was set up in one of the classrooms of the Campus of Cesena (University of Bologna), with a maximum capacity of 100 seats. The classroom has been equipped with two low-budget cameras, as shown in Figure 3.1, which have been installed on the ceiling, near the projector, with the aim of capturing images of the people in the classroom. In particular, we have gathered the pictures, building our dataset, during special sessions, by involving 48 volunteers, properly informing them about the project.

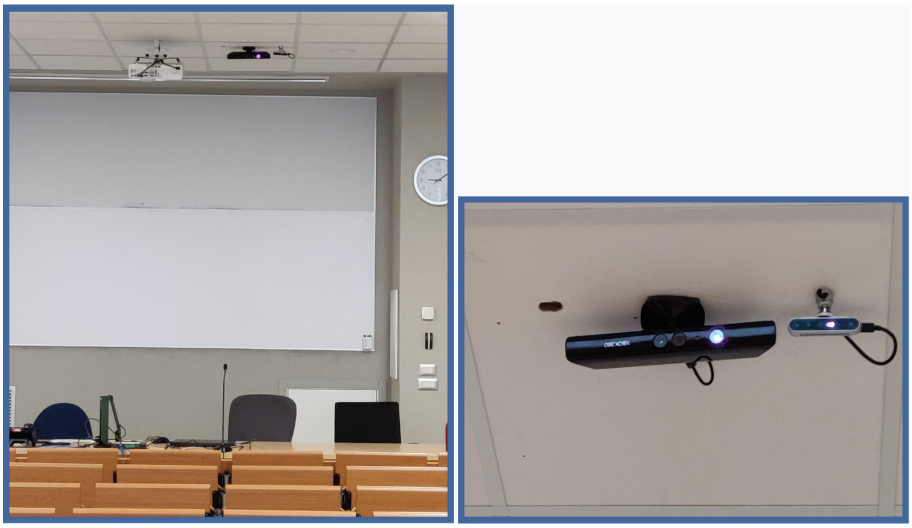

Fig. 3.1 Our first experiment: the video-cameras installed in one of the classrooms of the University Campus.

In order to evaluate the overall performance of our prototype, we have conducted some test sessions by involving some volunteers. It is worth noting that such tests have been conducted in accordance with privacy and data protection regulation, and all the volunteers were adequately informed about such a research project and about the use of the images we were taking, by signing an informed consent form, specially prepared for those collection sessions. We have conducted a preliminary evaluation by taking into account a subset of snapshots with different patterns in terms of people distribution captured in the classroom at the university campus and we have tried different scenarios, by considering the different amounts of people in the classroom at the time of the shots. The accuracy and results of the proposed people counting technology are based on YOLOv3 tool in two different pre-trained models: a lighter one (tiny weights), with which it's possible to compute it inside the Raspberry Pi 2, and another, more complete, one (full weights), which can be launched only by the server.

Real number (**R.N.**) represents the exact number of people who were present at the time of shooting (counted by a human operator). False Counting Number (**F.C.N.**) represents the errors of the system, defining those situations when the face of a person has been counted twice, as a result of a person's movement, or by counting the upper side of the T-shirt as a face. Predicted Number (**P.N.**) represents the number of people predicted by YOLOv3 tool. To assess the accuracy of the proposed people counting system, we have exploited the following formula:

$$Accuracy(\%) = \begin{cases} \frac{\mathbf{PN-FCN}}{\mathbf{RN}} * 100, & \forall\, \mathbf{PN} \leq \mathbf{RN} \\ \\ \frac{\mathbf{RN-FCN}}{\mathbf{RN}} * 100, & \forall\, \mathbf{PN} > \mathbf{RN} \end{cases} \tag{3.1}$$

All the results are exposed in the paper [161], and for the same tests, the best results, with the same image resolution, were obtained by Intel RealSense D415 camera both for full weights and tiny weights. In particular, the average accuracy of Intel Realsense D415 camera is 92.2% with full pre-trained model and 40.2% with the tiny pre-trained model, and the average accuracy of Microsoft Kinect camera is 85.7% with full pre-trained model and 21.7% with the tiny pre-trained model. Table 3.1 divides into three thresholds by density of persons (**R.N.**) the data of the four previous tables (each of which is the representation of one of the columns), where we have considered the tests conducted with 3/4/5 people as low density, those with 10/11 people at a medium density and finally those with 47/48 high-density people. In almost all cases the YOLOv3 network (both with full and tiny weights) works better in medium density (the only case is that of Intel Realsense D415 with full pre-trained mode).

	Kinect/Full	**Kinect/Tiny**	**Intel/Full**	**Intel/Tiny**
low	85,2	8,3	87,7	40,3
medium	**92,02**	**44,9**	94	**53,3**
high	76,2	9,7	**97,9**	18,2

Table 3.1 Accuracy per different density rates

3.4 On Investigating Tiny Deep Learning Models

Exploiting YOLOv3 [196] and, in particular, the pre-trained models available with it, we have achieved an interesting result of accuracy in the preliminary experiments, especially with one of the two cameras with which we performed the tests: Intel RealSense D415. We used 2 types of models: one called tiny which you can use on Raspberry Pi 2 and which received an average accuracy of 40.2%. The other model instead was called full, which requires computational performance too high for the single-board computer used and so we exploit a linux-based server to store images and apply the prediction, whose result of average accuracy is 92.2%. It is evident, as exposed in the paper [232], that on one hand this approach must be based on a client-server architecture so that the system can be defined as accurate, but on the other hand we have a scalability problem, in fact as the number of embedded devices increases, server computation will be increasingly difficult. So, the idea is to re-train the tiny model in order to achieve accuracy on our case study as close as possible to the full pre-trained model.

3.4.1 Tiny Model Re-training

In order to re-train the model we need to have our own dataset, and we took about 2,000 images during some data collection sessions (during which the students signed a release form privacy-compliant). After that, we created each label in the format that is appropriate to YOLOv3, the labels used are person, jacket and backpack. Once we generated a sufficient number of labeled images, we divided the dataset into training and test sets, the optimal result was achieved with an 80/20 ratio and to perform this split, the images were divided based on the number of participants present into the snapshot so as to have proportionally all the types of samples in both sets. Finally, the training was launched and the final decision concerns the number of iterations to be made to minimize errors, it must be sufficient to ensure that the model is able to correctly detect people, a too high number, however, would cause the phenomenon of overfitting, for which the model becomes excessively uniformed to the images of the training set and loses the ability to generalize and to operate adequately on new images. In order to select which was the optimal version the **mAP coefficient** was calculated for each of them and the most performing version (6,000 iterations) was selected, as shown in Figure 3.2.

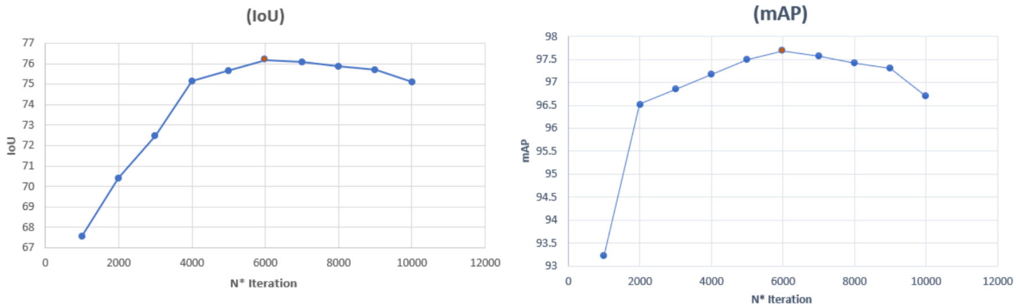

Fig. 3.2 On the left: how the value of the Intersection over Union coefficient changes during the iterations in the training phase. On the right: how the mean Average Precision coefficient value changes during iterations in the training phase.

Furthermore, the threshold parameter (0.25) was determined empirically, which indicates the confidence threshold to be overcome to consider a survey valid, in order to find the value that is able to minimize the number of false positives and maximize the number of correct detections. The trained model has produced satisfactory results, the required computational power is equal to that required to process the tiny model, while the accuracy is comparable to that found by the complete model, with a slightly smaller accuracy, but with fewer erroneous detections.

The accuracy of the model was measured on a subset of heterogeneous images (not used for the training/validation phase) by number and distribution of individuals, for each frame the correctness of the survey was calculated as a percentage. The formula is described above in 3.1. The test result tells us that the average accuracy on the classroom examined and in which we re-trained the model is 94.89% and its STD 5.58.

3.4.2 Cropping Images

We have expanded the project by applying the same system even in another classroom on the same campus. In this case, the classroom is larger than the first one in which we did the tests, the shape of the classroom is visible in the Figure 3.3 right. For this reason, we used two cameras powered and managed by a single Raspberry Pi 4 model B, one for the left side of the classroom and one for the right side as shown in Figure 3.3 right. We also tested our tiny model on these cameras by applying our weights to both the image on the right and on the left and summing up the prediction afterwards, and the accuracy results are very different in terms of accuracy compared to the first classroom. In fact, we measured the tiny model with the same number of heterogeneous images used for the previous test and the accuracy is 69.25% and its STD 11.35. It is clear that this is a case of overfitting on the first classroom in which we have trained the model and with a view to having cameras in all the classrooms and laboratories on the campus, it is not possible to think of a model re-train approach on each classroom. So, we need an approach that generalizes well on average in terms of accuracy, rather than one that works well in a single classroom and bad on all the others.

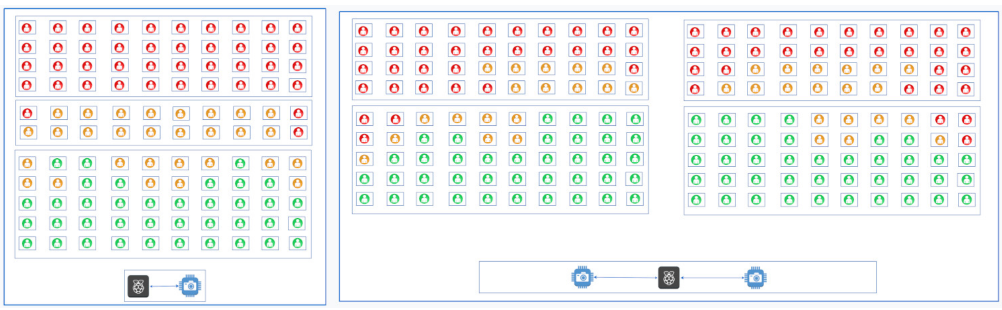

Fig. 3.3 On the left: shape of the first classroom and its critical area and safe area, on the right: shape of the second classroom and its critical area and safe area.

The proposed method arises from the intuition that in the images examined there are critical areas (red area in Figure 3.3 right and left), where the probability of finding and predicting a student is lower and safe areas (green area in Figure 3.3 right and left) where instead the probability is much higher. Furthermore, the yellow zones lie halfway between the critical zone and the safe zone in terms of prediction probability. In particular, the method is based on how YOLOv3 was designed and the concept behind anchor boxes because instead of directly predicting a bounding box, YOLOv3 (and v2) predict off-sets from a predetermined set of boxes with particular height-width ratios - those predetermined set of boxes are the anchor boxes. We took the pre-trained v3-spp model (running on Raspberry Pi 4 model B) with the standard anchor boxes that YOLOv3 makes available. We experimentally tested which type of cut was best so that the shape of the class under examination fitting with the standard anchor boxes. Six experiments have been made:

- **half columns (HC):** the images have been divided into two parts, internal columns (5) and external (5) parts with respect to the image.
- **half rows (HR):** the images were divided into two parts, lines closer (5) and far (4) than the camera.
- **all columns (AC):** the images were divided into 10 parts, one for each column.
- **all rows (AR):** the images were divided into 9 parts, one for each rows.
- **Hybrid columns (HyC):** the images have been divided into 5 parts, the first 4 parts refer to the inner columns while the last part covers the other 5 columns.
- **Hybrid rows (HyR):** the images have been divided into 6 parts, the first 5 parts refer to the rows closest to the camera while the last image covers the other 4 rows.

The results of accuracy and standard deviation with respect to the tests carried out are shown in the table below:

HC accuracy	**HC STD**	**HR accuracy**	**HR STD**
75.76%	10.81	**87.74%**	**9.1**
AC accuracy	**AC STD**	**AR accuracy**	**AR STD**
67.50%	14.72	70.26%	11.58
HyC accuracy	**HyC STD**	**HyR accuracy**	**HyR STD**
73.20%	12.02	75.31%	8.89

Table 3.2 Accuracy and standard deviation of cropping experiments.

It is clear that the best result in terms of accuracy is definitely **HR**, consequently we have also tested the same cut at the first classroom, and the results are the following: the accuracy is 88,30% and its STD 9.78.

3.4.3 Remove Duplicates Caused by Image Cropping

Analyzing the images cropped a posteriori of the prediction, we have noticed how in the majority of the cases the errors belonged to the duplicate count of people because of the crop of the image shown in Figure 3.4. The proposed solution exploits the two images resulting from the cropping phase in a different way. As for the top one (letter a in Figure 3.4), all the bounding boxes containing their $y = height$ of the image and a list A are taken instead. Instead, as regards the bottom one (letter b in Figure 3.4) all the bounding boxes containing their $y = 0$ are taken and inserted in a list B. Next, for each bounding box in list A the center is calculated. Finally, a match is searched between the bounding boxes of the list B and the center of the bounding boxes of the list A. Each time a match is found, the count is decreased by one with respect to the total of the people predicted by YOLOv3.

From the tests carried out, the results of the proposed algorithm have allowed us to eliminate almost all errors due to the duplicate count. A more extensive testing campaign has been planned, so as to get more results on the efficacy of our approach in eliminating duplicates and false positives in correspondence with the image cropping.

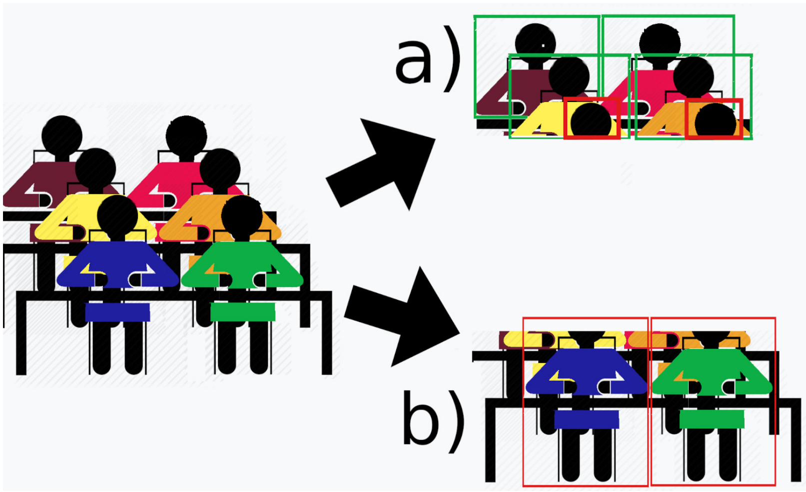

Fig. 3.4 Cropped image with duplicated bounding boxes in red.

3.5 Edge based Class Occupancy Detection

On the basis of the results reported above, we have we expanded the experiments and installed prototypes (updating the Raspberry Pi to version 4, in order to improve the computing power) in every classroom on the University Campus (due to the SARS-CoV-2 pandemic, it was possible to do tests only in eight classrooms), in which each room have different characteristics in terms of dimensions, persons capacity, orientation and position, and lighting (e.g., windows dimensions and position). An interesting performance evaluation review about edge computing is described in [91]. The results we have got after a first monitoring experiment show that our prototypes return different percentage of predictions' accuracy. This makes us query about how to generalize our occupancy detection algorithm, making our prototype more precise, with better generalized performances in people counting, without the need of training the system with a specific picture on the basis of a specific room. The machine learning techniques used to fall into the hat usually defined as *transfer learning*.

3.5.1 System Design

The system design of the platform by detailing the entire architecture composed of client side and server side each of which contains different layers inside. Unlike the architecture proposed in the preliminary experiments, a scalable architecture was chosen. In this sense, we have changed the weights of our architecture (*fat client - thin server*) by shifting the computation to client embedded device while maintaining a good level of accuracy for the prediction of the students number in a classroom. In this way we will have many benefits:

- **Higher scalability:** fat clients can complete the job independently of the other clients and after that send their result to the server.
- **Working semi-offline:** in fact, in this way it is possible predict a number of people detected and store that result directly on the single-board computer without the urgency to send the data immediately.
- **Higher availability:** Instead have a single point of failure, we have different clients that work independently. This allows the system to be more robust.
- **Privacy compliant:** how many people and the time in which the frame was analyzed are the only data stored in the client node and sent to the server side.

So, the **client side** in this architecture is surely the main component (as shown in figure 3.5), almost the whole computation occurs in this side.

Data Acquisition Layer

This layer is devoted to data acquisition, focusing on monitoring the actual occupation of classrooms and laboratories, compared with their capacity. In order to count the number of people in an indoor area, we took advantage and at the same time test two different kinds of low-budget cameras:

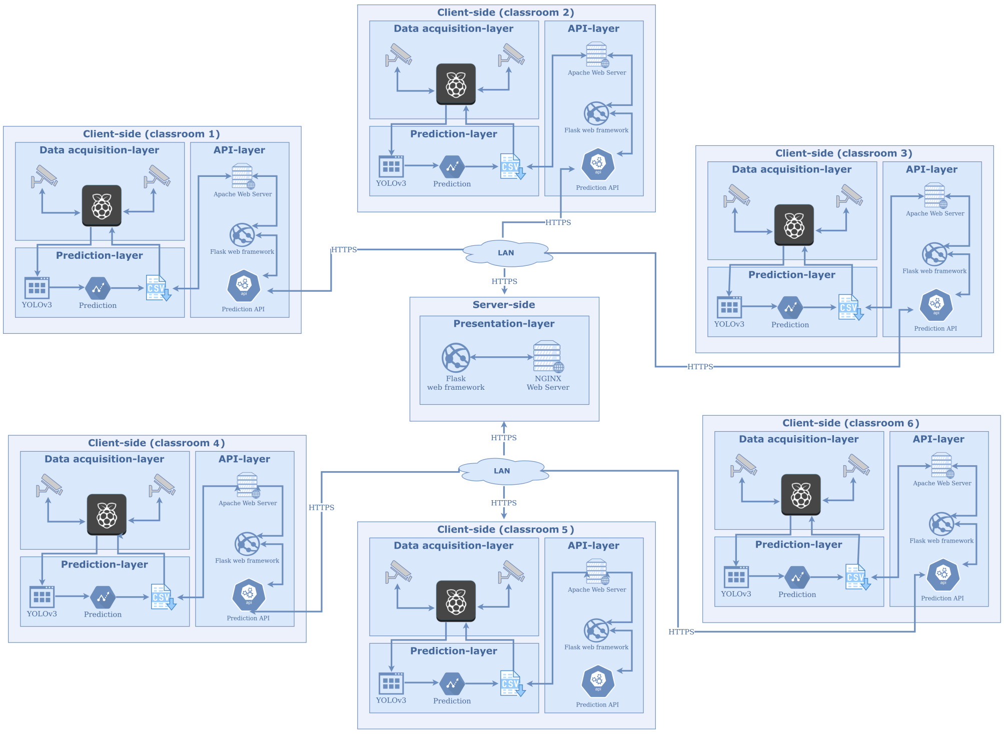

Fig. 3.5 The fat client-thin server architecture proposed. The server side is located in the center of the image, while the client nodes are located on the sides

- *an Intel RealSense D415 Depth camera:* this camera is USB-powered and consists of an infrared projector, a pair of depth sensors and with an RGB Sensor, with a resolution and a frame rate equal to 1920 x 1080-pixel at 30 fps. The RealSense technologies provide a suite of depth and tracking technologies, that makes it possible to count the number of people in a given area. We plugged-in (via USB) the camera to a Raspberry Pi 4 model B and we acquired 1280 x 720 pixel frame rate images every five minutes (this interval was set to better support the storing operations).

- *a Microsoft Kinect camera:* initially, the Kinect was developed as a gaming tool for Xbox 360. It contains three main components that work together to detect the user's motions and to create her/his physical image on the screen: an RGB color VGA video camera, a depth sensor, and a multiarray microphone. As for the cameras, both the video and depth sensor have a 640 x 480 pixel resolution and run at 30 fps. We plugged-in (via USB) the camera to a Raspberry Pi 4 model B and we acquired 640 x 480-pixel frame rate images every five minutes.

After performing the accuracy tests for each low-budget camerasas explained in our work [161], we chose to use Intel RealSense D415 Depth camera. The camera is chosen, which is devoted to the prediction phase, acquires the RGB image before applying our custom deep learning model.

Prediction Layer

The prediction layer retrieves data from the cameras, on the client side, and exploits a custom model based on YOLOv3 with the aim of predicting the number of people in a precise moment. This tool applies a single neural network to the full image. In particular, this network divides the image into regions and it predicts bounding boxes and probabilities for each region. The bounding boxes are weighted by the predicted probabilities. The model reports advantages over classifier-based systems. It considers the whole image at the test time, with the aim of letting the predictions be informed about the whole context depicted in the picture. This library can perform predictions with a single network evaluation, unlike systems just like R-CNN which requires thousands for a single image. This makes it extremely fast, approximately more than 1000x faster than R-CNN and 100x faster than Fast R-CNN [195]. Once the prediction is done, we store in a file with CSV extension the number of people predicted and the timestamp related to the exact time the image was taken.

API Layer

This interface layer has been created in order to make the state of each camera available on the server-side. in this sense, each camera displays the same set of APIs which, upon specific request. Over HTTPS protocol this layer respond useful information for the server-side presentation layer about the number of people predicted by the model in a specific range of time. This is an essential layer to maintain both the scalability and independence of each (client) node of the system.

Presentation Layer

Through the API layer is it possible for the presentation layer supports the data access and interaction. We implemented a rich-web base application by using standard web technologies, such as HTML5, CSS3, JavaScript, etc. The back-end system has been developed as a web application, by using a Python micro-framework, called *Flask*. Lastly, we have used *NGINX* as a web server and reverse proxy to make pages available on port 80. Thanks to this we can have a total view of the system. This layer of the system will be used by the administration staff and through this starting point it will also be possible to apply statistical and aggregation techniques to analyze the performance of the classrooms on the University campus.

3.5.2 Methodology

In this Section, we present our methodology for counting the number of people in the context of Smart Campus setting our previous work as a starting point for the proposed approch [161]. Eight classrooms have been set up, each of which is different in size, layout and number of seats. One or two cameras have been installed for each client node of the network, based on the size of the classroom. The number of cameras installed in the classroom was the discriminating factor in deciding our **CSC** (classroom student counting) dataset. In fact, we only took pictures from one of the classrooms with one camera for one client node installed (*tiny*) and another one that needs two cameras for a client node (*large*). The students signed a release form privacy-compliant during every data collection session.

The proposed transfer learning methodology is shown in Fig 3.6, starts with a deep learning model that has been pretrained on ImageNet dataset. In order to convert the pretrained model to class occupancy detection system, the model needs to be trained with a specific context dataset. Therefore, we collected our own dataset (**CSC**) as described above and we exploit a filtered portion of the COCO dataset as shown in purple rectangle of the Fig 3.6. After the training model is generated, our system is ready to process images from the camera Intel Realsense D415 to output the class occupancy. Finally, the results are stored inside the system as depicted in the green rectangle of the Fig 3.6. Therefore the framework is developed using deep learning libraries exploiting Darknet in the training phase

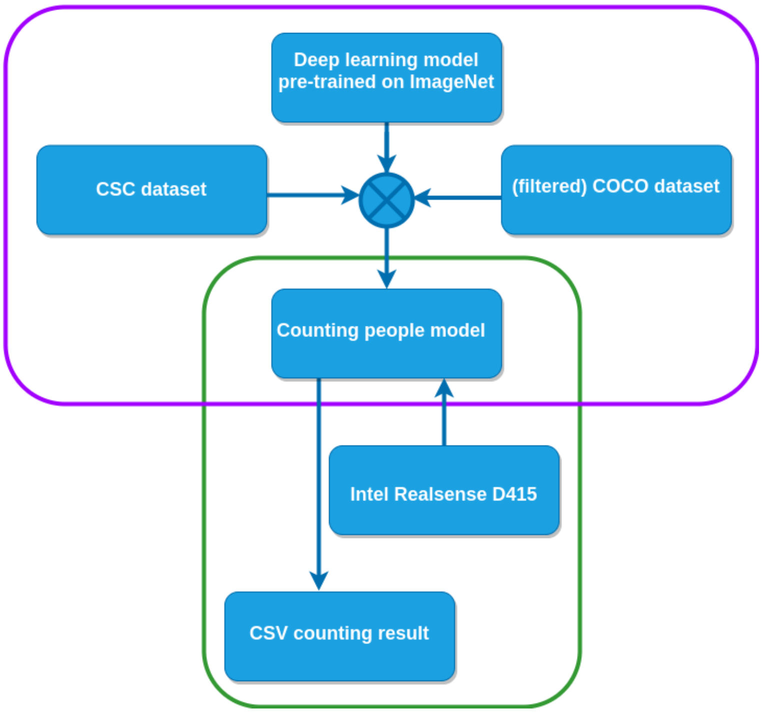

Fig. 3.6 The proposed transfer learning framework

Dataset Collection

The images of our **CSC** dataset were extracted on some data collection sessions during which the students signed a release form privacy-compliant. In order to introduce a learning challenge for the AI model, the dataset, as described above, we created the dataset by taking images from only two classrooms, one for each type (*tiny* room and *large* room). Therefore, we took 1196 images from a classroom with one client node installed (*tiny*) and 808 images from a classroom with two client nodes installed (*large*). After that, we have exploited a subset of COCO dataset, retrieving only the interesting images for our task and the total amount is 67316.

Annotating a huge amount of data manually requires laborious work, thus it is essential in supervised learning methods. In our specific case the images in COCO dataset was already labeled. Thus, in order to automate the process, via a script we searched all the images with the labels of our interester. The first label sought is obviously *person*, while the other are *jacket* and *backpack* used to minimize potential false positives. Instead, as far as CSC dataset is concerned we took advantage of a pre-trained model of YOLOv3 in the first instance. In this way, we have roughly retrieved most of the bounding boxes with *person* and *backpack* classes. After that, we created each labels manually in the format that is appropriate to YOLOv3 adding the labels not recognized by YOLOv3 and *jacket* labels in full. Finally, we divided the dataset into training and test sets, the optimal result was achieved with an 70/30 ratio and to perform this split, the images were divided based on the number of participants present in the snapshot so as to have proportionally all the types of samples in both sets.

Statistics about our Dataset

The Classroom Student Counting (CSC) dataset take care about three classes: *People*, *Jacket* and *Backpack*. As depicted in figure 3.7, the distribution of the people founded in the images retrieved are ranged from 0 to 54 for the tiny room with a mean of 13,6184 and with a standard deviation of 15,6566, and ranged from 0 to 83 for the large room with a mean 23,7289 and with a standard deviation of 20,7758.

The other two classes are depicted in figure 3.8. On the left is shown the jacket count distribution, that is ranged from 0 to 14 for the tiny room with a

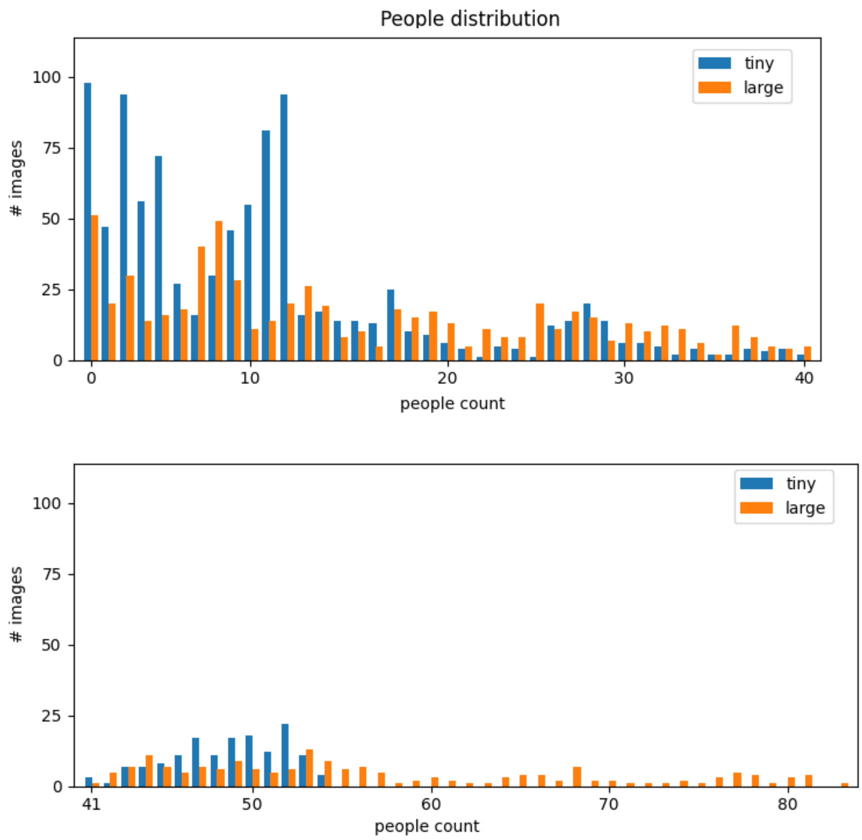

Fig. 3.7 People Count Distribution

mean of 1,7290 and with a standard deviation of 1,8913, and ranged from 0 to 83 for the large room with a mean 23,7289 and with a standard deviation of 20,7758. On the right is shown the backpack count distribution, the range is from 0 to 11 for both rooms, the tiny room has a mean of 2,5968 and a standard deviation of 2,3671 while for large has a mean of 4,0519 and a standard deviation of 2,4580.

For a typical training procedure of machine learning, we split the dataset into training and test set. The split ratio is 70:30 which includes 46,841 images for the first set and 22,486 for the second one.

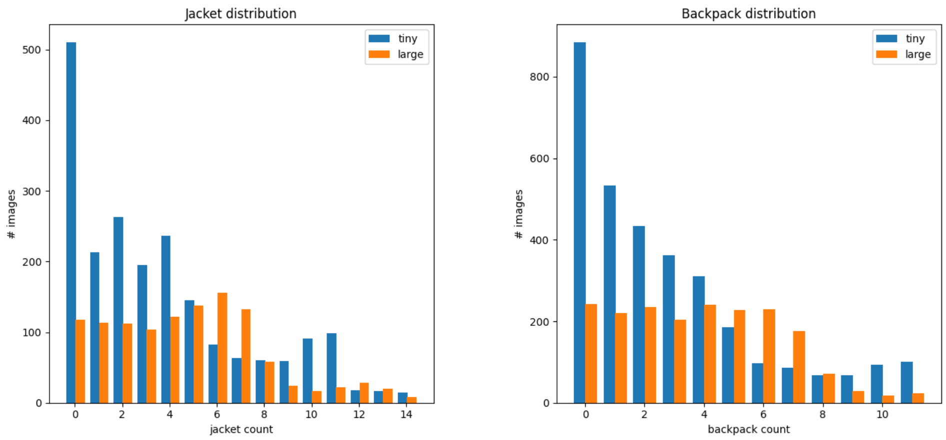

Fig. 3.8 Jackets Count Distribution (on the left) and Backpacks Count Distribution (on the right)

Re-train model

Once the dataset was ready, we started the re-training using the darknet[1] framework and in particular the YOLOv3 network. As a starting point we exploited the pre-trained *darknet53.conv.74* that contains the weights for the Darknet network originally trained for classification on the ImageNet dataset, which is used as the pre-trained feature extractor (backbone) for YOLOv3. To use this for detection the additional weights which are only present in the YOLOv3 network are randomly initialized prior to training. Therefore only the weights for the convolutional layers are included, excluding the weights for the final fully connected layer which outputs the class probabilities for classification. The input image size of the network is 608x608 with a learning rate of 0.001.

Finally, the training with the filtered COCO dataset and the CSC dataset was launched and the final decision concerns the number of iterations to be made to minimize errors. It must be sufficient to ensure that the model is able to correctly detect people, a too high number, however, would cause the phenomenon of *overfitting*, for which the model becomes excessively uniformed to the images

[1] https://pjreddie.com/darknet/yolo/

of the training set and loses the ability to generalize and to operate adequately on new images.

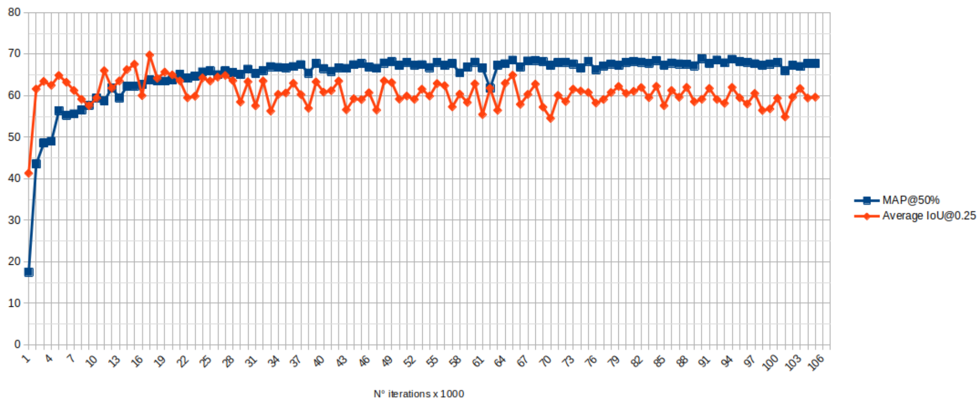

Fig. 3.9 People Count Distribution

In order to select which was the optimal weight, two evaluation metrics have been calculated for every 1000 iterations during the training process as depicted in Figure 3.9. Object detection systems make predictions in terms of bounding boxes and class labels. For each bounding box, it has been measured an overlap between the area of the predicted bounding box and the area of the ground truth bounding box. This is measured by intersection over union (*IoU*). Moreover, normally it is also calculated precision and recall using IoU value for a given *IoU* threshold and in our case the average *IoU@0.25* has been used. The second metric calculated is *mAP*, that is based on Average Precision, related to the area under the precision-recall curve for a class as described below:

$$AP = \int_{1}^{0} p(r)dr$$

where p and r are precision and recall coefficients respectively. Therefore, the process is iterated over each class and finally averaged. The confidence threshold parameter that we have chosen is 50%.

The total number of iteration in the training process is 105000 over the dataset, as tabulated in Table 3.3 and the most performing model was selected.

For the sake of brevity, the table shows for every 5000 iterations, the whole table is linked[2]. Based on our evaluation metrics, the best result was obtained at iteration number 65000.

batch	**mAP**	**precision**	**recall**	**F1**	**avg IoU**
1000	17,49	0,61	0,24	0,34	41,27
5000	56,35	0,83	0,57	0,67	64,83
10000	59,42	0,76	0,63	0,69	59,41
15000	62,27	0,85	0,6	0,7	67,54
20000	63,74	0,83	0,63	0,71	64,97
25000	65,93	0,8	0,6	0,72	63,48
30000	66,34	0,79	0,67	0,73	63,31
35000	66,66	0,76	0,69	0,72	60,61
40000	66,51	0,77	0,69	0,72	60,81
45000	67,7	0,74	0,71	0,73	59,02
50000	67,25	0,74	0,7	0,72	59,13
55000	67,99	0,78	0,69	0,73	62,89
60000	68,03	0,78	0,69	0,73	62,83
65000	**68,51**	**0,81**	**0,67**	**0,73**	**64,9**
70000	67,26	0,69	0,73	0,71	54,5
75000	68,23	0,76	0,71	0,73	60,73
80000	68	0,75	0,7	0,73	60,51
85000	67,31	0,72	0,72	0,72	57,54
90000	68,89	0,74	0,72	0,73	59,11
95000	68,17	0,74	0,72	0,73	59,45
100000	67,99	0,74	0,72	0,73	59,36
105000	67,67	0,74	0,71	0,73	59,6

Table 3.3 Batch iterations over training process. mAP metric is calculated at IOU threshold 0.5, the other metrics presented with threshold 0.25

[2]https://tinyurl.com/y7zcaxlc

3.5.3 Results and Discussion

The accuracy of the model was measured on a subset of heterogeneous images that it isn't used for the training or validation phase. As described in *The system design*, we have splitted the classrooms at our disposal based only on the number of nodes/cameras (tiny and large). For a total of 8 classrooms, of which 5 tiny and 3 large as shown in Table 3.4. The first of each category is the classroom used in the dataset for the training.

To test the accuracy and correctness of our system 100 images were acquired for each camera (100 frames for tiny classrooms and 200 frames for large classrooms) for a total of 1100 images. The correctness has been calculated as a percentage for each frame, by the number and distribution of individuals. The reference formula is the one shown in 3.1. The average of the accuracy formula has been calculated as reported in Table 3.4 (second column). Moreover, *standard deviation*, *root mean square error* and *mean absolute error* are also calculated for each set of images retrieved by every nodes.

Tiny classes				
Classroom	**Average accuracy**	**Standard deviation**	**RMSE**	**MAE**
1	97,10%	6,78	0.65	0.33
2	96,76%	9,05	0.55	0.21
3	94,07%	13,83	0.62	0.25
4	95,10%	8,58	0.79	0.47
5	95,80%	8,09	2.89	1.22
Large classes				
1	95,58%	6,70	2.23	1,14
2	93,44%	15,17	1.93	1.23
3	91,00%	14,76	1.78	1.12

Table 3.4 Accuracy results of our model

The own custom model created is robust as demonstrated by the average accuracy shown in Table 3.4. In fact, these values approximate that of the category of classroom of competence. Furthermore, it's obvious that the first classroom present in the Table 3.4 of each category (the one used in the training phase) has an average accuracy greater than the others. Moreover, it can be seen that standard deviation values are on average higher in the large classrooms compared to tiny classrooms and and lower average accuracy values. This is due to the higher complexity of the task, larger classrooms have more seats and are used for University courses with many students. Moreover, another problem is given by the position of the two cameras, in fact we calculated *average accuracy* and *standard deviation* by splitting the frames per camera inside each large classroom. The result shown in Table 3.5 proves how, even if partially, the positioning also has an impact on accuracy performance. This will surely be the reason for further investigations. Focusing deeply on tiny classrooms, most of the errors (false positives) are given by the over-counting when at least 30+ students are present in the classroom. Looking at the frames used for our tests, it is possible to notice how a critical area is present, and it corresponds to the last rows of the classroom. In that zone (from 8 meters to 12 meters from the camera) the bounding boxes are very small and people are also closer. Furthermore, it might be caused by the not enough examples in the dataset for the training phase.

The model is robust to the change of light during the day but suffer over-counting caused by students who are outside the classroom but near the classroom's windows. Problem easily avoided in our case, cropping the images ad-hoc before the prediction of the model. All the results reported and discussed above are available and located in the library repository[3].

Large classes				
	left camera		**right camera**	
Classroom	**avg accuracy**	**STD**	**avg accuracy**	**STD**
1	94,73	7,43	96,42	5,80
2	93,91	17,51	92,97	12,47
3	90,42	15,03	91,57	14,53

Table 3.5 Accuracy performance based on positioning of the cameras in the large classroms.

[3]https://tinyurl.com/yaapnbp8

3.6 Conclusion

In this chapter, we have presented three stage experiments. From the preliminary experiments, experiments with deep tiny models to an edge based system for the classroom occupancy detection in the University campus context. In particular, the model generated and the image cropping algorithm allowed to answer the RQ-1a. Through the transfer learning techniques instead, we have shown how it is possible to create a general model for each class on campus by acquiring images from only one class per type and therefore answering the RQ-1b. To enable the development, CSC dataset is collected and a filtered COCO dataset is retrieved to train a pretrained deep learning model for class occupancy detection.

We are planning new experiments, collecting new data samples and merge different sources. Through the use of the environmental data provided by the Canarin presented in [9], we would allow us to apply adequate strategies to estimate the human occupancy in accordance with user privacy and the GDPR directives. Moreover, the conduction of new experiments would give us the chance of better evaluating energy efficiency issues. Hence, we are working with different embedded devices and tinyML algorithms for real-time applications such as social distancing to help prevent the spread of COVID-19 within indoor environments and in particular the University Campus.

Chapter 4

Acoustic Comfort with a Machine Learning-based Noise Monitoring Platform

> How to monitor acoustic noise with low-end devices in order to improve the acoustic comfort within a smart campus?
>
> — **RQ-2**

Urban noise is one of the most serious and underestimated environmental problems. According to the World Health Organization, noise pollution from traffic and other human-activities, negatively impacting the population's health and life quality. Noise pollution can affect humans' comfort and performance both in indoor and outdoor environments, hence, it can play a significant role within the areas of a smart campus, involving its occupants.

It is worth mentioning that monitoring noise usually requires the use of professional and expensive instruments, called phonometers, able to accurately measure sound pressure levels. In many cases, phonometers are human-operated, therefore periodic fine-granularity city-wide measurements are expensive. Recent advances in the Internet of Things (IoT) offer a window of opportunities for low-cost autonomous sound pressure meters. Such devices and platforms could enable fine time-space noise measurements throughout a city. Unfortunately, low-cost sound pressure sensors are inaccurate when compared with phonometers, experiencing a high variability in the measurements. In this chapter, we present an unmanned noise monitoring platform that exploits artificial intelligence strategies to improve the accuracy of low-cost devices aiming at the answer at RQ-2. This platform was initially deployed together with a professional phonometer for over two months in Bologna (within the university campus), with the aim of collecting a large amount of precise noise pollution samples. The resulting datasets have been instrumental in designing InspectNoise, a library that can be exploited by IoT platforms, without the need for expensive phonometers, but obtaining a similar precision. In particular, we have applied supervised learning algorithms (adequately trained with our datasets) to reduce the accuracy gap between the professional phonometer and an IoT platform equipped with low-end devices and sensors. Results show that the platform, combined with the InspectNoise library, achieves a 2.24% relative error compared to professional instruments, thus enabling low-cost unmanned city-wide noise monitoring.

These results are encouraging, hence the defined library and low-cost IoT-based prototype can be exploited in a smart campus context, so as to monitor noise pollution in indoor and outdoor environments, enabling actions from the administration and the governance to eventually improve acoustic comfort for its occupants.

4.1 Introduction

Noise can be defined as an unwanted sound or a sound that is loud, harmful and annoying to the ear. Noise pollution has been known since the ancient Roman time [97], where ironed wheels of wagons were battering the stones on the pavement, causing disruption of sleep and annoyance. It could be a source of stress for many people and, if it persists for long periods, it can cause numerous negative effects on health [94]. In fact, it is ascertained how this issue can cause problems on a personal level, including the decrease in cognitive abilities, such as lower attention with the consequent cutback on working skills [206, 176, 140].

The causes of noise pollution are attributable to population growth, urbanization and the growth associated with the use of increasingly more powerful and varied noise sources, including means of transports (motorways, rails, and air traffic), which are considered as one of the main sources of the environmental noise [221, 222]. In particular, given the increasing spread of urbanization and roads, rails, and air traffic, the problem of noise pollution is constantly expanding [8], producing negative effects from different points of view, affecting social, economic and work aspects [218, 106], thus entailing a wide range of extra-auditory disturbances. In fact, according to the current literature, railway traffic [123, 45] represents the second most impacting noise source affecting human modern life style [124], after road traffic [64] [165, 202, 122], but before airports [85, 102], industries and wind turbines [82, 146], and port activities [30, 33, 83]. While sleep disorders with awakenings [168], learning impairment [256], hypertension ischemic heart disease [75, 25], and especially annoyance [147] are recognized as the most common negative health effects related to prolonged exposition to noise pollution.

In this context, it is crucial having precise data on noise exposure levels. Nowadays, noise measurements in urban areas are mainly performed by designated organisations, gathering data at one or more points of interest around the city. This way, it is possible to collect and store data for later analysis, by using expensive devices such as sound level meters. However, this collection method (using expensive equipment and requiring human manual intervention) does not scale, as the demand for the higher granularity of noise measurements in both time and space increases. A different perspective to mitigate this problem is to use an innovative approach relating to the interoperability of smart objects and their ability to access and retrieve data via the Internet, by applying the Internet of Things (IoT) paradigm [212, 228, 142, 127]. Thanks to the ever growing spread of low-cost and increasingly computationally efficient devices, it is possible to exploit artificial intelligence strategies (for instance, adopting machine learning algorithms) to compensate for the gap in terms of accuracy that affects low-cost sensors and devices. Moreover, the use of IoT is even more and more adopted to monitor different conditions, both in indoor [86, 160, 161] and in outdoor scenarios [42, 187].

In order to monitor noise pollution in smart campus contexts (so as to enabling action to preserve occupants' comfort), we have proposed an IoT platform, named RaveGuard, aimed to monitor noise pollution, based on low-cost sensors and devices, adequately trained and instructed by means of machine learning algorithms. In RaveGuard, the physical devices used for monitoring noise are microphones. There are various types, distinguished according to their operations, and for each type, there are various models, with different characteristics and price ranges. Obviously, models with very different prices indicate different measurement accuracy in terms of decibels (dB). Therefore, the purpose of our research in this context is to obtain a performance (in terms of accuracy in measuring noise intensity) similar to the one reported by the reference measurement instrument, even using low-cost microphones. In particular, in acoustic, such a reference measurement instrument is the sound level meter (phonometer). With our study [163], we aim at overcoming the precision gap between a low-cost microphone and a sound level meter calibrated. In order to reach this goal, we collected noise pollution samples by means of our IoT proposed platform, together with a professional phonometer, for two months, within the Campus of the University of Bologna. This allows us to create sample datasets, we have used to train different machine learning algorithms, with the aim of evaluating the one providing more accurate data, similar to the ones provided by the phonometer. Then, the most accurate machine learning algorithm has been exploited to create a library, named InspectNoise, that can be used by similar IoT platforms (equipped with low-cost microphones), supporting them in performing accurate noise pollution monitoring activities, in terms of sensing decibels. Another interesting point of attention is selecting the most appropriate dataset for adequately training a system by means of artificial intelligence strategies, as discussed in [197] and in [51]. In fact, in order to improve the quality of our training methodology, we have included also environmental data (such as temperature, humidity, air pollutant agents, and so on, collected by means of a multi-sensor station). Thus, we have obtained three different datasets (without environmental data, including dense environmental data, and including sparse environmental data) and we have applied four regressor models (choosing them among the most largely used in the literature). The training and the calibration activities have reported better results in terms of accuracy by using the second dataset, hence the one that includes also dense environmental data, showing an average error of 2.52 dB (against 5.20 dB, obtained without any artificial intelligence strategy to train the system).

The most innovative contributions of our study can be summarized as the following ones: (i) we have defined and proposed a low-cost IoT platform to monitor noise pollution; (ii) we have exploited artificial intelligence strategies to improve the accuracy of such a low-cost platform, making it comparable with the results obtained with professional and expensive equipment; (iii) we have added environmental data in the monitoring activities, enhancing the precision of the whole system in detecting noise pollution; finally, (iv) we have created three different datasets, on the basis of sampling activities last for 2 months, releasing them as available to the public audience.

This chapter is organized as follows: Section 4.2 reviews and discusses related works, comparing approaches in literature with the one we propose. Section 4.3 presents an overview of our IoT platform and of the InspectNoise library, describing their workflows. Section 4.4 describes the hardware equipment and the deplyoment of the sensors of our RaveGuard, presenting how we collected our datasets and comparing costs with professional equipment. Section 4.5 illustrates the methodology of the feature-based machine learning techniques we have exploited and the different datasets generated to improve monitoring of noise pollution, enhancing the accuracy of low-cost devices. Section 4.6 introduces the experiments, ground truth, and performance metrics, reporting their results. Finally, Section 4.7 discusses the results obtained by experiments we carried on and it concludes the chapter by presenting some limitations and future works.

4.2 Related Works

The growing popularity of the IoT devices with significant computational power, the ubiquitous access to Internet connectivity and a huge quantity of low-cost sensors open the door to a wide range of new applications [44]. In this perspective, it is, therefore, possible measuring the real impact of noise pollution through low-cost devices and microphones introducing a cheap, but powerful Wireless sensor network (WSN) platform that is readily available and widely deployed. Hereafter, we present the state-of-the-art in the area of environmental sensing, with a focus on noise pollution monitoring. In literature, we can find many works that we can categorize into three large groups that we will describe below.

4.2.1 Approaches Based on Propagation Models

Environmental noise is characterized as an abnormal and non-continuous phenomenon, and its intensity level changes rapidly over time. For this reason, countries such as European nations [148], United States, and Japan have developed their own sound propagation models so as to create noise maps by extrapolating local measurements to wider areas, showing the spatial distribution of noise exposure levels. The study described in [141] presents a field measurement approach that has been used in Karachi (Pakistan) to obtain information related to changes in traffic patterns and noise levels. Furthermore, it is possible to employ these models to produce exposure levels and to evaluate their effects on human health. [209, 138, 29] exploit such propagation models with the aim of validating noise levels. A different approach is studied in [269]: the authors investigated the temporal and the spatial variability of traffic noise in the city of

Toronto (Ontario, Canada), finding out that the variability of traffic-related noise was mainly related to the spatial dimension instead of the temporal one.

4.2.2 Approaches based on Mobile Crowdsourced Sensing

As already stated, prolonged exposure to noise can lead to various health risks, hence it would be strategic to densely monitor the noise, especially in the cities where traffic is constantly present [261]. Since the methods traditionally used for the detection of noise pollution use expensive and static equipment, they are not suitable for dynamic measurements [260]. Moreover, with the progress of technology and the spread of wearable devices, many avenues have been opened for the realization of applications for environmental monitoring [262]. Mobile Crowdsourced Sensing (*MCS*) is a human-centered detection paradigm, which allows citizens to provide data collected from their mobile devices, aggregate data collected in the cloud, extract knowledge and create awareness of some specific phenomena in the environment [137]. *MCS* represents a category of Smart Cities services that exploit citizens in the urban environment in order to collect and share data [259]. The large number of citizens and volunteers who adhere to these collection activities, as described in [135], could generate a huge amount of data and consequently increasingly accurate information, thus forming a more easily extensible architecture. The goal of *MCS* ecosystems is to inform citizens about the surrounding environment in real-time, so according to [137], users have a dynamic and always updated picture of the situation. In fact, smart mobility, together with the use of sensors for environmental monitoring and connectivity, can play a strategic role in providing useful information to citizens, so that they can improve their daily activities and the quality of their daily life [9]. These solutions are usually general enough to be used to monitor other kinds of environmental data, such as air pollution agents, contributing to the related analysis of fine particles. As an example, researchers from the University of Zhejiang, China, have developed a low cost sensor calibration method for air quality detection [125]. Furthermore, machine learning algorithms have been proposed in [223, 267]: such algorithms aimed at better calibrating low-cost sensors while monitoring air pollution in IoT scenarios, so as to improve the quality of those data gathered by such a kind of low-cost devices.

4.2.3 Approaches based on Wireless Sensor Networks

The last set of approaches that we present is the one based on Wireless Sensor Network (WSN). Such a kind of approach has been largely adopted in recent years, showing growing interest from the research community. An example is a system presented in [49], which lets monitor environmental noise by means of a WSN and users' health status through a Body Access Network (BAN) sensor. Another interesting study is presented in [204], where the authors designed and developed specific noise sensors, placing them in fixed places in the city, so as to perform the monitoring activity, through a WSN. Moreover, the increased computing capacity of the nodes that create the network is allowing the addition of processing algorithms and artificial intelligence that provide more information the environment as exposed in [171].

Indeed, WSN is a technology applicable to a wide range of contexts related to IoT and monitoring activities, such as: environmental monitoring and urban sensing [110], natural disasters [58], healthcare [112], smart building [88], target objects tracking [47]. WSNs can be based on specific sets of low cost and low power nodes and sensors, connected to a gateway, letting the data collected within the network to reach an external communication network. An interesting key point is the cost sustainability: a detailed evaluation is necessary to identify if traditional or similar approaches are cheaper on a large scale.

4.3 System Overview

This Section presents an overview of RaveGuard IoT platform, by describing (i) the system architecture (Subsection 4.3.1) and its main components devoted to sense noise and environmental data; and (ii) the main issues and workflow of the *InspectNoise* library (Subsection 4.3.2), we have designed and developed after the training phase (as described in the following Section 4.5), where we have chosen the machine learning algorithm and the dataset which provide the best result in terms of accuracy, with the aim of overcoming the gap between professional equipment (phonometer) and a low-cost microphone, hence letting an IoT platform monitor noise pollution with high precision. The combined use of our IoT platform, equipped with a low-cost microphone, together with the InspectNoise library, will let us monitor noise pollution with a limited error in terms of sensed dBs, as described in the rest of the chapter.

4.3.1 Our Platform Architecture

Figure 4.1 illustrates an overview of the IoT platform architecture we propose, which employed two sensing systems. One is aimed to noise pollution sensing, which takes over dB SPL (decibel Sound Pressure Level), based on a Raspberry Pi 2 model B and a low-cost microphone (a USB condenser microphone). In the data collection phase, we have equipped our RaveGuard platform with an UDOO Neo embedded device and a calibrated phonometer too (as depicted in Figure 4.1). That has been necessary to gather noise samples from both professional equipment and a low-cost one. In particular, the calibrated sound level meter (on the UDOO New embedded device) represents the reference sound level meter (**RSlm**), while the USB condenser microphone (on the Raspberry Pi 2 mobel B) represents the device to be calibrated (**DtbC**). After the calibration phase and the training phase (exploiting artificial intelligence strategies), our IoT platform could perform noise pollution monitoring with just the low-cost sensors, avoiding the use of expensive and professional equipment.

The second component is an environmental sensing system that can monitor temperature, relative humidity, air pressure and Particulate Matter (PM), in particular PM 1.0, 2.5 and 10, based on a Canarin II multi-sensor platform [9]. This is a crucial component to gather additional environmental data and include them in the training activities, during which we can evaluate and quantify how such information can improve the precision of the whole noise sensing platform, with the aim of reaching our goal: overcoming the precision gap between a low-cost microphone and a sound level meter calibrated. A detailed description of the whole hardware equipment we exploited in our proposed platform will be provided in Section 4.4.

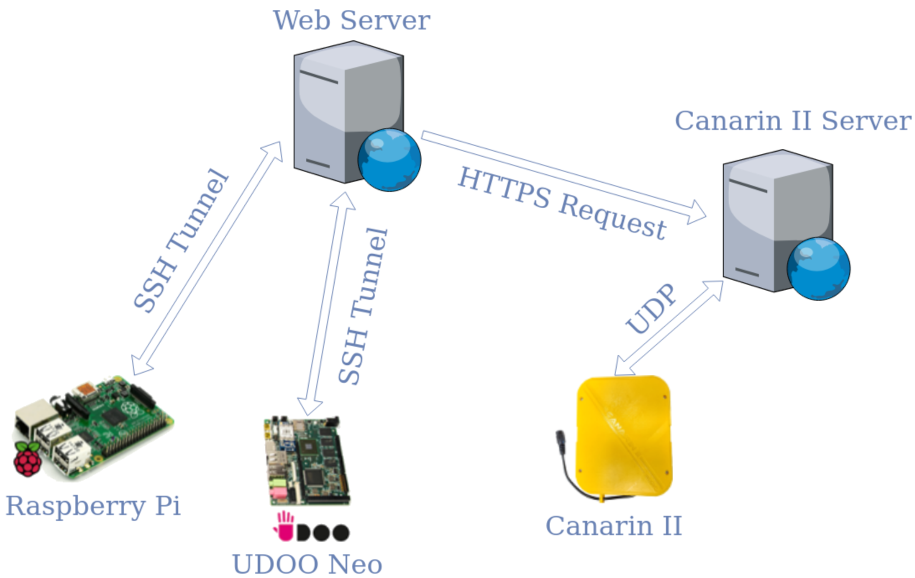

Fig. 4.1 RaveGuard experimental architecture

In a first phase of our study, these two different components of our IoT platform architecture were meant to gather noise samples so as to create datasets, that will be exploited to train the whole system, by using the most performing machine learning algorithm. In particular, our RaveGuard collected data in different ways, generating three different datasets:

- *Tiny dataset*: this dataset is generated by the noise samples collected by the USB condenser microphone (**DtbC**) and by the calibrated sound level meter (**RSlm**).

- *Full-sparse dataset*: this dataset is generated by the noise samples collected by the USB condenser microphone and by the calibrated sound level meter, enriched with the environmental data gathered by the Canarin II multi-sensor station. Downsampling techniques have been applied on the noise pollution data in order to obtain the same sampling frequency of the Canarin II multi-sensor kit (1 per minute, against 1 per second of the noise monitoring component of our platform), this is why this dataset is considered *sparse*, when compared with the following dataset.

- *Full-dense dataset*: this dataset is generated by the noise samples collected by the USB condenser microphone and by the calibrated sound level meter, enriched with the environmental data gathered by the Canarin II multi-sensor station. In this case, upsampling techniques have been applied on environmental data collected by the Canarin II multi-sensor station, so as to obtain 60 occurrences per minute (using linear interpolation).

In generating these two latter datasets (*full-sparse* and *full-dense* datasets), downsampling and upsampling techniques have been necessary, because the data sampling frequency of the two architectural components is different: the noise monitoring component performs a sampling frequency of 1 per second, while the environmental monitoring component performs a sampling frequency of 1 per minute. Such sampling frequencies have been affected by the hardware equipment we have exploited in the experiment we have performed, as detailed in Section 4.4. In particular, the phonometer we have used allows a discrete sampling with 1 sample per second as sampling frequency, while the PM sensor within the Canarin II multi-sensor station generates one sample per minute, requiring time-consuming and resource consuming operations (in terms of computation). Hence, downsampling and upsampling techniques allow us to create uniform datasets, aligning sensed data over time. In general, our InspectNoise library and the whole RaveGuard system can perform and compute different sampling frequencies, with different rates (until 44,100 samples per second), on the basis of the capabilities of the hardware equipment actually used for the monitoring activities.

All datasets are open and available[1].

[1]https://github.com/LorenzoMonti/inspectNoise/tree/master/dataset

Our three datasets have been then employed to define two models that can be found within the InspectNoise library and they have been then instrumental for the training phase.

Such a training phase is necessary, because, after adding a correction equal to the average of differences between the errors, the difference in terms of dB SPL (decibel Sound Pressure Level) between **DtbC** data and **RSlm** data is 5.20 dB, as depicted in Figure 4.2. In fact, such a Figure represents the sound level samples we have gathered during two months, comparing the noise levels monitored by our low-cost microphone and the professional phonometer we have exploited during the data collection phase, during which we have observed an average error of 5.20 dB. Hence, it is interesting investigating and evaluating how the adoption of some artificial intelligence strategies (such as machine learning techniques and methodologies) to train the low-cost version of the IoT platform, could bridge the accuracy gap of low-cost sensors and professional equipment results.

Regarding the network topology, our prototype (and the experiments we carried out) refers to a topology known in the literature as a star topology, where there is a single central node known as a hub or switch, while each other node of the network is connected to such a hub.

4.3.2 InspectNoise Library

In our study, we have designed and implemented the **inspectNoise**[2] library as the result of the datasets collection and of the machine learning training phase. The library takes into account two models: (i) the *Tiny model*, in which we analyze the USB condenser microphone dataset and the calibrated sound meter dataset; and (ii) the *Full model*, in which we analyze the datasets included in the tiny model, plus the dataset generated by the environmental data monitored by the Canarin II platform. The main goal of NoiseInspect is to support our RaveGuard platform, collecting and storing data and, once machine learning models were created, test them directly. Indeed, NoiseInspect has been trained using our three datasets and some machine learning algorithms, and it could be exploited by

[2]https://github.com/LorenzoMonti/inspectNoise

Fig. 4.2 The amount of **DtbC** and **RSlm** data collected. The samples are aligned over time.

other similar IoT platforms, that could be equipped (using the full model) or not (using the tiny model) with environmental sensors.

This library has been developed in Python 3, exploiting in turn some libraries such as *PyAudio* and *Pydub* to manipulate input/output audio streaming *Numpy* in order to operate efficiently on audio data structures and *pickle* for serializing Python object structures. The system is basically in the *off state* and, when it is triggered, it will be brought to the *on state*. In particular, it is possible to set the number of seconds, which represents the duration of the noise monitoring activity.

A schema representing the InspectNoise states (when the system is *on*) is depicted in Figure 4.3. At any time the system can return to the *off state*, when the *sigterm* is received, as well as after the preset operating time has elapsed. Figure 4.3 represents the behavior of the system, which is divided into six states:

1. **Setup:** In this state, the flags passed to the program are evaluated and the variables are prepared to perform the subsequent tasks.
2. **Record:** Ambient noise is monitored by creating audio segments.
3. **dB evaluation** The dB SPL for the previously detected audio segments are calculated.
4. **Collect data:** The data are compared with the previous ones to obtain at the end statistics as a minimum, maximum, and average.
5. **Loggin on file:** The dB value, obtained from the audio segments of the iteration, is written in the file, together with the timestamp identifying when the measurement took place.
6. **Write audio segment:** The audio segments are written in the memory, so as to be later exported in audio files.

4.4 Hardware Equipment and Deployment

This section is devoted to providing detailed information related to the Rave-Guard hardware equipment and the sensors deployment. Moreover, a cost comparison between our low-cost platform and regular equipment devoted to noise monitoring can be found in Subsection 4.4.5.

In order to monitor environmental noise, our system has been equipped with a USB condenser microphone (**DtbC**), and a calibrated sound level meter (**RSlm**). They have been associated with an embedded device, having access to an Internet connection, so as to monitor the status of our platform. These devices have been configured to collect data and, independently, share them, in an automatic way, hence without the need of an explicit human intervention.

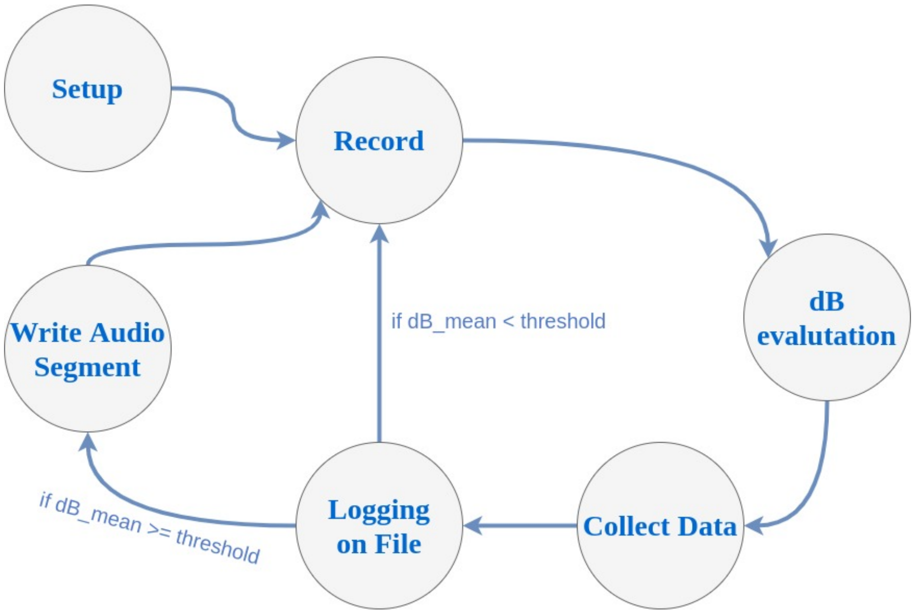

Fig. 4.3 States of InspectNoise

This strategy was implemented to collect a sufficient amount of data, so as to implement proper machine learning strategies predicting the calibrated decibels of the **RSlm**. In this scenario, IoT devices have been used to facilitate and to automate the data retrieval and sharing procedure.

In order to create a machine learning algorithm to calibrate low-cost microphones, a proper amount of data to train the machine learning models is necessary. First of all, a key point is the creation of datasets. As reported in [268, 125, 223, 267], it is necessary to use a device that has to be calibrated, i.e., the microphone **DtbC**, and a device that provides reliable reference measurements, **RSlm** (taking into account the specific field of acoustics), so as to collect data that would create the datasets that will be used to instruct the machine learning models, as described in the following Section 4.5.

To ensure that the activity carried out by our platform can be monitored (without the need of a direct connection) and to form an architecture that supports maintenance activities, both such devices have been connected to embedded systems equipped with internet access. As already anticipated in SubSection

4.3.1, the devices used were: (i) a Raspberry Pi 2 model B with a low-cost USB condenser microphone, (ii) a UDOO Neo platform with a calibrated phonometer and lastly (iii) a low-cost environmental multi-sensor platform, named Canarin II. The following subsections provide a detailed description of all these devices.

4.4.1 Low-cost microphone and Raspberry Pi

In order to retrieve data from the USB microphone **DtbC**, we have used a Raspberry Pi 2 model B, a single-board CPU, an embedded system that incorporates on the same board a series of components, such as a microprocessor, a GPU, a RAM memory, a timer, a WiFi module, etc. The device is equipped with a series of analog and digital pins, so as to be able to interface with a wide range of sensors and equipment (available on the market). In fact, it has all the standard interfaces, such as USB, HDMI, etc. Thanks to these features, it is possible to connect the "*Mini Akiro*" microphone directly via the USB port. The WiFi module integrated in the card allows us to have an autonomous device that can share on the Internet all the data collected during the monitoring activities.

The InspectNoise library lets us monitor the noise level in real time (acquiring noise in terms of decibels, dB) from any USB microphone connected to our platform. Such a library, developed in Python, it allows to save and store the samples taken in different files and formats. Sampling is carried out once per second, for a monitoring period that can be set from the command line. The microphone we have used in our prototype has been chosen for its availability on the market and its low cost. From the analysis of the data collected from the sound level meter and the microphone in Table 4.1, it seems clear that the values measured by the latter are not calibrated, since the difference between the values is very high.

The Raspberry Pi and the microphone therefore compose one of the edge-nodes of our platform, designed to monitor environmental noise.

Datetime	$dB_{microphone}$	$dB_{phonometer}$
19:00:07	48.07	52.12
19:00:08	46.03	50.59
19:00:09	47.15	49.14
19:00:10	47.90	49.70

Table 4.1 Comparison of dB_{SPL} measured by the microphone and the sound level meter

4.4.2 Calibrated phonometer and UDOO Neo

The UDOO Neo embedded has been devoted to obtaining the sound level meter data (**RSlm**) too, another single-board CPU device that incorporates all the components necessary to perform its tasks. This device is also equipped with the WiFi module, integrated into the board, which allows a simple connection with the other components of the architecture, so as to let exchange data. The sound level meter in question is the Uni-T UT351/352, a class 2 phonometer with a large range in terms of decibel (for our purpose), from 30 dB to 130dB. Through the analog input of the board, we have connected the sound level meter by capturing its voltage by jumpers. The sound level meter expresses 10mV in output for each decibel measured in the input. Thanks to the hybrid architecture proposed by UDOO Neo, which contains both a microcontroller (Arduino-like) and a microprocessor (Raspberry-like), it was possible to acquire and save data via a microcontroller in a simple and compact way, managing the network and forwarding these data via such a microcontroller. This IoT device, consisting of the UDOO Neo and a calibrated sound level meter, compose the second node of our developed edge architecture. On the contrary of the node described in the previous subsection, this has been equipped with a sound level meter, that constitutes the reference device for calibration.

4.4.3 Canarin II

A peculiar characteristic of our RaveGuard platform, which represents a very innovative aspect of our proposed solution if compared with the other noise monitoring systems, is the inclusion of a multi-sensor platform devoted to collect environmental data.

In particular, in our prototype, we have exploited the Canarin II architecture, an in-house printed circuit board (PCB) hosts the board and the sensors welded, summing up the PCB and the battery fits in a 19x15x7 cm, weighting about 900 gr. The PCB is contained in a in-house 3D printed PLA box, which has been designed to wrap the battery too. Such a platform has been developed and used for research purposes thanks to the synergistic collaboration among University of Bologna, Macao Polytechnic Institute, the Asian Institute of Technology, and the Pierre and Marie Curie Sorbonne University. This multi-sensor station is equipped with different sensors, such as environmental sensors to sense air contaminants, gathering formaldehyde, PM1.0, PM2.5, and PM10 values. In addition, temperature, relative humidity and air pressure sensors are included in such a station. The communication between the station and our Web server is managed by a WiFi module that allows the device to act as a node in our infrastructure. During the data acquisition phase, the platform was placed alongside the other embedded devices in order to obtain a different kind of data, so as to have a better calibration level. Therefore, the measures of the environmental components collected by our Canarin II include: *temperature*, *relative humidity*, *PM10*, *PM1.0*, *PM2.5*, and *pressure*. A more detailed description of the Canarin II platform, its characteristics and performances can be found in [9] and in [233].

4.4.4 Sensors deployment

All the nodes described in the previous subsections compose the entire RaveGuard platform architecture, as shown in Figure 4.1. In this subsection, we are going to present at a higher level of abstraction, illustrating the sensors deployment. First of all, the nodes used to acquiring the data relating to noise pollution have been positioned: the first consists of the Microphone-Raspberry Pi, while the second consists of the Phonometer-UDOO neo. Both devices were placed close together and at the same height, so that they performed equally and were subject to the same conditions. Each of them uses the reverse SSH tunneling technique (as depicted in Figure 4.1), so as to be able to connect to our server (placed within the university campus) to communicate, be reachable, and upload data. The samplings were performed by the devices with a frequency of one sample per second, for a period of about 12 hours a day, therefore having 43,000 occurrences available every day. For a period of about 60 days, more than two million records make up the dataset. The Canarin II platform was also placed close to the microphone and the sound level meter to capture environmental data and thus achieve optimal calibration levels. In this case, such a multi-sensor station generates data with a frequency of one sample per minute. This is mainly due to the PM sensor, which requires a specific computational time. Gathered data are then forwarded via UDP protocol and stored on an ad-hoc server. This way, it is possible to query our server in order to interact and access all the necessary environmental data.

The entire monitoring process was carried out regularly for a period of about two months, with daily sampling lasting about twelve hours. At the end of the process, the data collected by the phonometer and the microphone have been transferred to the server, by using the existing SSH tunnel and through HTTPS request for the Canarin II platform. It is worth mentioning that such a technique is not mandatory to let our platform work: it has been necessary to overcome some connectivity limitations we experienced in the geographic location where we placed our prototype to collect the data for our experiment. Actually, once we have gathered the samples we needed to create the datasets, our RaveGuard platform can be used with similar hardware equipment, with other IoT-standard protocols, with other networks, and with other connectivity capabilities. The same is for our NoiseInspection library, which could be exploited in IoT contexts.

Hence, thanks to such a sensors deployment for this specific experiment, it was possible to create a dataset large enough to perform the machine learning strategies, as described in the following Section 4.5.

4.4.5 Costs Comparison

As we are going to describe in Section 4.2, several solutions already exist that provide noise pollution monitoring and sensing activities. One of the most interesting and innovative aspects of the platform we propose is the exploitation of environmental data (to collect more and different information to instruct the machine learning models) and the low cost of the hardware equipment, with performances and efficacy that can be compared with professional and expensive equipment.

In Table 4.2, we report the costs related to the sensors and the components that compose our platform and the costs of a professional out of the box solution, so as to compare them.

The sensing platform we propose is an open-source, low-cost and intelligent solution (thanks to the machine learning models we have adopted to train the system), which can real-time and continuously (24/7) monitor noise pollution. In particular, our RaveGuard is a scalable solution, because all the computation activities take place on the device; moreover, exploiting embedded devices, our platform is efficient in terms of energy consumption too, if compared with other monitoring stations and units that are often used to gather environmental data. Indeed, this is not true if we compare the energy consumption required by the Raspberry Pi 2 board with other IoT devices. In fact, Raspberry Pi 2 is less effective in this sense than other similar devices [17].

inspectNoise		**phonometer**	
Raspberry Pi 2	∼33 euros	Uni-T UTI 351	∼288 euros
Mini Akiro USB microphone	∼15 euros	Power supply	∼7 euros
Power supply	∼7euros		
microSD 8Gb	∼5 euros		
Total	∼60 euros	**Total**	∼295 euros

Table 4.2 Costs comparison between our platform and a calibrated phonometer (devices used to retrieve data and create the dataset)

4.5 Training RaveGuard: our Methodology

In this section, we provide an overview of the methodology we have used to train our system. In fact, in order to improve the accuracy of low-cost microphones in our experiments, some machine learning algorithms have been exploited and examined for each dataset. In particular, we took advantage of four of the most widely used regressor models in the literature (linear regression, logistic regression, random forest and support vector regression), as described in the following subsections.

4.5.1 Linear Regression

Linear regression is a basic and commonly used type of predictive analysis. It predicts the relationship between two variables such as in the case (i) *tiny* dataset, in which we have only the microphone samples that represent the independent input variable X, while the calibrated values collected by the sound level meter the dependent one, to be predicted in output Y as show in 4.1 and the model in equation 4.1.

$$y_{reference}(t) = \beta_0 + \beta_1 \times [dB_{microphone}] \tag{4.1}$$

A natural generalization of the simple linear regression model is a situation including the influence of more than one independent variable to the dependent variable, again with a linear relationship such as with the (ii) *full* dataset, that includes environmental data. This is quite similar to the simple linear regression model, but with multiple independent variables contributing to the dependent variable and therefore multiple coefficients for determining and complex calculation due to the added variables as shown in equation 4.2.

$$Y_{reference}(t) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n \tag{4.2}$$

4.5.2 Polynomial Regression

The polynomial models can be used in those situations where the relationship between study and explanatory variables is curvilinear and a linear regression is not enough. So, it is used to overcome the underfitting problem, sometimes a nonlinear relationship in a small range of explanatory variables can also be modeled by polynomials and we need to increase the complexity of the model. As shown in 4.3, this is a linear model, because the coefficients/weights associated with the features are linear.

$$Y_{reference}(t) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + ... + \beta_n x_i^n \tag{4.3}$$

A *grid search* has been prepared to test all polynomial values. Furthermore, to avoid *overfitting*, by increasing the degree of the polynomial, the *Ridge Regression regulation* was introduced to limit the $theta$ values calculated by the algorithm, via an origin-centered hypersphere.

4.5.3 Random Forest

Random Forests is a learning model based on ensemble learning, so, in this case, different algorithms are combined to obtain a better prediction model, solving regression and classification problems [37]. In this case, the results obtained from different decision trees are combined, which are aggregated to form a forest. This algorithm extrapolates N random records from the dataset, to build a decision tree based on the latter. This procedure is repeated N times, so as to create N decision trees that cooperate in the regression or classification task. In brief, a random forest model consists of a large number of individual decision trees that work as an ensemble. Every decision tree in the random forest generates a class prediction and the class with the most votes becomes the model prediction. It will be necessary to choose the minimum number of decision trees to build the forest, and each tree will be built using a bootstrapped random sample from the training set. The design of the decision tree required the choice of an attribute selection measure and a pruning method. Exists several approaches to select the attributes for the decision tree induction and most approaches assign a quality measure directly to the attribute. The most frequently used attribute selection measures in the decision tree are the Gini Index [38] and the Information Gain Ratio criterion [190]. The random forest classifier uses the Gini Index as an attribute selection measure, which measures the impurity of an attribute with respect to the classes. For a given training set T selecting a value at random and saying that it belongs to some class C_i, it's possible to write the Gini Index as:

$$\sum\sum_{j \neq i}(f(C_i,T)/|T|)(f(C_i,T)/|T|)$$

where $f(Ci,T)/|T|$ is the probability that the selected case belongs to class C_i. Every time a tree is grown to the maximum depth on new training data using a combination of features. These fully grown trees are not pruned. As exposed by Quinlan [190], this is one of the major advantages of the random forest classifier over other decision tree methods. Therefore, the random forest method consists of N trees, in which N is the number of three, where the users can define any values. To classify a new dataset, each case of the datasets is broadcasted to each of the N trees. In this case, the forest chooses a class having the most out of N votes.

4.5.4 Support Vector Regression

The SV algorithm is a nonlinear generalization of the *Generalized Portrait* algorithm developed in Russia in the sixties [240, 241]. The support vector machine (SVM) in its present form was largely developed at AT&T Bell Laboratories by Vapnik and co-workers [242]. SV learning has now evolved into an active area of research and it is widely applied to various fields, such as regression estimation, pattern recognition, and probability density function estimation. It is an exclusively data based modeling technique with a powerful potential for function estimation application. It was originally developed for classification purposes (SVC), before being extended also to regression problems (SVR). More formally, a support vector machine constructs a hyperplane, or set of hyperplanes, in a much higher dimensional space, which can be used for classification or regression. The support vector regression method aims at finding optimum hyperplane using the *max-margin* idea and minimizing the training error between the training data and identified function by means of the loss function. SVR maximizes the margins around the separating hyperplane. The decision function is fully specified by a subset (usually small) of training examples, called *support vectors*. Intuitively, we can use the optimization of *max-margin* to reduce the number of weights that are nonzero to just a few that correspond to the important features in order to separate line. Moreover, to keep the computational load reasonable, the mapping used by SV algorithms are designed to guarantee that dot products of input data vectors must be processed in terms of variables in the original space using the kernel function $k(x,y)$ selected to fit the problem.

4.6 Results

In this section, we are going to present the application of the previously described machine learning algorithms, on the basis of our three datasets, reporting and comparing the obtained results. In particular, with the phonometer collected data as ground truth, four error metrics were used to compare all combinations of algorithms and datasets. The error metrics include mean square error (MSE), relative error, R^2 coefficient and root mean squared error (RMSE). The following subsections report the results we have obtained for each dataset.

4.6.1 Performance of the calibrated dB starting from microphone ones (Tiny dataset)

This first approach involves the creation of the simplest dataset (the so-called *tiny* one), consisting of the samples gathered by the microphone **DtbC** and the sound level meter **RSlm**, then used as a basis for the realization of the following methods. The dataset was divided into training set (2/3) and validation set (1/3), used respectively for training and model evaluation.

The linear regression method, as shown in table 4.3 (first column), reports a value of 0.81 for the coefficient R^2, while the prediction shows an average error of 5 dB (Root Mean Square Error, RMSE). Finally, the relative error, which indicates the average error percentage of the predicted values compared to the real ones, is 7%. This linear model overlaps on the training set data, as depicted in Figure 4.4 (top left).

The best results obtained with polynomial regression, shown in Table 4.3 (second column), were obtained with a polynomial of degree 50, which is the maximum tested, and with 0.1, as the weight of the regularization. It is worth noting that, by continuing to increase the degree of the polynomial, the error did not undergo major changes. It is therefore not necessary to continue increasing the degree as higher computational resources would be needed to obtain a non-significant increase in terms of accuracy. This model approximates the variability of the data better than the previous one, since it has an R^2 coefficient of 0.85. Moreover, in the prediction of the calibrated decibels, it reports an average error of about 4.15 dB. Finally, the relative error is 5.77%. As Figure 4.4 (top right) shows, this polynomial model overlapped on the training set data.

The grid search technique was used for the random forest model, to search for the number of decision trees that would provide the greatest possible accuracy in prediction. Up to 140 decision trees have been tested. The best result was achieved precisely with 138 trees. The values of the model evaluation parameters are shown in Table 4.3 (third column). This model approximates the variability of the data as it has an R^2 coefficient of 0.85. Moreover, in predicting the calibrated decibels, it reports an average error of 4.16 dB, slightly higher than the previous model. Finally, the relative error is 5.77%. The Random Forest model overlapped on the training set data is depicted in Figure 4.4 (bottom left).

The Support Vector Regression method, as shown in table 4.3 (fourth column), obtains a coefficient R^2 of 0.85. Moreover, the average error of the prediction is 4.19 dB. Finally, the relative error, which indicates the average error percentage of the predicted values compared to the real ones, is 5.75%. The

Support Vector Regression model overlapped on the training set data is depicted in Figure 4.4 (bottom right).

	Linear reg	**Poly reg**	**R.F.**	**SVR (rbf)**
MSE	22.328	17.262	17.326	17.561
Rel. avg error	7.08692%	5.77911%	5.77192%	5.75414%
R^2 **coefficient**	0.81034	0.85337	0.85283	0.85083
RMSE	4.725	4.154	4.162	4.1906

Table 4.3 First experiment: evaluation coefficients for linear regression, polynomial regression, random forest and Support Vector Machine with rbf kernel

4.6.2 Performance of the calibrated dB starting from the microphone ones and from the Canarin II data, using a frequency per second (Full-dense dataset)

In this second approach, in order to predict the calibrated decibels, we have taken into account not only those ones measured by the microphone, but we have considered also the environmental data collected by Canarin II platform. The goal is to have a calibration precision more accurate than the one obtained with the previous method, by including the set of environmental data in the analysis. For the creation of the dataset, the data referred to **DtbC** and **RSlm** are the same used in the previous model, plus the environmental data.

The Canarin II station gathers data with a sampling rate of one minute, which leads to a number of occurrences of 59/60 lower than the sampling carried out by **DtbC** and **RSlm**. We decided to maintain the frequency used by the latter, which leads to the need to expand Canarin II data to obtain 60 occurrences per minute taking into account the 30 day period, thus obtaining a number of occurrences exceeding one million. *upsampling* techniques were applied from minute to second using the linear interpolation strategy. A fragment of this second dataset is reported in Table 4.4.

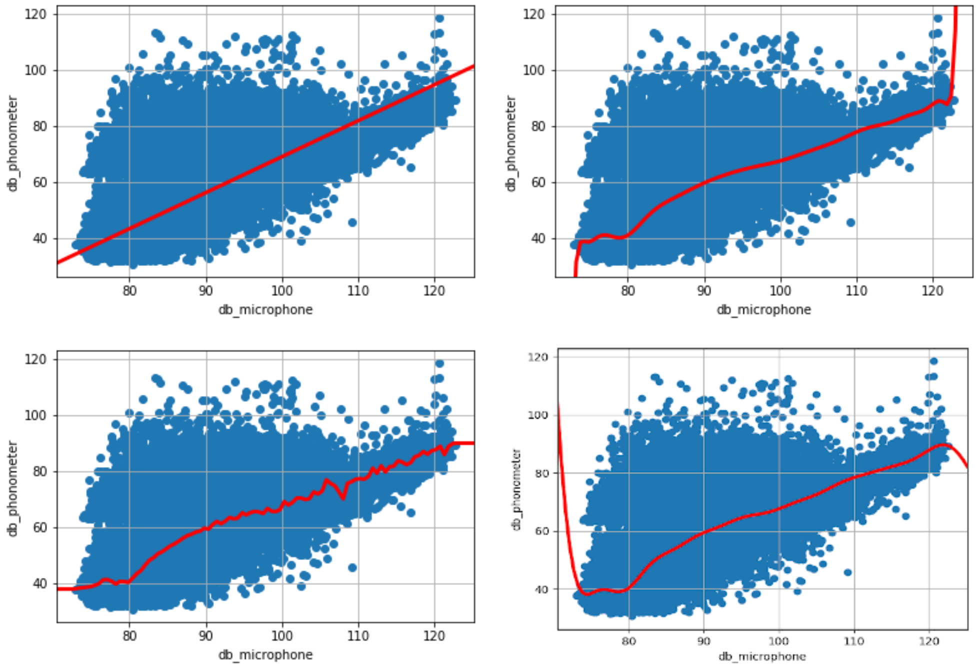

Fig. 4.4 All the images show the correlation between the **DtbC** dB and **RSlm** dB. The top left image shows the univariate linear model, the top right image instead shows the polynomial model, the bottom left image the model based on Random forest and the bottom right image the model based on Support Vector Regression

Also in this case, the models tested will be linear regression, polynomial regression, Random Forest and Support Vector Regression, and the results obtained in this second approach will be reported. The data were divided into training (2/3) and validation set (1/3). Unlike the previous case, the regression will be multivariate, i.e., the value of the dependent variable Y is estimated starting from the value of a set of independent variables X.

The first model tested, the linear regression model, shows the results as reported in Table 4.5 (first column). It is possible to notice that through the addition of new features relating to environmental data, the simple linear regression model leads to slightly better results than those ones obtained from the linear

DateTime	db_{mic}	db_{phon}	PM1.0	PM10	PM2.5	Pres	Temp	Hum
19:00:13	48.18	51.07	3.0	7.0	5.0	1007.7	21.9	59.2
19:04:19	46.80	48.90	3.0	6.0	5.0	1007.7	21.9	59.2
22:06:54	54.10	59.37	3.7	5.7	5.0	1009.0	22.7	57.2
06:58:10	63.98	69.93	3.0	5.0	5.0	1008.8	24.9	58.4

Table 4.4 Exemplary part of the second dataset

regression applied to the first dataset. Having a lower relative error and a higher R^2 coefficient, consequently also the average error resulted in each prediction (RMSE) is lower.

The polynomial regression model was tested and, as well as in the previous case, the grid search technique was used as a regularization technique, so as to avoid overfitting by increasing the degree of the polynomial. Polynomials up to grade eleven were tested, the latter also allowed to achieve the best result. The models have been tested with and without regularization, obtaining practically the same result. Table 4.5 (second column) shows the best results obtained with a three grade polynomial. It is interesting to note that such a model approximates the variability of the data very well, leading to an R^2 coefficient of 0.91 and an RMSE of 3.25 dB.

In the previous case, the Random Forest model has allowed, with a reasonable number of trees (100), to achieve the same results as the polynomial model with a degree 20 polynomial. In Table 4.5 (third column), the results obtained by applying this machine learning model with this second dataset. The latter results show how the model best represents the variability of the data, obtaining an R^2 coefficient of 0.94, while the average error committed in the predictions (RMSE) is only 2.52 dB.

The gradient boosting model was also tested, also based on decision trees. In this case, each observation is weighted equivalent to the creation of the first tree. In this case, the weight associated with difficult to predict observations is increased, and vice versa, the weight of easily predicted observations is decreased. A second tree is then built on these new weighted data. Once this is done, the regression error made by joining these two trees is calculated to build a third tree. This procedure is performed iteratively, to decrease the residual error each time, for a number of times equal to those specified by its hyperparameter. Also in this case a grid search has been set up to search for the best value of the hyperparameters. The models were tested with a limited number of hyperparameters, as the results did not improve significantly. Up to 100 iterations (boosting stages) have been tested and the results obtained are those one reported in Table 4.5 (fourth column).

Regarding Support Vector Machine model, the results are shown in Table 4.5 (fifth column). The variability of the data expressed through R^2 coefficient is 0.92. Moreover, in predicting the calibrated decibels, an average error of 3 dB is obtained.

	Linear reg	**Poly reg**	**R.F.**	**G.B.**	**SVR (rbf)**
MSE	19.942	10.574	6.3558	11.978	9.4129
Rel. avg error	6.41215%	3.62220%	2.24996%	3.93945%	3.10973%
R^2 **coefficient**	0.83268	0.91128	0.94667	0.8995	0.92102
RMSE	4.465	3.251	2.521	4.011	3.0681

Table 4.5 Second experiment: evaluation coefficients for linear regression, polynomial regression, random forest, gradient boosting and Support Vector Machine with rbf kernel

4.6.3 Performance of the calibrated dB starting from the microphone and from the Canarin II ones (Full-sparse dataset)

In this third approach, the acoustic data collected by the microphone and by the sound level meter, already prepared in the initial dataset, and those ones gathered by the Canarin II are used again. Also in this case, considering the same features of the previous one, multivariate regression is carried out with the aim of obtaining better results to perform the calibration. Despite the similarity to the previous approach, in this case we exploit the sampling frequency of the Canarin II (hence, one sample per minute, instead of one per second), as shown in Table 4.6, which reports a fragment of the third dataset. This means that, performing the sampling for 60 days, we collected about 40,000 occurrences, made available for a third dataset. Also in this case, we have based the experiments on the machine learning models tested in the previous subsections.

DateTime	db_{mic}	db_{phon}	PM1.0	PM10	PM2.5	Pres	Temp	Hum
19:07:22	47.40	52.69	4.0	7.0	6.0	1007.7	21.9	59.3
19:08:22	46.96	50.43	3.0	5.0	5.0	1007.7	21.8	59.3
19:09:24	44.40	45.68	3.0	6.0	5.0	1007.7	21.9	59.3
19:10:25	45.78	48.25	3.0	6.0	4.0	1007.7	21.8	59.2

Table 4.6 Exemplary part of the third dataset

The first test, also in this case, is based on the linear regression model, whose results are presented in Table 4.7 (first column).

Regarding the polynomial regression model, also in this case, the best values of the hyperparameters are obtained by using the search grid technique. Having a much lower number of occurrences, it was possible to increase the degree of the polynomial, but failed to achieve better results than those ones obtained with the polynomial regression using the previous dataset. Table 4.7 (second column) shows the results obtained with degree 4 polynomial and regularization weight 11.

Since the number of samples was much lower than in the previous analysis, it is possible to test the Random Forest model with a greater number of decision trees (up to 300). The best results, shown in table 4.7 (third column), are those ones obtained with 269 decision trees. Despite the radical increase in the number of decision trees involved in ensemble learning, it has not been possible to approach the precision achieved through the random forests applied to the previous (larger) dataset.

Lastly, the Support Vector Regression with Gaussian kernel (that is shown in 4.7, fourth column), obtained the best result in this experiment. This model approximates the variability of the data as it has an R^2 coefficient of 0.90. Moreover, in predicting the calibrated decibels, the average error reported is of 3.42 dB.

	Linear reg	**Poly reg**	**R.F.**	**SVR (rbf)**
MSE	20.226	12.216	13.073	11.76
Rel. avg error	6.48700%	3.97385%	3.87727%	3.70047%
R^2 **coefficient**	0.83203	0.89855	0.89143	0.90234
RMSE	4.497	3.495	3.61	3.4292

Table 4.7 Third experiment: evaluation coefficients for linear regression, polynomial regression, random forest and Support Vector machine with rbf kernel

All the results reported in these three experiments are reproducible and the code is located in the library repository inside the tests folder[3].

4.7 Discussion, Conclusion and Future Works

The second experiment, described in the previous section of this chapter, is the one that holds the best result in terms of accuracy. This is mainly due to the pre-processing of the dataset (that is the *full-dense* one). In fact, in addition to the very high number of occurrences (over one million), it also contained all the features relating to environmental conditions. By analyzing the models applied to this second dataset, it is worth noting that the best accuracy is achieved by the regression model based on the random forest. By using a limited number of decision trees (100) (to avoid a disproportionate increase in training times), it was possible to achieve very good results (see Table 4.8). In fact, the average error (in making predictions) is approximately 2.52 dB, with respect to the values measured by the reference device, i.e., the sound level meter. Furthermore, the model approximates the variability of the data in a very good way, having a coefficient R^2 of 0.94 and a relative error of 2.24%. Furthermore, it is important to highlight that such results should be compared with the RMSE error reported

[3]https://github.com/LorenzoMonti/inspectNoise/tree/master/tests

without the use of any type of machine learning technique, which is 5.20 dB (vs 2.52 dB obtained with our RaveGuard platform, adequately trained).

Feature importance scores play an important role in a predictive modeling project, including providing insight into the data, insight into the model, and the basis for dimensionality reduction and feature selection that can improve the efficiency and effectiveness of a predictive model on the problem. For this reason, the scores of each feature taken into consideration for the experiments was calculated and shown in Figure 4.5. The chart presented on the upper side in Figure 4.5 shows all the features of the experiment dataset. It shows how the feature that corresponds to the microphone data (*dB_mic*) has a greater importance (an order of magnitude more than the other features). In order to make the other features more readable, the *dB_mic* feature is omitted on the lower side of the figure, bringing out the *Humidity* and the *Timestamp* as other important features.

	Best model	R^2	**RMSE**	**Rel avg error**
Experiment 1	Polynomial regression	0.85	4.15	5.77%
Experiment 2	Random forest	0.94	2.52	2.24%
Experiment 3	Support Vector Machine	0.90	3.42	3.70%

Table 4.8 Best model for each experiment

The ultimate goal of training these learning models is to export and integrate them into a real-time noise monitoring tool. Such a monitoring tool will be employed on embedded systems (Raspberry Pi 2), with the aim of sensing noise pollution within a University Campus, by means of a low cost microphone on our prototype (the one calibrated for the definition of the datasets). Once equipped with an algorithm that can monitor calibrated decibels, it will be possible to contribute to the detection of noise pollution in a more accurate way. Two different models have therefore been implemented for this purpose in our noise detection tool, which can be used via the command line. From the results obtained by the training phase of the learning models, we carry out two different

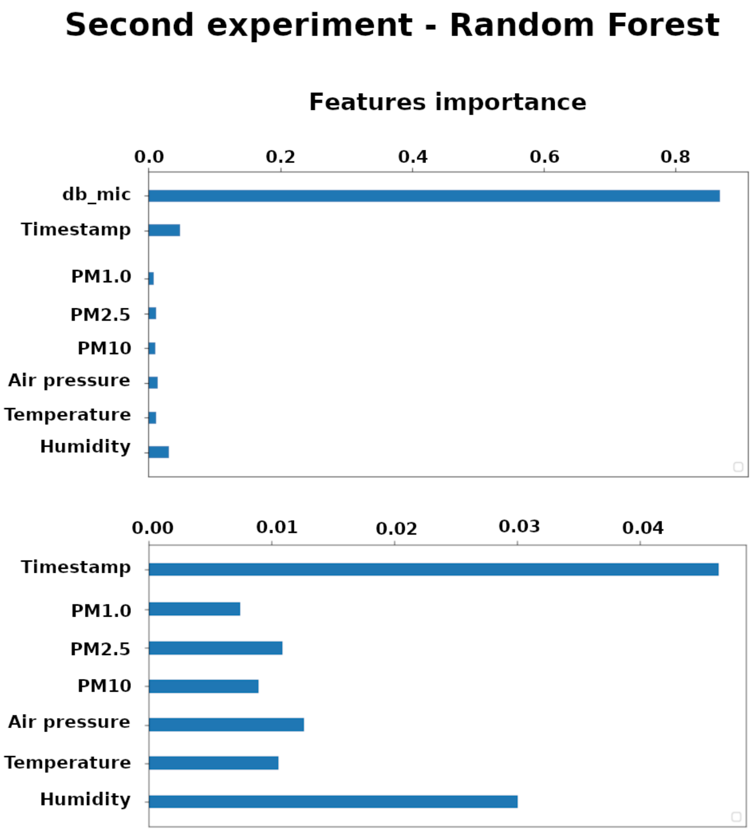

Fig. 4.5 On the upper side, shows all the features of the second experiment dataset. The *dB_mic* feature has a greater importance. The *dB_mic* feature is omitted on the lower side to make the other features more readable.

calibrations, one simple (**tiny**) and one more complete (**full**), as described in the following:

- **Tiny calibration:** this type of calibration is designed to be as light and simple as possible, so that it can be carried out with the use of the least number of components. This calibration is based on the best calibration model obtained from the first method, which is the polynomial regression model (see Table 4.3, second column). It could be based, in an indifferent way, also on the model trained using the random forests, being the results almost identical. These models are based on the prediction of decibels calibrated starting only from the samples carried out by the microphone (univariate regression). This is why they do not require any additional component and the edge previously prepared for the construction of the dataset can be used directly. Once the decibel value has been obtained from the audio segment collected by the microphone, it is necessary to feed it to the model previously loaded from a file, so as to obtain the prediction of the calibrated decibels. These values, as shown in Table 4.3 (second column), will have an average error of 4.15 dB.

- **Full calibration:** this calibration aims to be more precise, hence requiring the use of a greater number of components. It can take advantage of the best tested model, hence the model based on random forests applied to the second dataset (see subsection 4.6.2 Random Forest). This multivariate regression model bases its predictions on a set of independent variables (X) consisting of both the decibels detected by the microphone and the environmental data made available by Canarin II. By integrating this model into our noise monitoring tool, it is necessary to equip the Raspberry Pi (or more generally the embedded system used) with all those sensors useful for monitoring the environmental data necessary to obtain more accurate predictions. This is necessary because it is necessary to have all the information available on the same device, so as to provide a real-time sampling service. Once the decibel value has been obtained from the audio segment collected by the microphone, it is then necessary to input it into the model, together with all the other environmental data. Hence, it would therefore be necessary to equip the Raspberry Pi with sensors for: humidity, atmospheric pressure, temperature, PM1.0, PM10 and PM2.5. The model, once all this information has been received, predicts the decibels calibrated with an average error of 2.52 dB.

Hence, two different application methods have been proposed in our study, with the respective models applied, so that, depending on the resources available, it is possible to integrate the models (and the related accuracy and precision) in the system. The *tiny* calibration method available in the library[4], is simpler to be applied, as it does not require the purchase of additional components. On the other hand, if the sensors required to detect the aforementioned environmental data are available, then the *full* calibration method would allow us to achieve better precision.

Concluding, in this chapter, we have proposed RaveGuard, a noise pollution monitoring platform that exploits machine learning algorithms to improve the accuracy of low-cost microphones. Three different experiments were carried out, each of them with three different starting datasets. To collect the necessary data, an experimental setup consisting of three different nodes was deployed. The first node consists of a Raspberry Pi and a low-cost USB condenser microphone; the second node is composed of a UDOO Neo and a calibrated sound level meter, and, finally, the third node consists of a Canarin II platform, devoted to acquiring environmental data. The simplest dataset includes only the data of the low cost microphone and the calibrated sound level meter which acts as ground truth. The other datasets include environmental data, acquired and saved thanks to the Canarin II platform. Different regression models have been applied to each dataset, with the aim of mitigating the problem of the low accuracy of low cost devices (compared to the calibrated ones). The results achieved within this study reduced the accuracy gap from an RMSE error of 5.20 dB to 2.52 dB, with our best model applied to the denser dataset, and to 4.15 dB, with our best model applied to the less dense dataset. Two different models have therefore been generated in our noise detection tool, which can be used via the command line. The first one (named **tiny**), is designed to be as light and simple as possible in order to be used with the minimum number of components, while the second one, that is more complete (named **full**), achieves the best accuracy.

It is worth mentioning that we did not take into account the various spectral characteristics of the microphone and of the professional sound level meter, because our main goal was to create datasets and a library to support monitoring activities, considering only the specific hardware equipment we exploited for our

[4]https://github.com/LorenzoMonti/inspectNoise/blob/master/calibration/model.bin

experiment, even if this could represent a limitation in our study. An interesting configuration and customization of our library and our platform could be planned and designed by considering such characteristics and by adapting the whole monitoring system on the basis of the specific microphone used for the sensing activities (i.e., distinguishing among low cost USB microphones and professional sound level meters).

In this sense, through the platform described, it is possible to extensively monitor the noise pollution of the building, both internal and external. The ultimate goal of our experiment is to improve the acoustic comfort of the occupants and consequently their performance answering the RQ-2. We are currently working on the effective deployment of multiple instances within our University Campus to map noise pollution. Moreover, new models will be tested to further improve the system performance, on the basis of deep learning models, such as ANN or auto-encoder. We are confident that such models could improve the overall accuracy provided by the monitoring platform, but further investigations and comparisons have to be done. Moreover, together with the accuracy of the noise monitoring activities, it would be necessary to evaluate and then to find an appropriate balancing between the obtained accuracy and the corresponding efforts in terms of computation time and load of the proposed platform.

We are planning new experiments, collecting new data samples. This would allow us to apply adequate strategies to adequately collect and detect data from events related to the weather, such as rain and wind. In fact, in our experiment we did not acquire such kind of data, but they are fundamental in acoustic measurement, so as to properly clean the data from anomalous events. Indeed, this would significantly concur in improving the accuracy of our datasets and our InspectNoise library.

Moreover, the conduction of new experiments would give us the chance to better evaluating energy efficiency and scalability issues. Data about the specific energy consumption could be obtained and accurate estimation could be observed and then predicted. The same is for considerations about the system power, which should be connected to the electricity grid for long periods, hence an evaluation involving pros and cons related to the positioning of the whole monitoring platform should be provided, improving the overall efficacy of the system. Regarding scalability, another issue that should be taken into account and evaluated is the data storage capabilities and the comparison among the proposed solution (which is edge computing based) and other different architectural solutions (i.e. distributed ones). In particular, during our experiment and data collection activities, we did not experienced any problem in terms of storage capabilities. However, a comparison among edge computing solutions and distributed solutions can contribute to enriching the state of the art in this field.

Chapter 5

Human-Smart Campus Interaction Methodologies

> Which are the Human-Smart Building-Interaction methodologies in order to improve the community awareness inside a campus?
>
> — **RQ-3**

Interconnected computational devices in the Internet of Things (IoT) context make possible to collect real-time data about a specific environment. The IoT paradigm can be exploited together with data visualization techniques to put into effect intelligent environments, where pervasive technologies enable people to experience and interact with the generated data. In this chapter, we present a case study where these emerging areas and related technologies have been explored to benefit communities, making their members actively involved as central players of such an intelligent environment. To give practical effect to our approach and to answer RQ-3, we designed and developed a system, applying the paradigm of *Smart Campus*, composed of: i) an infrastructure made of sensors to collect real-time data in a University Campus, and ii) a rich web-based application to interact with spatio-temporal data, available in a public interactive touch monitor. To validate the system and grasp insights, we involved 135 students through a survey, and we extracted meaningful data from the interactive sessions with the public display. Results show that this Campus community understood the potential of the system and students are willing to actively contribute to it, pushing us to better investigate future scenarios where students can participate with ideas, visualizations/services to integrate into the web-based system, as well as sensors to plug into the infrastructure.

5.1 Introduction

As the history of the first university of the west world teaches us, central to such an establishment is its community that can be built in any *place* where students are willing to meet with teachers with the goal to share and absorb knowledge. This is the origin of the University of Bologna, born in 1088 as the home of free teaching and the first place where absolute freedom of research was ratified [uni]. The University was founded by students and for students. Coming into the city during the XI century from many lands, students of the middle age organized themselves in order to hire and pay teachers and to nominate the rector, attending the lectures directly in the teacher's private houses. While the concept of University is itself grown around a community of students sharing learning spaces and resources, the first use of the word *campus* was done to describe a field nearby the University of Princeton, in 1774 [cam]. Nowadays, the term *campus* is used to identify buildings and ground, or more generally places, where a university is situated.

In order to investigate new futures for higher educational spaces and experiences, recently, different concepts of *smart campus* emerged [7], with the aim of enhancing the experience of studying and sharing learning contexts, in time and space where smart devices, building management systems, and artificial intelligence shape communities. Two dimensions drive this evolution: (i) the availability of sophisticated smart environment technologies, applied to the specificity of a learning space, which produces and uses data, and (ii) the presence of lively student community, mainly composed by digital native equipped with smart devices and willing to actively participate.

In other words, the smart campus concept is a refinement of the umbrella term *intelligent environment*, defined as a physical environment where innovative and pervasive information and communication technologies enable people to experience and interact with space and generated data [40]. In such intelligent environments, the role of users is becoming more and more relevant [156], moving from passive beneficiaries of services to active participants [188], data explorers [194] and contributors [152], also by means of their activities on social media [235]. This is the context where the concept of hyperlocal data emerged as crucial for empowering a community. Such term expresses the information generated within a specific geolocalized community, that can be used to better inform the community members and improve their experience in interacting with the community spaces. To inform such a community about the collected hyperlocal data, making its members participates, the interaction with data is fundamental; this can be carried out in different ways, such as by exploiting data visualization methodologies, providing the information in a visual way [59].

With this study [187], we present our approach in creating a smart campus system, providing a set of intelligent environment tools targeted to the need of a specific community [162]. As a real-world case study, we considered a new building, hosting the Cesena Campus of the University of Bologna (one of the five campuses part of the University of Bologna) working on three main aspects: i) augmenting a University campus with low-cost smart technologies and sensors, ii) deploying displays in public settings to let users interact with the hyperlocal data, being informed about specific phenomena in a spatial-temporal dimension, and iii) including the community members as active participants in exploring and in benefiting from the intelligent environment and the data it produces.

The remainder of this paper is organized as follows. Section 5.2 presents main works related to smart campus, while Section 5.3 describes the system architecture, presenting the sensors used and the Data Visualization interfaces. In Section 5.4, we present the mixed methods analysis we performed collecting both qualitative and quantitative data. Finally, section 5.5 concludes the paper with a discussion on how to empower students exploiting our platform and the next planned steps.

5.2 Related Work

In this section, we briefly present some projects and studies based on the concept of *smart campus*.

The idea of *smart campus* is at the basis of several studies [179, 7]. However, it is not clear what designing and building a smart campus means in practice. It is worth mentioning that currently there is no common and shared definition of smart campus, even if some researchers conveyed the definition on the basis of different approaches [166]. Three main different groups of such approaches can be identified: (i) technology driven, (ii) smart city concept adoption, and (iii) based on the development of an organization or business process [246].

Taking into account the technological approach (the first group of approaches), a smart campus results from the development of a digital campus, by exploiting IoT service providers [162] and cloud computing [63]. The idea behind this approach is transforming common objects which can be traditionally found in a university environment into a unique intelligent campus environment [52].

On the other side, the smart city concept adoption (at the basis of the second group of approaches) is based on the assumption that a smart campus shows several similarities with a smart city. By using the same paradigm, a smart campus should adopt modern technology to support different users (students, researchers and professors, employees, visitors, etc.) [139]. Summing up, a smart campus can be intended as a small and self-contained city, taking into account the number of functions, users, activities, and connections [179, 18]. In this second group of approaches, the users (as members of a specific community) can play a key and active role, being involved in crowdsourcing and/or crowdsensing activities [186], [198].

Finally, according to the third group of approaches, a smart campus is developed through the effective use of resources, by providing services to environmental communities [7], reducing costs and improving the quality of life (inside and outside the campus) [16]. In this sense, collecting data about environmental aspects (i.e., air quality, by monitoring pollutants, such as CO2 and Particulate Matters, or PM, [13], [233]) can play a fundamental role and can be improved by the adoption of the first two concepts too.

The smart campus system we propose in this work applies approaches coming from these three groups, since it exploits IoT and smart environment technologies (group i), it involves the community members through crowdsourcing and crowdsensing initiatives (group ii), with the aim of developing effective use of the resources, improving the quality of life of the whole university community (group iii).

5.3 System Architecture

In this Section, we present the architecture of our smart campus system. As presented in Figure 5.1, the system includes four main components: i) the sensors infrastructure; ii) the storage/database management; iii) the data visualization interfaces; and iv) the web server. In the following, we provide a detailed description of the main layers (more details can be found in [162]).

5.3.1 Sensors Layer

The campus has been built including a sensors infrastructure (building management system - BMS) with the aim of increasing the sustainability of the building. Such sensors can monitor and manage CO2, temperature, light, and other values. Even if these data are interesting to analyzed, we were intrigued by augmenting such infrastructure by including other sensors, both for indoor and outdoor measurements. We took this approach with three goals in mind: i) to collect data about other environmental conditions and phenomena; ii) to validate the collected data comparing the different data sources; iii) to make the data collected with our sensors available thought open-data repositories [233].

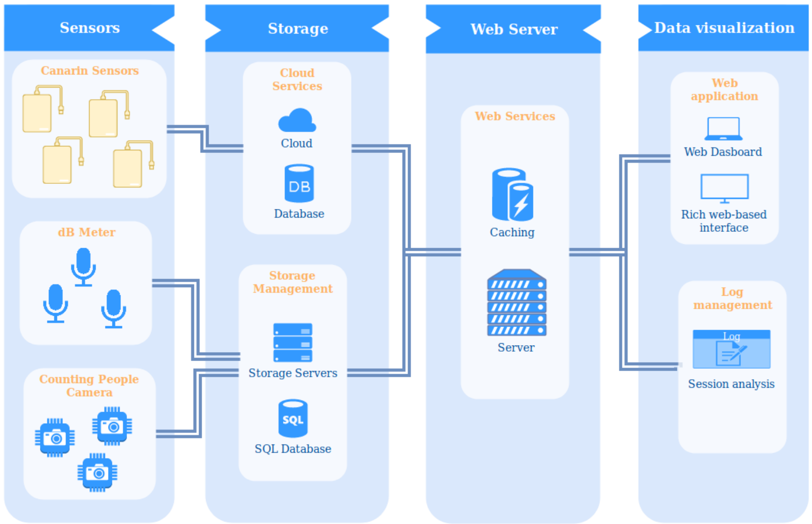

Fig. 5.1 Our Smart campus architecture.

At the current stage, our sensors infrastructure is composed of environmental sensors (indoor and outdoor), noise sensors, infrared and thermal cameras.

Focusing on the collection of environmental data, we relied on sensor stations (i.e., Canarin II [9]), equipped with different sensors: sensors to detect air contaminants, gathering formaldehyde, PM 1.0, PM 2.5 and PM 10 values, temperature, relative humidity, and air pressure. At this stage, we placed these sensor stations: i) outside the building (3 in total), in strategic positions facing different pollution sources and urban and natural conditions; and ii) inside (2 in total), to monitor peculiar interior spaces, such as the library warehouse that requires a specific temperature and humid degree to avoid damaging the books. Moreover, to collect data about the indoor conditions, we are exploiting CO2 sensors provided by the BMS that have been placed in every classroom and laboratory so as to monitor the quality of air, in order to activate the heating, ventilation, and air conditioning (HVAC) system when needed.

Concerning the noise monitoring and measurement, after an analysis of accurate and low-cost microphones, we opted for a USB condenser microphone named *"Mini Akiro"* which has an omnidirectional pattern, a signal-to-noise ratio of 85 dB and a frequency response from 100 Hz to 16,000 Hz. This sensor provides us with an interface for monitoring, collecting, storing and then analyzing the surrounding sound signals. To compute the signals caught by the microphone we used a Raspberry Pi 2 model B, a powerful, versatile and low-cost single-board computer. Furthermore, we used an USB Wi-Fi module for enabling the communication with the web server using the wireless network managed by the University of Bologna. The signals captured by the sensor are then computed by the Raspberry Pi before being stored in the database. To do that, we exploited a Python package called SoundMeter[1] that returns a RMS (Root Mean Square) value every 30 seconds. This value is then converted to Decibel. The idea is to provide campus staff with the possibility of automatically receives a notification in case of strong noise detected.

Considering, in particular, the indoor campus services, we focused our attention on how much the classrooms and the laboratories are exploited with respect to their actual capacity. In this sense, in order to count the number of people in an area, we are testing three different technologies to understand the one which can better suit our needs, considering also the balance between costs and performances. The three investigated technologies are: i) a RealSense camera[2], ii) a Sony PlayStation Camera[3], and iii) a thermal camera. We placed them in three classrooms, with different layouts, to test the accuracy of each approach. In the future, we plan to provide all the classrooms and laboratories as well as the library and study rooms, with a counting people system to provide more and better services to the community.

5.3.2 Database Layer

Thanks to the database layer, the data collected in real-time by the sensors can be stored and queried, and made available to the web-based application. In details, the sensed data are stored in a MySQL database every 30 seconds/one minute, depending on the sensor typology and the purpose. For example, air quality

[1] https://pypi.org/project/soundmeter/
[2] https://realsense.intel.com/
[3] https://www.playstation.com/en-gb/explore/accessories/playstation-camera/

and noise data are saved every 30 seconds, while camera data every 1 minute. Considering the environmental sensors stations, each entry stored in the database is represented by the raw sensed data, the timestamp, and the georeferenced coordinates.

In addition to the databases for the real-time sensed data, we are also exploiting an open data collection[4] of information related to the University community, and in particular, relevant for the students. This dataset is made freely accessible by the University of Bologna and includes a variety of data, ranging from the lessons timetable to a collection of georeferenced points of interest. To interact with the open data, we used *ckan*[5], an open-source DMS (data management system).

The use of different sources of information allows us to provide the community with data covering different aspects of the University life on campus. For this reason, we designed and implemented the system so as to be easily configured, letting the integration of external data repositories.

5.3.3 Data Visualization Layer

The Data Visualization layer is composed of two different web applications: i) a rich web-based application that allows the Campus community to interact with the hyperlocal data, making them more aware of the data generated by the campus, as a whole system (see Figure 5.2); ii) a log management web interface that enables to perform analysis and visualize data about the students sessions (an example of a visualization is presented in Figure 5.3). Both the applications have been implemented using standard web technologies, including HTML5 and CSS3, JavaScript, and specific libraries to visualize and represent the data, such as D3.js and Chart.js.

The rich web-based interface can be explored by the campus community thanks to a public touchscreen display (32" capacitive touch panel monitor), located at one of the two entrances of the main building (see Figure 5.2, on

[4]https://dati.unibo.it/

[5]https://github.com/ckan/ckan

the right). The interface is composed mainly of three main UI components corresponding to four interaction modes, as detailed below.

The map-based interaction. The application has been designed focusing on the map-based interaction. In fact, the main component of the interface is the 2D map of the campus building levels. The implemented interface is based on an open source project [131] that we customized and extended to suit our needs and requirements. The map-based interaction enables the user to select a specific level in the SVG map. After selecting a level (floor), it is possible to visualize all the points of interest and to interact with them. Moreover, in all the SVG maps it is possible to visualize the facilities, such as toilets, stairs, and elevators. Once selected a specific point of interest (PoI), the information collected about it are popped-up in a panel at the bottom of the screen, and the location is highlighted in the map with an animated, color-coded marker.

The search-based interaction. The search-based interaction enables users to access the information exploiting a search function to filter content by keywords. In this way, it is possible to easily access information without knowing the actual position of the related PoI. The system provides a list of all the PoIs including the searched keyword. Selecting a specific PoI from the list, the application displays the right floor where the PoI is located, with a market to highlight the actual location.

The interaction by categories. The right side of the interface is used to present collapsed categories. Each category can be expanded to provide a list of different PoIs in such a category. In particular, the represented categories are: classrooms, laboratories, professors' offices, courses lessons, and sensors. Selecting a specific PoI, the map opens at the right level, presenting its location and the associated information.

The sensed data interaction. Besides the information about the PoIs in the campus (e.g., classrooms, professors' offices, libraries), we exploited data visualization techniques to represent in an intuitive way data gathered by the sensors that compose our smart infrastructure. The interface presents the real-time data, with values refreshed every minute, as well as historical data, with the

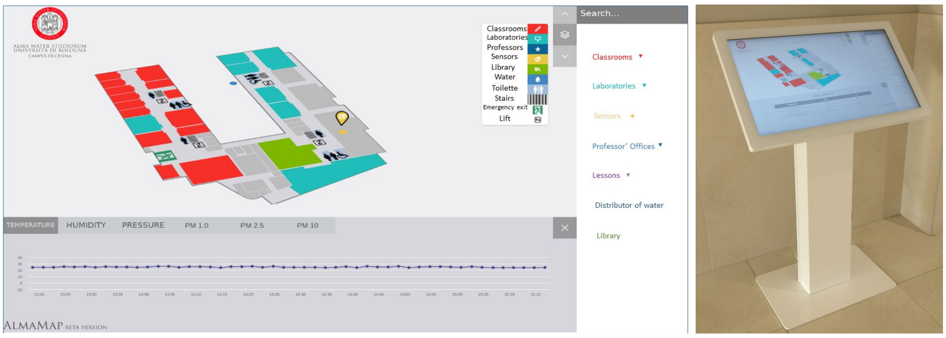

Fig. 5.2 The Smart Campus application: on the left, a visualization of the data gather by an indoor sensor; on the right, the kiosk hosting the application

possibility to interact with the timeline. This allows users to become aware of environmental conditions (both indoor and outdoor) concerning the University campus. Figure 5.2 (left) shows an example of visualization of sensed data in an indoor space. To manage real-time sensed data visualization we exploited some libraries, such as Socket.IO[6] that enables real-time, bidirectional and event-based communication between the browser and the server.

5.4 System Evaluation

To evaluate our approach, we collected qualitative and quantitative data by exploiting two different methods. Firstly, we analyzed data collected automatically from the students' interactions with the public display, then, we provided students with a questionnaire to better understand some phenomena emerged from the activity logs and to enrich that information with qualitative observations and feedback.

5.4.1 Sessions Analysis

We stored all the interactions that happened with the rich web-based interface along a month (30 days). These data are related to: i) multi-touch interactions

[6]https://socket.io/

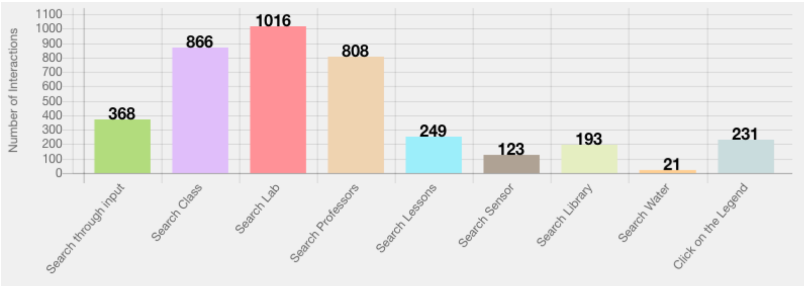

Fig. 5.3 A chart representing the typologies of interactions (captured from the log manager interface)

(information about the selected DOM object and its position in x,y coordinates); ii) typing in the search input box; iii) sessions duration (such as average, each session lasted 1 minute and 45 seconds). Integrating this information enables us to understand how students use the system, interact with the public display, and enjoy the hyperlocal data. The first interesting result emerges analyzing the way students look for information (e.g., typing a search keyword or touching the map). Data show that the majority of students experienced the provided information through the map-based interface. In fact, the number of meaningfully map-based interactions (#3495) is more than three times the number of interactions that happened with the aside menu (#1036) and almost ten times the number of typing in the search input box (#375). This is a confirmation of our intuition to provide hyperlocal data on a map-based interface, letting emerge their spatial dimension.

We also analyzed the exploited content, aggregating the different interaction modes on the basis of the needed information. Figure 5.3 shows the data aggregated per typology of the exploited content. The data clearly reveal that students commonly look for classrooms and laboratories (for a total of almost 2,000 interactions). From the data emerges that there were only a few interactions and exploitation of data coming from the sensors. The explanation can be found in some comments collected from the questionnaire. In fact, some students emphasized and understood the relevance of using those data to provide new services, but they also maintained that *"[...] representing real-time data in their raw format can make difficult to extract meaningful information of the ongoing* *phenomena, making difficult to figure out their importance".* Thanks to these important comments, we are working on improving the visualizations to let emerge meaningful scenarios.

5.4.2 A Survey involving a Smart Campus Community

To collect qualitative and quantitative data we provided students with an online questionnaire and we shared it with students of the bachelor degree of the Computer Science and Engineering program of the University of Bologna, campus of Cesena, attending the Web Technologies course. The decision to involve this specific target audience was driven by the fact that these students are acquiring competencies and skills in web technologies, layout design and user experience. For this reason, they were able to provide detailed comments and feedback, with a more accurate and expert point of view. The questionnaire was divided into seven sections, based on different topics, for a total of 36 items, including open-ended, multiple answers and Likert scale questions.

The first important result was concerning the amount of participation in the study: 135 students (out of a class of 152) voluntarily answered to the questionnaire, expressing their interest in the project. The group was composed of 108 (80%) males and 24 (17.8%) females (three students preferred to not declare their gender). The participants' age ranks between 20 and 42, with 89 (66%) having 21 years-old. Nonetheless, 16.3% (#22) are working-students, only 8 declared to come to the campus rarely (#5) or just for taking exams (#3). Within this context, it is interesting to report that 61 students (45%) declared that they enjoy the campus every working day (the building is closed during the weekend) for studying or attending the lessons, while 65 (48%) answered that their being into the campus is strictly related to the days they attend lessons. These data reveal that the majority of the students who participated in our study (126 out of 135) spend a considerable time of their week inside the Campus spaces.

Entering in the details of the system usage through the public display, 56% of users (76 out of 135) interacted at least once with the system. On the basis of this answer, we presented users with different items to better investigate the reason behind this choice, both in the positive and the negative case. Starting from the latter, the major motivations behind the not usage of the system are two: i) students (#22) didn't notice the public display at all, falling in the so called "display blindness" issue [167]; ii) students (#49) didn't feel attracted or interested in the system, motivating the rationale behind this feeling in different ways. Some examples are: *"I was already confident with the location of classrooms and laboratories, so I didn't find it useful"*; *"I've never felt the need of using it but I am aware of its relevance in providing information about the campus"*. Regarding the former group (76 students who used the system at least once), 46% (#35) of students used it two or three times; 42% (#32) interacted with it just one time; 11% (#9) more than three time. The majority of students in this group considered the system usable (#38); information easy to find (#40); and with a good interaction (#45). All the values are presented in Figure 5.4, using a 5-values Likert scale from 1 (strongly disagree) to 5 (strongly agree). We also asked the students to assign a value to their experience (from 1 to 5): 36 (out of 76) selected 4 and 8 (out of 76) selected 5.

To all the students (135), we asked for feedback, ideas and suggestions, and critical issues to improve the user experience and the utility of the system. Students showed a strong interest and motivation in using the data to create new services. For example, a student suggested exploiting the data collected by the cameras used to count people for providing empty classrooms and labs to use such a space for studying activities. Different students provided ideas for services exploring different sensors. For example, a proposal was related to notifying students about the number of available shared bikes (located in a kiosk outside the building). Moreover, some students express the desire to enjoy the system also as a mobile application, with the aim of integrating location-based services, such as indoor navigation supported by short-range communications technology (e.g., iBeacon).

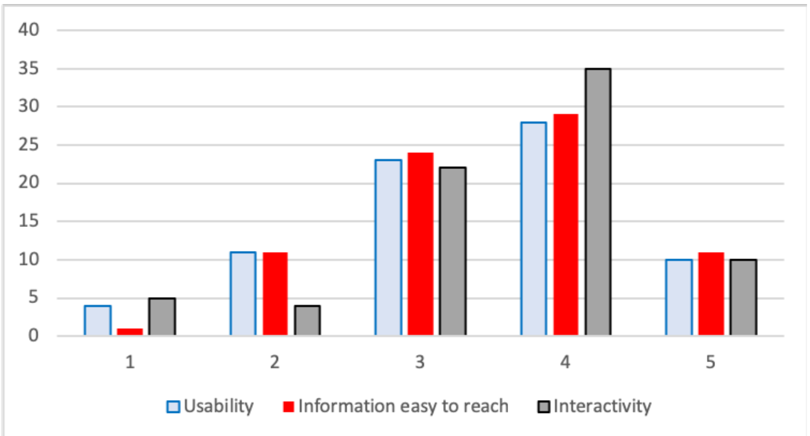

Fig. 5.4 Students' opinions on usability, information easy to reach and interactivity, using a 5-values Likert scale

5.5 Conclusion and Future Works

In this chapter, we have presented a *Smart Campus* system, designed and deployed in a new campus of the University of Bologna. Such a system acts as a proof of concept of the importance of considering the community members as key players of an intelligent environment, not only as passive beneficiaries but also as active contributors. In order to prove our concept i) we deployed an IoT infrastructure to gather data about different environmental conditions, concerning both indoor and outdoor phenomena, and ii) we designed and put available with a public installation a rich web-based interface, to let students interact with hyperlocal data. To evaluate the system, we employed a mixed methods approach, collecting and analyzing both qualitative and quantitative data through a survey (involving 135 students), and web session logs (for a total of more than 10.000 interacts). Positive results push us to expand the project, including other scenarios of students involvement. In fact, we are planning to make our data available (with APIs and open data) to students, letting them free to contribute to the system with ideas, services and applications, IoT nodes to plug into the infrastructure, and data visualization layers. In fact, the campus hosts undergraduate and graduate students of Computer science and Engineering, Electronic Engineering, and the Architecture and Design degrees. Therefore, students living the campus are developing all the skills needed to suggest services based on their needs and to actively participate in the design and development of such services. Hence, the platform, which is compliant with the main features of the HCSC (in particular with the context aware one), can act as a tool to facilitate the participation of students and to increase the potential of hyperlocal data with the final goal of benefiting the comfort and performance of the whole campus community.

Chapter 6

Methodologies and Technologies to Enable Accessible Smart Moving across a University Campus

> How to provide support for moving around a University Campus?
>
> — **RQ-4**

Moving across a University campus (outdoor, among the buildings, and indoor, among classrooms and offices) could represent a barrier for students with disabilities, affecting their independence while they conduct their daily activities. Providing support by means of smartphones thanks to location technologies can be a useful means of integration and inclusion, with the effect of facilitating also tourists, newbies, or freshmen. This is particularly true in those contexts where the universities are hosted in historical buildings in old towns, which is a typical situation in European countries. Moreover, more generally, it is possible to improve the occupants' awareness of exploiting way-finding systems, and consequently their comfort and performance. This chapter presents AlmaWhere [72], a system based on beacon technology, designed and developed with the aim of equipping students of the University of Bologna with an indoor navigation system, providing them support in finding classes, labs, and libraries, improving their awareness and comfort, with specific attention those users with disabilities. The chapter describes the main design issues, the system architecture, and technologies we have analyzed in order to design a prototype and two scenarios that involve personas aiming at answering at RQ-4.

6.1 Introduction

The University of Bologna was founded in 1088, it is the oldest university in continuous operation and it is located in 5 *campi*, with a central body in Bologna city centre. This area, known as “Cittadella Universitaria” is composed by many historical building around via Zamboni, where the University, many Schools and Department have their headquarters. Freshmen, students from outside the city, tourists and generally all people that are not used to attend this area are generally disoriented by the complexity of the neighborhood and the internal structure of the buildings. This is especially true for students with disabilities and specifically students with visual impairments who cannot rely on signs, maps and other visual supports to be guided to their destination. It is also very true for tourists, who are looking for specific cultural heritage beauties that are usually hidden inside classes, meeting rooms, offices or simply aisles.

To overcome these issues, we studied a solution based on beacons [69] [155], a precision positioning and content delivery technology mainly used in consumer push applications in order to track customer visits and provide context aware information and offers. Beside this main market-centred applications, other significant uses have been deployed exploiting the possibility offered by beacons to discover a location and to provide other relevant contextual information about it. This includes application of context-aware digital signage [227] which delivers location based information based on interactive and environmental awareness. Traditional signs are limited, in terms of quantity of information they can effectively provide, language used, and accessibility. Moreover, their efficacy relays on their visibility and, in historical environments, they risk to compromised the aesthetic value of ancient buildings. This is why the possibility offered by beacons to provide a rich, accessible and practically invisible context-aware digital signage has been used in different situations, from museums guides to smart city applications [116] [89] [169]. Beacons have been widely employed also in indoor RTLS (Real-time Locating Systems [36]) in places (like inside buildings or in metro) where usual locating system based on GPS, such as Google maps, fail. In indoor RTLS, beacons can be used to guide people to a destination, providing a rich, accessible and practically invisible indoor pathfinder system [10].

In this chapter, we present AlmaWhere, a system based on beacon technology, designed and developed in order to equip students of the University of Bologna with an indoor navigation system able to provide them with support in finding classes, labs, libraries and other significant places coupled with a context-aware digital signage tool able to improve their knowledge about the historical buildings where the University is located. The application has been studied with the double aim of supporting disabled students (and specifically visually impaired ones and the ones with physical impairments) in moving inside the Cittadella with personalized and accessible paths [153] and of providing information related to places, their story and their use, to all students and visitors.

The remainder of this chapter is organized as follows. Section 6.2 briefly presents main related work, focusing on projects about indoor way-finding and navigation systems for users with disabilities and on projects devoted to support users with disabilities while they are visiting museums and cultural places. Section 6.3 is devoted to describe main design issues which have driven our project. Section 6.4 focuses on two different scenarios, describing how users with special needs could exploit our proposed approach. Finally, section 6.5 concludes the chapter with some final remarks and future work.

6.2 Background and related work

In this section, we briefly introduce some related work, presenting some cases based on different indoor way-finding systems for people with disabilities and then we present some work with the aim of supporting users with disabilities while they are visiting museums and cultural sites, enhancing their orientation, while enjoying information about pieces of art and historical information.

During the years, different studies have concerned indoor and outdoor way-finding for people with disabilities, considering different impairments, technologies, and scenarios [153], [154]. While most of the outdoor navigation systems use GPS, indoor ones are based on different approaches, depending on how the user's position is localized.

A first approach consists in using Radio Frequency Identification (RFID) tags that, attached to objects, can automatically identify and track these ones through the use of electromagnetic fields. Tsirmpas et al. [236] propose an indoor navigation system with an RFID-based architecture that is able to navigate a visually impaired senior. In particular, they describe an innovative localization and obstacle avoidance algorithm, starting from a predefined grid structure of RFID tags.

Another approach takes advantage of the wireless sensors network. The type of the sensors, used in these networks, can significantly vary. For example, Lopes et al. [130] exploit the use of synchronized acoustic beacons. They introduce an acoustic indoor positioning system that takes advantage of smartphone audio I/O and processing capabilities in order to perform acoustic ranging in the audio band using noninvasive audio signals.

A third approach is based on QR codes, a type of two-dimensional barcode, that is a machine-readable optical label, containing information. AssisT-In [230] is an Android application that navigate the user towards a graph of QR codes. Every time he scans a QR code, the system provide indication in order to reach the next QR code. Hence, the application will guide the user from the initial node to the second, and then on to subsequent nodes, following a trail of nodes leading to the destination node.

Further approach exploits the potentiality of using Bluetooth low-energy (BLE) beacons, devices that broadcast their identifier to nearby portable electronic devices so that they can perform actions when in close proximity. Ahmetovic et al. [10] developed and tested NavCog, a smartphone-based turn-by-turn navigation system for blind users. This system makes use of a network of Bluetooth low energy (BLE) beacons to localize the user with an approach based on the K-nearest neighbor (KNN) algorithm.

Tourism is a sensible source of income for a nation, in a special way for states with a long historical and cultural tradition, such as the European countries. *Culture*, *accessibility* and *inclusion* are the three keywords that will lead these few considerations on the features of museum education for disabled adults like described in [Montani].

In this context, "accessible tourism" was born. This term has been defined by Darcy and Dickson [67], aiming of integrating the accessibility for specific disability (mobility, vision, hearing and cognitive) in tourism and in recreational activities. In [200, 201], Rodriguez explains how, thanks to the ubiquity of mobile devices, it is possible to apply way-finding techniques so as to improve the context-awareness of all users, especially those ones with disability. We can find an example in [150], which describes the development of a smartphone and tablet application letting people with hearing impairments enjoy their visit at "Museo di Palazzo Massimo". This system translates LIS (Italian Language Sign) and ALS (American Language Sign). One of the main difficulties was based on linguistic issues among own and specific lemma, because ad-hoc technicians, historians and scientists lemma were included. These corresponding signs were introduced ex-novo by the deaf Italian community, or borrowed from foreign sign languages (like the signs of the Greek gods derived from the Greek sign language), and were therefore included in a glossary in the application. Visits to art museums are a major component of culture and heritage tourism. Poria [184] focuses on the obstacles that Israelis with disabilities face while visiting art museums. Tests were conducted by involving 30 people who used wheelchairs or crutches and 15 visually impaired people. Some interviews were submitted to such users with disabilities, revealing a low level of the museum experience. Participants emphasize the non-physical elements of the museum environment (e.g. staff attitudes and interaction with other visitors), as being major difficulties in achieving a full museum experience.

Another interesting approach has been represented by the one applied by *Ping!*[117], a system with the aim of making museums more accessible to visitors who are blind, visually impaired, or otherwise print disabled. It lets the users navigate in museums while interacting with a smartphone, listening to audio description. This system works thanks to a wireless network of user-activated audio beacons that are triggered through a smartphone interface. Another kind of assistive technologies in museum context regards techniques based on the touch sense. As an example, in [50], two-dimensional pieces of art are transformed into tactile representation, providing great support to blind and visually impaired people. Another approach, provided within the project described in [50], is based on some alternative translation strategies, implemented by a computer-based tool, to determine the most effective one in delivering blind or visual impaired people a correct perception of painting or pictorial artworks in general. Similar initiatives have emerged in some international and world wide famous museums, such as the *British Galleries at Victoria and Albert Museum* in London, where a tactile display for blind and visual impaired user has been exploited. *MoMA, Tate Modern, Louvre and British Museum* have organized personalized touch tour with a selection of original sculptures or special replicas for visitor who are blind, deaf, deaf-blind and with physical disabilities. In all the previous projects and approaches, a key role is played by the personalization of the content, of the alternatives, of the user interface, and of the experience [157], where profiling users' needs become strategic [203]. From the nineties Italian museums have dedicated initiatives for a visitor with disabilities, and some of the most significant cultural institutions are: the *Civic Museum of Natural History of the City* (Trieste), an accessible museum for those who have difficulty reading and learning; *Italian museum of technologies for people with disabilities* (Genova), a multi-sensory pathway, in the total absence of light, with visitors accompanied by blind guides; the *Tactile Museum Omero* (Ancona), museum created by two blind people for blind and impaired vision visitor, in which it is possible touch all works in the museum; the *Tactile Anteros Museum* (Bologna), tactile painting museum that provides three-dimensional translations of pictorial masterpieces with prospective bas-relief technique.

6.3 Design Issues

In this section we present some main design issues. In particular, subsection 6.3.1 and 6.3.2 describe, respectively, the system architecture and the way finding system. Subsection 6.3.3 analyzes the localization techniques, while subsection 6.3.4 presents a brief overview of current beacon technologies, which has driven our choices.

6.3.1 System Architecture

This section presents a brief description of the system architecture. As shown in Figure 6.1, the main components of our architecture are the following ones:

- *Server*: the server will store the data about which buildings are mapped and, for each building, the information about the topology of the network. Furthermore it will expose a RESTful API used by smartphones application to retrieve data about buildings.
- *Web Application*: a web application will allow user administrator to:
  - Perform CRUD operations on buildings and for each one, configure the topology of the graph, adding/removing nodes or edges, changing the beacon associated with a node or modifying the additional data of a node or edge.
  - Check the status of the battery level of beacons placed between all buildings, through the use of API provided by Kontakt.

- *Beacons*: each beacon will be configured in order to emit its UUID, with a predefined communication protocol and will be placed in the established position.

- *Smartphone application*: an application for both Android and iOS operating systems have to be developed. The main requirement is the use of Bluetooth in order to communicate with beacons.

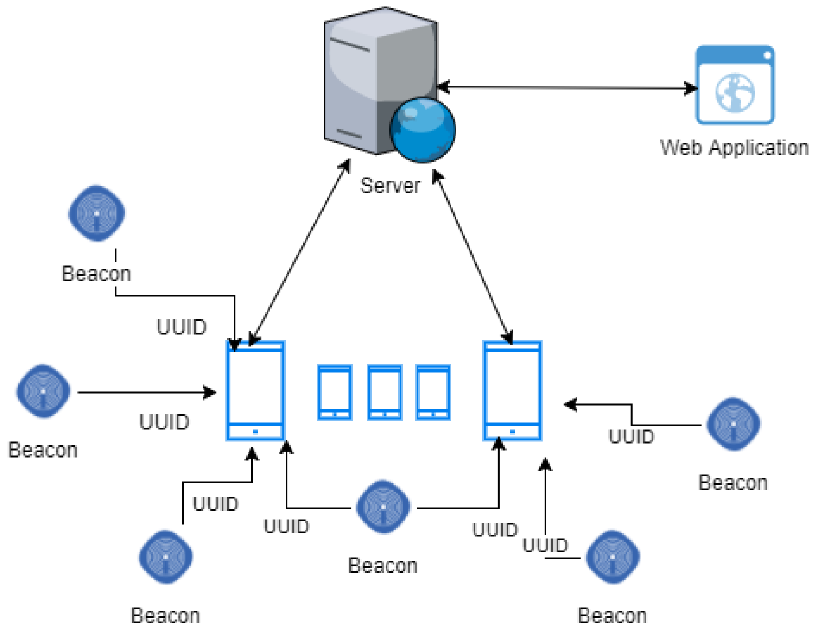

Fig. 6.1 System Architecture.

6.3.2 Way-Finding System

The idea at the basis of our work is to map the physical building with a graph G = (V, E) where V are nodes (vertex) and E are edges between nodes.

Every node will have the following features:

- *Beacon*: every node has a beacon associated with it, through the use of its UUID.

- *Typology*: we identify different types of nodes, such as professors' offices, classrooms, toilets, lifts and artwork.
- *Name*: optionally it is possible to define a label associated to the node.
- *Description*: it is possible to add a brief description of the node. For example, an office can be shared by two or more professor and a description is need so as to provide such an information.
- *Link*: eventually it is possible to add a link to a resource that contain a complete description of the node. This can be useful especially because a building can contain artistic works such as paintings or statues of historical figures.

Instead, edges will have the following features:

- *Linked nodes*: it contains the two nodes linked by the edge.
- *Weight*: it is the distance, expressed in meters, of the two nodes.
- *Degree*: it contains the approximative angle between the linked nodes.
- *Impairments*: for each impairment considered, it indicates if a user can go across this edge.

Once the graph is defined, it is necessary choose an algorithm for finding the shortest paths between nodes in a graph. The obvious choice is the Dijkstra's algorithm. The complexity of such algorithm depends on the data structure used to represent the priority queue. The most efficient one is the Fibonacci heap, by which it is possible to compute the shortest path between two nodes with a complexity O(E * log(V)), where E is the number of edges and V the number of nodes.

The representation of the physical building with a graph described before allows to map effectively all the points of interest in a building, making possible to find paths between nodes. Despite this, it does not allow to model the environment with a higher level of detail. For example, it is not possible to map obstacles such as furnishings or plants. This is not necessarily a problem, in fact between all the impairments considered, it would be a problem mainly for blind people. But it is also true that they often have a white canes or a guide dog, hence we decide to not consider obstacles in our solution.

6.3.3 Localization Techniques

We analyzed different localization approaches proposed in literature, try to understand which of them was the most suited to our need. One of the many classifications of localization methods identify the following classes:

- *Proximity*: this technique allows to locate a terminal that is in the radius of one or more proximity devices. If a terminal is localized, it is assumed that the position of the terminal is simply the position of the proximity device. If different proximity devices detect a terminal, this one is assumed to be located with the device that receives the strongest signal. This approach is very basic and easy to implement [126].

- *Triangulation*: it estimates the target location using the geometric properties of triangles. It has two derivations: lateration and angulation. In the first one, the position of a target is estimated by measuring the distance between it and several reference points. This is why these kinds of techniques are also called range measurement. There are several metrics for the distance. Examples are Received Signal Strengths, Time Of Arrival, Time Difference Of Arrival, and Roundtrip Time Of Flight. Instead, angulation techniques locate objects through the computation of angles of several reference points [126].

- *Fingerprinting*: this technique determines the position of the terminal thanks to the comparison of the value of signal power measured with values stored in the archive. There are two phases: offline and online. In the off-line phase, values of signal power of each device are measured in different position and, subsequently, they are stored in the archive. In the on-line one, also called pattern-matching, the signal power is measured and compared with the ones in the archive, choosing the closer one. So it is possible to compute, or better approximate the position of a user. The accuracy of this technique depends on the data sampled in the off-line phase. Obviously, the more samplings, the better probability to get, in the on-line phase, a right position. The disadvantage of such method is that a change of the position of an access point, requires to do a new off-phase. To avoid this problem, it is possible to define a model of the environment but it is not so easy because it depends on the environment and multiple factors [208].

- *Pedestrian Dead Reckoning*: it is a relative navigation technique that determines the position of a target, starting from a known position, adding successive position displacements. This displacement can be estimated as Cartesian coordinates or in heading and speed or distance. Because of the recursive nature of this technique, the result of the localization tends to accumulate a considerable error, due to the multiple estimations made. But with sufficiently frequent absolute position updates, dead reckoning linearly growing position errors can be contained within predefined bounds [27].

Between all of the techniques described before, we choose to use the Fingerprinting one combined with the Pedestrian Dead Reckoning. The other techniques have been excluded because the Proximity it is not enough precise since it only detects the presence of the user in the coverage range of the individual access points. Instead, the Triangulation does not consider any problems of reflection or refraction due to the environment or other parameters.

There are many algorithms that are based on the Fingerprinting technique. The most suited to our need is the RSSI Probability distribution, that is based on the Gaussian linear regression. This algorithm, thanks to the Gaussian linear regression, can generalize a continuous model, starting from a limited set of data.

6.3.4 Beacon technologies

We analyzed different beacons placed on the market by different brands in order to choose the one more suited to our needs. We considered several factors, including:

- *Chipset*: fundamental component of the beacon that affects performance and battery life.
- *Firmware*: having a customizable firmware allows to set up the interval and the power of the signal, according to the needs and the communication protocol in order to save battery life.
- *Configuration and maintenance*: it is important considering the presence (or absence) of a mobile application or a web service that allows to configure and maintain beacons, especially for medium-size (or large-size) projects.
- *Communication protocol*: the main communication protocols are iBeacon and Eddystone. While some devices support one or both of them, others ones uses further protocols, usually defined by the manufacturer.
- *Documentation*: the possibility to have a complete and exhaustive documentation is an important aspect for the developer but not all manufacturers take it into account.

We choose to use Kontak Beacon Pro, mainly for the following reasons:

- *Chipset*: it mounts the Nordic Semiconductor nRF52832, that supports Bluetooth 5.0.
- *Firmware*: it gives the possibility to set up not only interval and power of the signal emitted but also the protocol used.
- *Configuration and maintenance*: Kontakt provides both a web service and an Android and iOs application to configure and maintain beacons.

Through these applications, it is possible to set up some preferences and also easily check the battery life status.

- *Communication protocol*: it supports both iBeacon and Eddystone
- *Documentation*: Kontakt makes available a complete and exhaustive documentation for developers.

6.4 Scenarios

The University of Bologna, founded in 1088, is the oldest university in continuous operation [205]. It has grown hand to hand with Bologna over the years and now it has buildings all over the city. Offices and classrooms are mainly located in historic buildings situated in the old town. Often students have classes in different buildings so it's not easy for them to orient, especially for freshmen. Obviously, people with disabilities face greater difficulties. Blind students have to find a tactile map or have to ask someone for information. Students in a wheelchair have to find an elevator if the classroom is not on the ground floor. Thus, in the buildings there many artworks, many of them without a description.6

We choose the School of art, humanities, and cultural heritage as case study. In particular, we have analyzed the historic Palazzo Riario, from the '500. In particular, in this palace there are:

- the Sala Marco Celio;
- the laboratories for the Ancient History Section;
- the Tibilleti classroom;
- the Ancient History Library.

Giuseppe is a student of the University of Bologna, enrolled in the first cycle degree in Philosophy. He chooses "*Concetti e Contesti*" as curriculum. He uses a wheelchair ever since he was seven. He moved in Bologna from Calderino, a

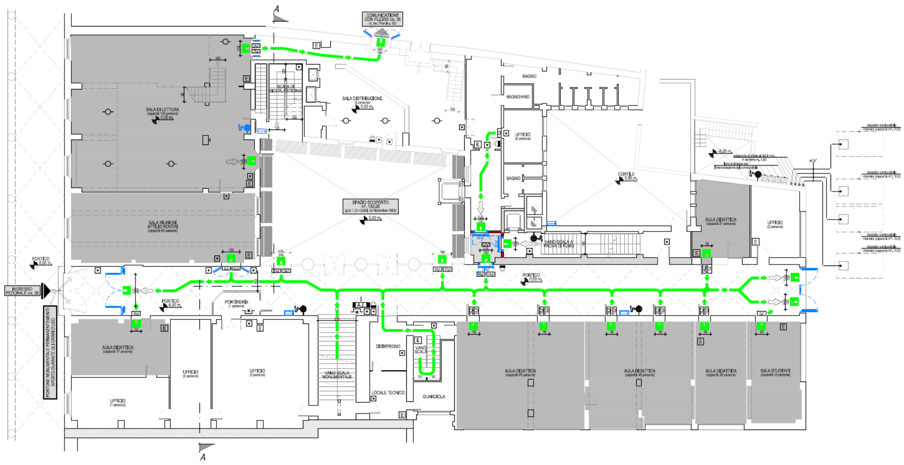

Fig. 6.2 Building grid of the ground floor of Palazzo Riario.

small city near Bologna, for the purposes of studies. He loves music and films and he often goes to the cinema with his friends. He is a freshman and he adds in his curriculum the course of Philosophy of Science.

Giuseppe has his first class of Philosophy of Science in the Tibilleti classroom, which is on the second floor. He opens AlmaWhere and selects Tibilleti classroom as the destination point. The application senses his position, using signals received by nearby beacons, and creates a path so that Giuseppe can reach the destination point. When Giuseppe signed up for the application, he inserted in his preferences that he uses a wheelchair. For this reason, the way finding system does not consider stairs and the small elevator, present in the building but creates a path that passes through the wheelchair lift. Once the application has generated a path, Giuseppe can start the navigation. The application guides him through the floor, using nearby beacons to determine his position until he hasn't reached the Tibilleti classroom, previously set as a destination point. While he's going to class, Giuseppe passes near a half-bust. The application proposes to Giuseppe to read a brief description of this artwork. Since Giuseppe does not recognize the person, he decides to read the description and discover that is a tribute to Giosuè Carducci. Then he continues to follow the navigation instructions.

Fig. 6.3 Corridor of Palazzo Riario

Linda is a student of the University of Bologna, enrolled in the first cycle degree in Philosophy. She is born blind and she has always lived in Bologna. She is with Bob, her guide dog for three years. She loves book and spent much of her free time reading books of every kind. She is a sophomore and she adds in her curriculum the course of Philosophical Anthropology.

Linda has a class on Philosophy of Knowledge in the classroom 5, which is on the second floor. When she arrives at Palazzo Riario she opens AlmaWhere and selects Tibilleti classroom as the destination point. The application senses her position, using signals received by nearby beacons, and creates a path so that Linda can reach the destination point. When Linda signed up fpr the application, she inserted in her preferences that she is blind and that she prefers stairs instead of lift because of Bob. For this reason, the way finding system does not consider lifts but creates a path that passes through the stairs. Once the application has generated a path, Linda can start the navigation. The application, thanks to vocal synthesis, guides her through the floor, using nearby beacons to determine her position until she hasn't reached the classroom 5, previously set as destination point.

6.5 Conclusion and future works

In this chapter, we have presented AlmaWhere, a system based on beacon technology, designed and developed in order to equip students of the University of Bologna with an indoor navigation system able to provide them with support in finding classes, labs, libraries and other significant places coupled with a context-aware digital signage tool able to improve their knowledge about the historical buildings where the University is located. The final intention of this experiment is to improve the building's awareness, the comfort of the occupants and consequently their performance. The application has been designed with the double aim of supporting disabled students and their comfort (and specifically visually impaired ones and the ones with physical impairments) in moving inside different buildings such as the Cittadella, with personalized and accessible paths and of providing information related to places, their story and their use, to all students and visitors in order to improve the awareness. The chapter presented the main design issues that have driven our study and two scenarios describing how users with disabilities could exploit the prototype version of AlmaWhere we are developing aimining to answering at RQ-4.

In the next experiments, we would like to merge with the experiments in the Chapter 3 in order to make the occupants aware of the number of people in the various areas of the building by reporting it in the app and generating new accessible paths that are also based on how crowded the various areas are. Moreover, we are planning to develop the infrastructure in the different old and complex building of the Bologna University and collect data about its usage.

Chapter 7

Improving the air quality comfort through strategic sensor deployment of air pollution models

> How to deploy sensors in a smart campus to collect environmental data in a more accurate and effective way?
>
> — **RQ-5**

This chapter presents a study and a preliminary experiment done to identify potential problems and issues in setting up a testbed for air pollution measurement and modeling. Air pollution is a phenomenon with negative effects on population health, and its monitoring can help the comfort of the occupants of a building such as a University Campus. Our final testbed, part of a joint research activity between the University of Bologna and the Macao Polytechnic Institute, will be composed of three lines of the air pollution sensors Canarin II and it will be used to produce spatio-temporal open data to test third-party air pollution models. Here, we present a preliminary experiment based on a single line of sensors, showing interesting insights into the actual open challenge of air pollution modeling techniques validation, taking into account the effects of air pollutant emissions sources, meteorology, atmospheric concentrations and urban vegetation, with the aim of answering at RQ-5.

7.1 Introduction

Air pollution is a phenomenon by which solid and liquid particles and gases contaminate the environment with negative effects on population health [182, 107]. The effects can be really serious, even lethal, as stated by the World Health Organization (WHO) that renominated this phenomenon *the invisible killer*, estimating in 7 million the number of deaths every year caused by the exposure to fine particles in polluted air [177]. In the same report WHO also claimed that 9 out of 10 people worldwide breathe polluted air and more than 80% of people live in urban areas where the air quality levels exceed the WHO guideline level [177]. Different strategies can be employed to tackle this problem and achieving sustainable development, such as sustainable transport, more efficient and renewable energy production and use and waste management [175]. The first action that local governments and policymakers should tackle is the gathering of air quality data to reflect their commitment to air pollution assessment and monitoring [238]. Having the data, it becomes relevant to develop models able to understand and predict the way pollutants behave in the atmosphere, so as to state the actual air quality in an area [237], and then equipping citizens with tailored services (i.e., mobile apps computing personalized pedestrian and cycling paths in the urban environment [152, 186], keeping the citizens in mind, as well as their preferences and needs [156, 151]).

Several mathematics theories and numerical tools have been studied in the literature, under the umbrella term *air pollution modeling*, to understand the causal relationship between emissions, meteorology, atmospheric concentrations, deposition, and other factors [224]. The techniques used are several (see, for example, [66, 12, 14]) but the common goal is to make an assessment of pollutant impact over a given area using a defined set of data.

In the last years, new technologies are emerging, which provide an alternative and cost-efficient approach to measure air pollutants [220]. Being low-cost and adequately precise, this new generation of pollution sensors are completely changing the possibility to be aware of the air quality in the urban environment, also applying intelligent routing to alleviate the traffic congestion [73], and thereby improve the overall traffic flow [257, 258]. In this context, we are involved in the development and test of Canarin II, the result from the collaboration among the University of Bologna, the Universitè Pierre et Marie Curie, the Macao Polytechnic Institute, and the Asian Institute of Technology. The Canarin II architecture works on a UDOO Neo Full, an Arduino-powered Android/Linux single board. It measures PM_1, $PM_{2.5}$ and PM_{10}, pressure, temperature, humidity and UV [9].

The availability of Canarin II sensors drove us in designing and setting up an air quality testbed, with three goals in mind:

(i) To produce a set of spatio-temporal open data in different weather conditions in order to provide third parties with air quality data to test their own models. Other measures (e.g. sensed wind, detailed map of the area, vegetation distribution) will be provided in order to offer a complete set of data to appropriately test pollution diffusion models.

(ii) To develop models to measure and test the accuracy and efficacy of air pollution modeling techniques, using outdoor air quality data collected under the presence of specific circumstances that can affect the outcome, such as present and future barriers. To make the defined models even stronger, in the future, such dataset could be integrated with data recorded using mobile sensors provided to users and gathered while moving in the surrounding area (e.g. using sensors on shared bikes [9]).

(iii) To determine the best configuration needed in terms of the number of sensors and distance between each sensor in order to collect air quality data and assess with high accuracy the validity of air pollution models.

To address the three research issues, with our study [233] we designed a preliminary experiment using a set of sensors that are being deployed around a new building, 30.000 m_2 wide, which is the new seat of the Campus of Cesena of the University of Bologna (in the Cesena city). The building is located in a particular area, surrounded both by pollutant sources (e.g., a highway and a railway) and by residential/green areas. Due to the peculiar characteristics of the area and the shape of the building, a strategic sensors deployment will let us collect a rich dataset that incorporates phenomena affecting the air quality assessment.

7.2 Air pollution models assessment

As briefly mentioned, several air pollution modeling techniques have been studied and developed to address three main concerns: to assess the existing air quality situation and calculate the population exposure to pollution; to forecast changes in pollution levels and prevent or inform about oncoming predicted critical episodes; to define an air quality planning program. Often these models have been used i) in various forms, ii) with not-standardized and not accurate enough datasets, and ii) with differing and often incomparable quality assurance methods, at both national and local levels. This scenario let emerge the urgent need to harmonize the way these models are validated so as to achieve reliable results.

Different factors affect the outcome resulting from the application of air pollution modeling techniques and need to be considered in the design of the models to avoid uncertain results [100]. Such issues include:

- urban vegetation: vegetation can, directly and indirectly, affect local and regional air quality by altering the urban atmospheric environment [173];
- background concentration: this factor indicates the concentration that would be measured if local sources were not present [19];

- urban layout: buildings can alter the concentration and deposition values [66];
- terrain: the conformation of the area needs to be considerate to simulate the movement of pollutants in the atmosphere [66];
- water source: water, in form of rivers, lakes, or oceans, may transport pollution for long distance, and, sometimes, in high concentrations [98];
- meteorological data: information about wind speed and direction, temperature, humidity are relevant in air pollution modeling [207].

Acquiring precise and variegated enough input data to test the models is a hard task. Some projects have been created with the aim of creating an open data collection of air quality data. One example is represented by OpenAQ[1] with a dataset aggregating air quality measurements, obtained by government agencies, from 8,589 locations in 67 countries. Even than this project is really interesting and has high potential as a tool to inform people about monitored pollution, the dataset can not be used for air pollution modeling since it doesn't include important information related to the context the data are collected, neither the accuracy of the used sensors. Unfortunately, this problem is common to several government open data air quality measures collections. For this reason, with this experiment we want to fill the gap by providing an open dataset of spatio-temporal data, providing all the information needed to assess in a rigorous way the accuracy of thirty-party air pollution models.

7.3 The spatial context

Our testbed is being set up in the Campus of Cesena of the University of Bologna. It is a new building (partially under construction), located at the border between a park (see A in Figure 7.1, west direction), a residential area (B, sud), a not operating industrial zone (C, east) and the railroad/highway area (D, north). The

[1] https://openaq.org/

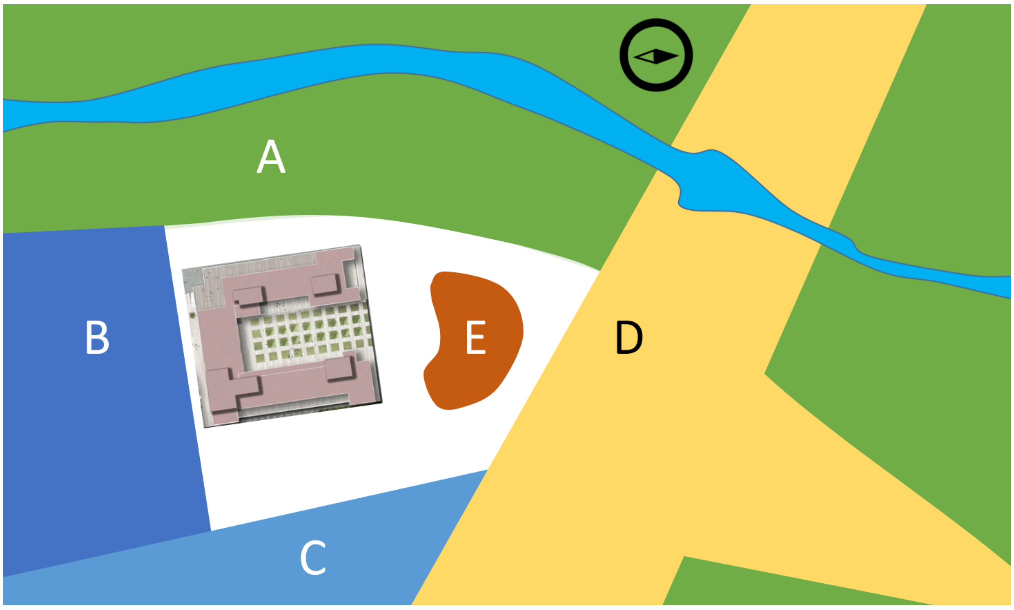

Fig. 7.1 Areas around the campus building.

park is part of the Savio River Reserve, which extends along the River Savio in the part where the reserve enters the urban area of Cesena[2]. The not-operating industrial area is occupied by two buildings originally devoted to fruit storage and distribution. The highway and the railroad enter the city of Cesena going parallel. The highway goes underground to cross the city center nearby the campus building (300 m). The railroad reaches the station 1.2 Km after the campus building. In order to protect the building from pollution coming from the railroad and the highway, an artificial hill (E, north) was created in the north garden, between the building itself and the railroad/highway area.

Figure 7.2 shows a more detailed map, where the main sources of pollution are depicted respectively in white (H, the highway) and yellow (R, the railroad). A minor source of pollution is via Macchiavelli (M, in blue in figure 1). All other streets around the building (depicted in light blue) can be considered irrelevant due to the very limited traffic flow.

[2]https://en.wikipedia.org/wiki/Savio_River_Reserve

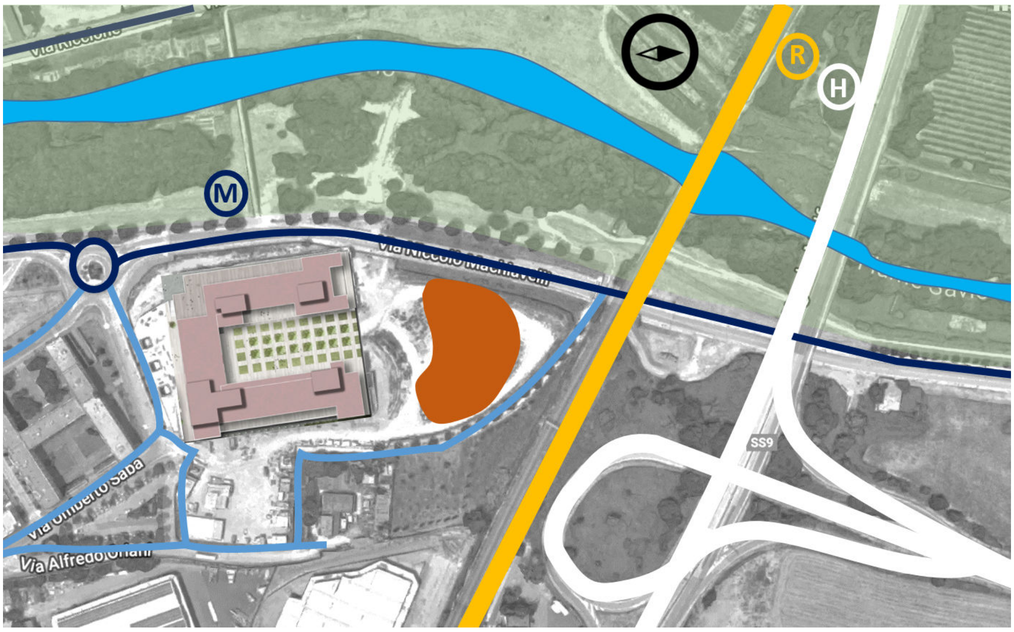

Fig. 7.2 Detail of roads around the building.

The artificial hill E partially protects the building from pollution coming from the D area. Figure 7.3 shows the view of the railroad and the highway taken from the internal part of the courtyard garden. While the hill protects the right part of the view, on the left both the railway and the highway are visible. Similar pictures can be taken from the east side of the building.

7.4 The sensors station

The Canarin II [9] is the result of the collaboration among the Macao Polytechnic Institute, the Asian Institute of Technology, and the Pierre and Marie Curie Sorbonne University.

The sensors station senses different air quality and environmental conditions, such as PM 1.0 (<10 microm) particles, PM 2.5 (<2.5 microm) particles, and PM 10 (<10 microm) particles, temperature, relative humidity, and air pressure.

Fig. 7.3 The artificial hill created to protect the building from pollution coming from the railroad and the highway.

The architecture is based on UDOO Neo Full [3], an Arduino-powered Android/Linux single board computer that overcomes some limitations emerged in the first version of the sensors station [234], such as:

- a new 1GHz ARM Cortex-A9 microprocessor;
- the inclusion of PM_1 (<1.0 microm) particles concentration and formaldehyde sensors;
- a more powerful SD card;
- a new Wi-Fi module for a stronger connection stability;
- better management of the sensed data: if the Internet connection is missing, the data are saved on the local SD and send to the server when possible.

The new system architecture is, therefore, structured around three layers: (i) all the sensors run on an Arduino UNO-compatible platform that clocks at 200 MHz, based on a Cortex-M4 I/O real-time co-processor; (ii) a Linux based OS stores the data into files and it establishes a connection to the server in order to send data; (iii) a server side that provides a data repository and data intelligence

[3] https://www.udoo.org/udoo-neo/

as well. The sensors station design is based on an in-house printed circuit board (PCB) that hosts the board and the sensors welded. The communication is based on Wi-Fi and the board is also configured to be connected to GSM network using the EAP-SIM (EAP Subscriber Identity Module) authentication framework by means of a USB SIM reader. The communication protocol is based on a customized UDP and it communicates to an enhanced MySQL database version.

We also designed an in-house 3D printed PLA (polylactic acid) box to wrap the battery, the PCB, and the sensors together. Everything fits in a 19x15x7 cm and it weighs about 900g due to the battery and the enclosure; a smaller and more portable 3D printed box is about to be produced.

7.5 The sensors deployment

As shown in Figure 7.4, our testbed will be set up using three outdoor spaces: the west terrace, facing via Macchiavelli (1.WT - located at second floor of the campus building), the courtyard garden (2.CG - located at the ground floor) and the east terrace (3.ET - located at second floor of the campus building). Canarin II pollution sensors station will be located in three parallel lines of 4, one every 20 meters. The testbed is completed by an anemometer, to measure the speed of the wind, located on the rooftop of the building (4.AN, located at the roof of the third floor of the campus building).

The setup of the whole testbed will be completed in the next months, accordingly with the completion of the building construction. This chapter presents some preliminary tests conducted on a partial sensors' infrastructure, located in the WT (this area of the building has been already completed). The dislocation of one line of sensors stations in the WT area is shown in Figure 7.5, with a distance of 20 meters between each Canarin II. Having four sensors station in line allows as to overcome issues related to the accuracy and calibration of the specific sensor. We estimated in 20 meters the right distance to collect data affected by different factors. In the next future, more tests will be made to define the best distance needed between each sensor, and if this value is affected by the

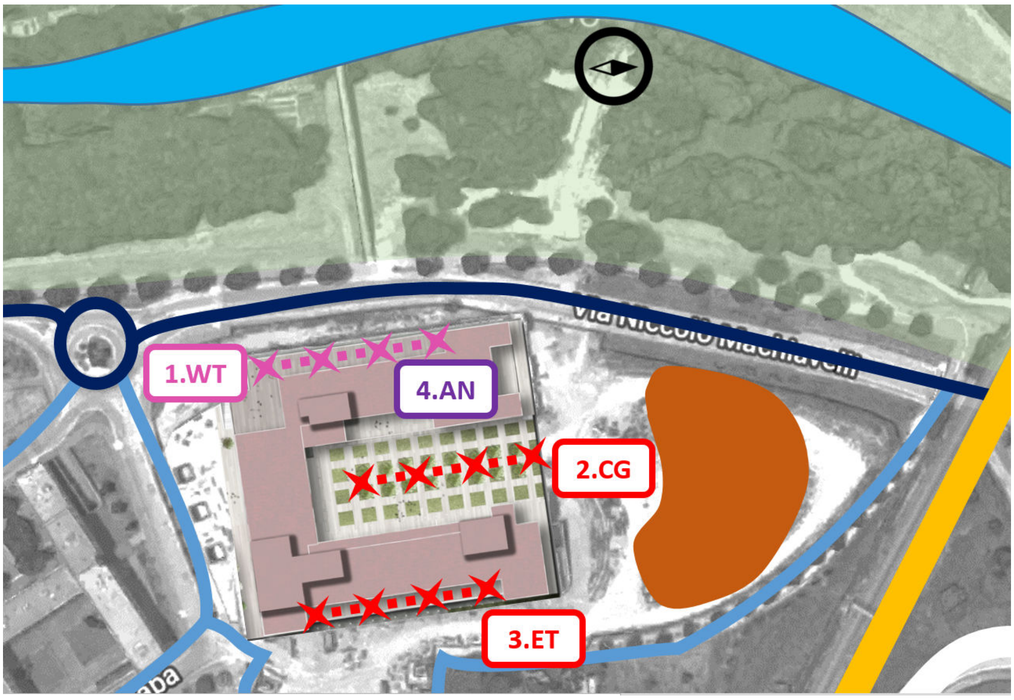

Fig. 7.4 Testbed design and experimental setup.

position of the sensors in the different areas (i.e., WT, GT and ET), settled to capture different urban scenarios and pollution sources.

In a month of data gathering, we already gathered 714,240 complex entries in our database. Each entry includes several values (such as PM_1, $PM_{2.5}$, PM_{10}, humidity, temperature, wind direction and speed, air pressure) contextualized in space (the GPS coordinates) and time.

7.6 Conclusion and future works

In this chapter, we have presented a preliminary experiment to strategically deploy sensors stations in a new University campus. The aim is to monitor it in order to improve the comfort and performance of the occupants and answering at RQ-4. At this stage, the campus is composed of a single building that is located in a peculiar area, allowing to sense air quality data affected by different factors,

Fig. 7.5 The deployment of one line of sensors

including vegetation, different mobile pollution sources, a specific urban layout, and the proximity to a river natural reserve.

With this research project, we intend to address three open issues: i) producing an accurate open data collection that can be exploited by third parties to assess their own air pollution models; ii) developing models to measure the accuracy and test the efficiency of air pollution modeling techniques; iii) defining strategic deployment configurations of air quality and environmental sensors (e.g., the distance between each sensor, the number of sensors, positions) to improve the occupants' health and air quality comfort.

As an initial deployment, we used a line composed of four Canarin II sensor stations. Each sensors station is able to accurately sense PM_1, $PM_{2.5}$, PM_{10}, relative humidity, temperature. Moreover, we augmented the sensing platform with an anemometer, to measure the speed of the wind. In a month, we already collected 714,240 spatio-temporal entries, where each entry is composed of all the sensed environmental conditions at a given time and location.

We are planning to extend the actual deployment including other two lines of sensors located in strategic positions in the building, facing areas with different characteristics (such as vegetation, layout, exposure to pollutant sources). Moreover, we are considering to integrate our dataset with data gathered using mobile air quality sensors (e.g., on shared bikes as described in our paper [9]) to create an even more accurate and variegated collection of open data.

Chapter 8

Monitoring indoor environmental conditions for preservation in Smart Libraries

> How to find strategies to stem the problem related to the books preserving?
>
> — **RQ-6**

Monitoring environmental conditions can provide great benefits, allowing users to be aware of ambient parameters, such as temperature, humidity, pressure, lights, pollution, etc. Collecting and measuring such kind of information means that, after adequate analyses, specific actions can be decided and applied by policymakers in urban scenarios and in public smart buildings, with the aim of improving humans' comfort. Observing and keeping environmental conditions in a specific range is fundamental also for the conservation and the preservation of goods, such as cultural heritage, pieces of art, and also papery documentations. Hence, IoT and smart objects can play a strategic role in equipping smart buildings with systems devoted to such monitoring activities.

In this chapter, we present an investigation and a related experiment we have conducted with the aim of comparing sensed data obtained with different assessment scenarios, applied in library storage within a university campus, so as to answer RQ-6. We have monitored the indoor environmental conditions for three days for each assessment scenario, collecting data about temperature, relative humidity, pollutants. To do that, we have exploited a low-cost multi-sensor platform, named Canarin II, applying the IoT paradigms. We here discuss the results we have obtained, reflecting on the pros and cons of each sensor configuration in the library storage, for better preservation of its books and papery documents.

8.1 Introduction

The wide diffusion of connectivity, together with the application of the Internet of Things (IoT) paradigm and the availability of smart objects and sensors, opens a broad and exciting range of opportunities in several contexts: from smart cities [144] to smart buildings [187], from the health field ([136], [243], [193]) to the education/school one [229], from the Industry 4.0 [132] to the museum/cultural heritage context [61, 48].

IoT can be intended as a technical revolution we are witnessing, representing a promising paradigm of computing and communications [92]: it is based on augmenting physical objects and devices, equipped and enriched with sensing, computing, and communication capabilities, that form a network and enjoy the collective effects of networked objects [23]. In the last years, significant research efforts have been made in IoT related contexts, from different points of view, including the thing-oriented perspective [21], the social side of the IoT [22, 155], and also the human-IoT interactions [215].

A significant wealth of research is devoted to study how IoT and smart objects can be exploited in buildings and environments so as to make them *intelligent* and then, on the one side, improving humans quality of life in their homes or workplaces [46] and, on the other side, saving energy [164]. Indeed, the term *smart buildings* can be referred also to environments with other purposes, such as educating, learning, and studying (e.g. university campuses [6], libraries [39], museums [149]). Many studies aim at identifying solutions for better monitoring and managing indoor parameter conditions, in terms of Indoor Environmental Quality (IEQ) [213]. Usually, IEQ is intended to accomplish humans' comfort, but there are some specific cases where other requirements should be addressed. An example is when preservation and conservation of the building and/or of the elements and objects inside it are critical [181], for historical and documentary related reasons [231]. In these cases, it can be important to monitor additional environmental data, such as pollutants (e.g., Particulate Matter), which can affect the preservation of goods [220].

An interesting case is monitoring environmental conditions of rooms devoted to store books and papery documents, where it is important to steadily check temperature, humidity, pressure, light, and pollution agents. Guaranteeing proper environmental conditions is strategic in these contexts, and it belongs to those care activities required to adequately maintain the *persistent accumulation of knowledge* [53]. Thanks to IoT and smart objects, it is possible to constantly measure those parameters, so as to ensure optimal conditions, supporting paper conservation and preservation. But how many sensors? And how to assess them in a books/documents storage to better sense such conditions?

In order to contribute to the discussion about these topics, this chapter presents an experiment that we have conducted in a university campus [160], where library books and papery documents are stored in a dedicated repository, equipped with a Heating, Ventilation, and Air Conditioning (HVAC) system. In this experiment, we have exploited the Canarin II, a low-cost multi-sensor platform, placing three of them according to different assessment scenarios, for three consecutive days for each configuration, and collecting all the environmental conditions. In this chapter, we report the data we have collected, focusing on three environmental parameters that contribute in paper deterioration (i.e., temperature, humidity, and Particulate Matter); we compare the information resulting from the three different sensors configurations, and we discuss pros and cons for each parameter, providing some reflections that could be useful in similar contexts.

The remainder of the chapter is structured as follows. Section 8.2 describes our case study, focusing on the Canarin II, the multi-sensor platform we have exploited in our experiment, and on the sensors assessment scenarios in the library storage. Section 8.3 discusses the obtained results, providing some reflections about the different configurations for the monitored parameters. Finally, section 8.4 concludes the chapter, illustrating main future work.

8.2 Our Experiment

In this Section, we present the main elements at the basis of our experiment, describing the low-cost multi-sensor platforms we have exploited to sense temperature, relative humidity, PM_{10}, etc. (subsection 8.2.1) and the assessment scenarios we have adopted to collect the environmental data in our library storage (subsection 8.2.2).

8.2.1 Canarin II, a low-cost multi-sensor platform

In our experiment, we have exploited the Canarin II architecture, which is based on its previous version [234] and now relies on a UDOO Neo Full, an Arduino-powered Android/Linux single board computer, running thanks to a 1GHz ARM Cortex-A9 microprocessor. The new system architecture is structured on two layers:

- all the sensors runs on an Arduino UNO-compatible platform that clocks at 200 MHz, based on a Cortex-M4 I/O real-time co-processor;
- a Linux based OS stores the data into files and it establishes a connection to the server in order to send data.

The communication is based on WiFi (and in particular, in our case study we have exploited ALMAWIFI, the University of Bologna WiFi, which can be freely used by students, staff and faculty members). The communication protocol is based on UDP, as well as the Canarin 1.0 protocol, and it communicates to an enhanced MySQL database version. Basically, the system can collect data about Particulate Matters, temperature, relative humidity, and air pressure.

An in-house printed circuit board (PCB) hosts the board and the sensors welded. The PCB is contained in an in-house 3D printed PLA box, which has been designed to wrap the battery too. Figure 8.1 shows a picture of it, see the yellow box in the foreground. Summing up, the PCB and the battery fits in a 19x15x7 cm, weighting about 900 gr (this is basically due to the battery and to the enclosure). A smaller and more portable 3D printed box is going to be produced.

Fig. 8.1 A picture taken in the library storage, with the three Canarin II sensors located according to the first assessment scenario

It is worth mentioning that this new version overcomes some limitations that have emerged in Canarin 1.0. In particular, the new board has been equipped with an external SD card, and this lets store a significant amount of data, on the basis of the SD card capacity. A better connection between the node and the router is available thanks to a new network card, which also enables WPA2-Enterprise connection, such as Eduroam in universities. Actually, a stable connection is not necessary: in fact, the board can collect data even without it, storing the GPS location and the date and the time of the sampling. The board sends such data to the server once a connection can be established. Finally, the board has been equipped with an enhanced PM sensor that can detect and collect data about PM_1 and formaldehyde in addition to the $PM_{2.5}$ and PM_{10}. Moreover, a more accurate temperature and relative humidity sensor has been provided, together with a sensor that can detect Ultra Violet Index (UVI) values.

A more detailed description of the Canarin II platform can be found in [9] and in [233].

8.2.2 Assessment Scenarios

In this SubSection, we present the three different assessment scenarios we have exploited to collect environmental data in our library storage. That storage is placed at the ground floor of the main campus building and it covers a 310.22 mt^2 area (22.48 mt x 13.80 mt), with 4.02 mt height, with a total amount of 1,247.10 mt^3 as volume of that room. Two doors allow to access the storage, while a room side is equipped with adjacent windows along all its length, at the very top, closed to the ceiling. The library storage is equipped with shelves and cupboards (with an height of 2.02 mt and a depth of 0.58 cm) placed along the walls and in 8 lines in the middle of the room. Each line covers a length of 7.50 mt, while the distance between two shelves lines is approximately 1.50 mt. With the aim of collecting data from different points of the library storage, we have placed our sensor platforms according to three different configurations. Figures 8.2, 8.3, and 8.4 depict a simplification of such assessment scenarios within the room.

In particular, in the first scenario (Figure 8.2), all the sensor kits are placed at the same height on the top of the shelves (2.02 mt), along a central line, at the same distance (two Canarins at the beginning and at the end of the line, and one in the middle). The second scenario places the sensor platforms in different lines and at a different height, as shown in Figure 8.3: a first Canarin II is placed on the floor in a corner, at the beginning of the first line of shelves, a second Canarin II is placed in a central line at the height of 1.01 mt, while the third

Canarin II is placed on the top of the last line of shelves, in the corner, at the end of the line. Finally, in the third assessment scenario, the three Canarins II are placed in a central line of shelves, at the center, at different heights: on the floor, in the middle (at 1.01 mt), and on the top of the shelf, as shown in Figure 8.4.

These three different assessments have been chosen with the aim of evaluating differences among the sensed data in the same indoor environment. In particular, our goal is to investigate which configuration can monitor more differences in the collected values, so as to better set the HVAC system. The three assessment scenarios would let us investigate how the sensed values could vary according to the sensors position, also in terms of height. Each assessment scenario has been kept for three days, during which the sensor kits have collected environmental data (i.e., temperature, relative humidity, air pressure, PM_1, $PM_{2.5}$, PM_{10}). Data were measured every minute ca.; some delay occurred in some cases, due to network delays and/or to the communication needed to send monitored values to the Amazon Cloud, as reported in [231] and in [234].

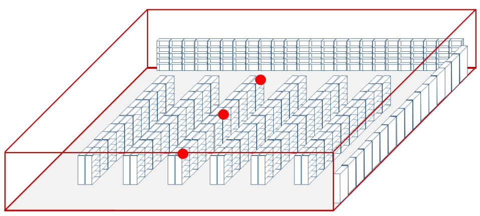

Fig. 8.2 First Assessment Scenario

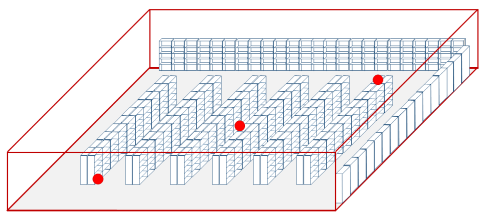

Fig. 8.3 Second Assessment Scenario

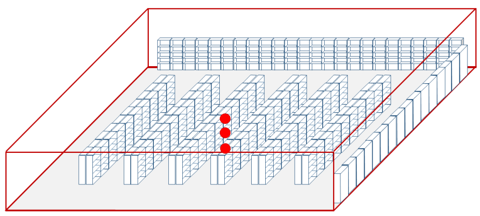

Fig. 8.4 Third Assessment Scenario

8.3 Results and Discussion

This section presents the main results obtained by our monitoring experiments, describing the data coming from the three different assessment scenarios, comparing them, and providing some reflections about the placement of the sensors and about the sensed environmental conditions.

It is worth noting that the results we have gathered are obviously influenced by architectural and structural elements (such as windows and doors), by indoor and outdoor conditions (such as the building HVAC and the external weather conditions during the monitoring periods). In particular, six HVAC cassette units are present in the library storage ceiling, distributed in three rows, two units per row (equidistant from each other). Moreover, some variations could also be due to storage access from the library staff personnel. During our experiment, the Canarin platforms just performed monitoring activities, the building HVAC system automatically worked according to its standard configuration, conditioning the temperature and activating the air recirculation, as usual. In this context, having many sensors in a large indoor environment lets us collect and monitoring different environmental conditions at different points of the room. Hence, identifying critical positions where displacing the sensors can be strategic, with the purpose of adequately setting the HVAC system, so as to limit significant variations in terms of temperature, relative humidity, and air pollution. [174]. In fact, even if the environmental conditions are kept within the range of safe values for books and papery documents conservation (e.g., temperature should be maintained between 18 and 22.2 C°, while humidity should be greater than 30% and less than 50% [133]), having significant fluctuations in short time interval can damage library goods and should be avoided for better preservation. Moreover, research indicates that relative humidity values at the lower end of this range are preferable since deterioration then progresses at a slower rate [174]. A monitoring system, based on many multi-sensors, can help in reaching this purpose, measuring and catching the worst cases, and our experiment aims to discuss pros and cons of the sensors assessment. At a first sight, this can be intended as an optimization problem, similar to the assessment problem for

Wireless Sensor Networks. Indeed, it is necessary to keep into account that our sensors are devoted to monitor data in specific points in the space of an indoor room [113] and that in our context it is interesting to catch as many variations as possible, with the aim of limiting and preventing significant changes in the values in short time intervals.

For these reasons, we have here reported all the values sensed for the three monitored environmental quantities in the three assessment scenarios we have set up. In particular, Figure 8.5 shows the temperature values, Figure 8.6 depicts relative humidity values and, finally, Figure 8.7 reported PM_{10} values collected according the three scenarios we have set up during our experiment. In these Figures, (a) corresponds to the first assessment scenario, (b) corresponds to the second, and (c) corresponds to the third scenario. Data were gathered by the three Canarin platforms we have exploited, and, in particular, the green line corresponds to the values coming from Canarin1; the orange line corresponds to the values coming from Canarin2, and, finally, the blue line corresponds to the values coming from Canarin3. These data shows that more heterogeneous values seem to be collected in the second and the third scenarios for temperature and relative humidity, and in the first and the third assessment scenarios for PM_{10}. In order to better evaluate the value fluctuations, Table 8.1 reports the standard deviations computed for each environmental conditions in each assessment scenario. In particular, the highest standard deviation for the temperature can be found in the second assessment scenario, for the humidity in the third scenario, while for the PM_{10} in the first one.

Figures 8.8, 8.9, and 8.10 shows boxplots reported the distributions of the values of (respectively) temperature, relative humidity, and PM_{10} in the three different assessment scenarios (the first scenario is reported in red, second scenario in blue, and the third scenario in green boxes), reporting some outliers, in general in the second scenario for all the quantities, and in particular in monitoring relative humidity (in all the three scenarios).

All these data rise some considerations and reflections about the different assessment scenarios. On the one hand, temperature and relative humidity values vary in a significant way according to the height of the sensors position. Hence having sensors at a different heights from the floor can provide more heterogeneous values, and this is confirmed by our experiment, in the second and in the third scenarios, where sensors where placed on the floor, at 1.01 mt and at 2.02 mt. On the other hand, PM_{10} have shown heterogeneity also in the values collected in different horizontal positions in the plan of the library storage. All this said, having data collected in an assessment scenario similar to our second one seems to be situation where more heterogeneous data can be measured. This would bring better control of the indoor environment, with the aim of reducing significant variations in environmental conditions.

Table 8.1 Standard deviation for each scenario measurement

		Temperature	**Humidity**	**PM10**
Scenario1	**Canarin1**	0.6726	2.1176	12.8279
	Canarin2	0.5623	1.7574	14.2506
	Canarin3	0.6401	1.9563	15.0005
Scenario2	**Canarin1**	0.2445	1.1440	3.3651
	Canarin2	0.4293	1.0781	2.3969
	Canarin3	0.6450	1.4374	2.4502
Scenario3	**Canarin1**	0.5558	1.8816	9.7626
	Canarin2	0.2200	1.3406	10.2383
	Canarin3	0.3616	2.1371	11.0221

8.4 Conclusion and future works

This chapter presented an experiment we have conducted with the aim of exploiting IoT so as to monitor environmental conditions in a storage devoted to preserve books and papery documents. We have set up the experiment by exploiting a low-cost multi-sensor platform, named Canarin II, and we have focused our attention on measuring temperature, relative humidity and pollutant, which can negatively affect the correct conservation of papery documentations and aimining to answering at RQ-6. Dealing with three Canarin II platforms, we have placed them according to three different assessment scenarios, with the aim of evaluating the different sensed data. The results we have obtained in the scenarios are compared and discussed, as well as pros and cons on the basis of the evaluated conditions. Additional experiments are necessary to monitor environmental data for longer periods, to test different assessments by exploiting more and different multi-sensor platforms, so as to provide more insights.

Collecting all these data can be strategic in order to define better how to configure the HVAC system, letting it be more effective in terms of papery goods. In particular, the use of machine learning algorithms can be very interesting. An example is the use of a neural network to predict the best HVAC configuration, according to the sensed environmental conditions, preventing significant variations in terms of temperature and relative humidity, improving books conservation.

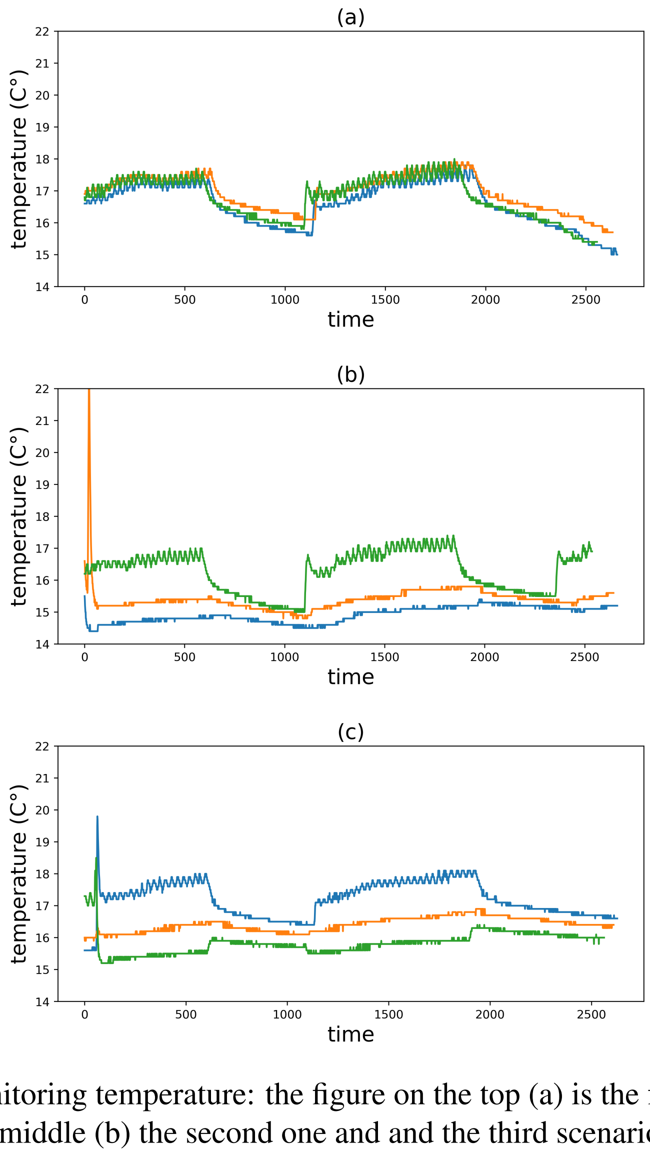

Fig. 8.5 Monitoring temperature: the figure on the top (a) is the first assessment scenario, on middle (b) the second one and and the third scenario on the bottom (c)

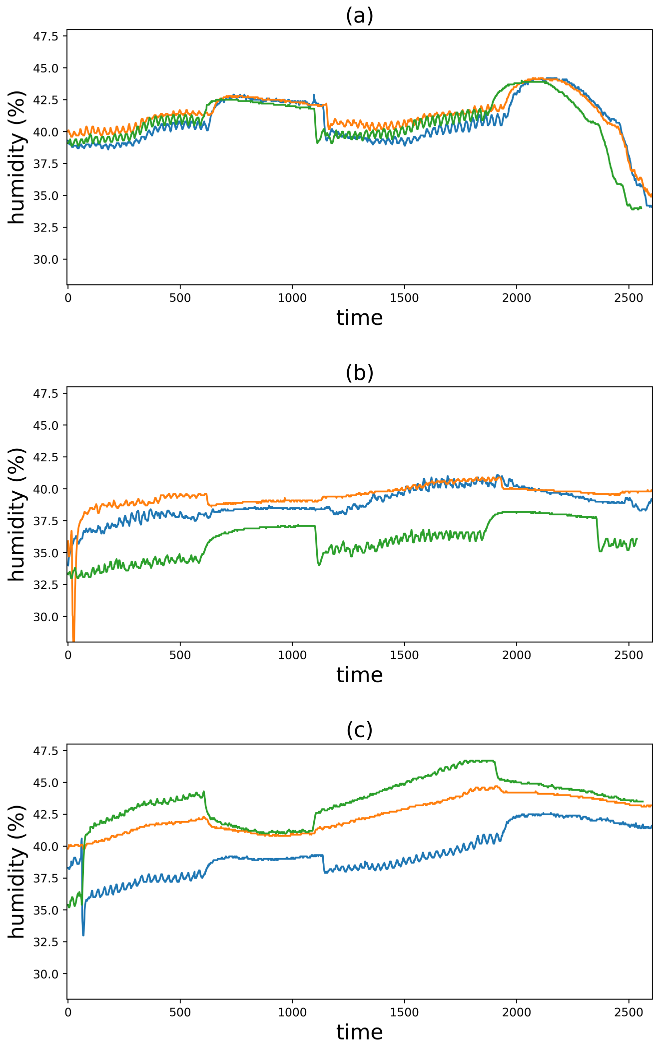

Fig. 8.6 Monitoring humidity: the figure on the top (a) is the first assessment scenario, on middle (b) the second one and and the third scenario on the bottom (c)

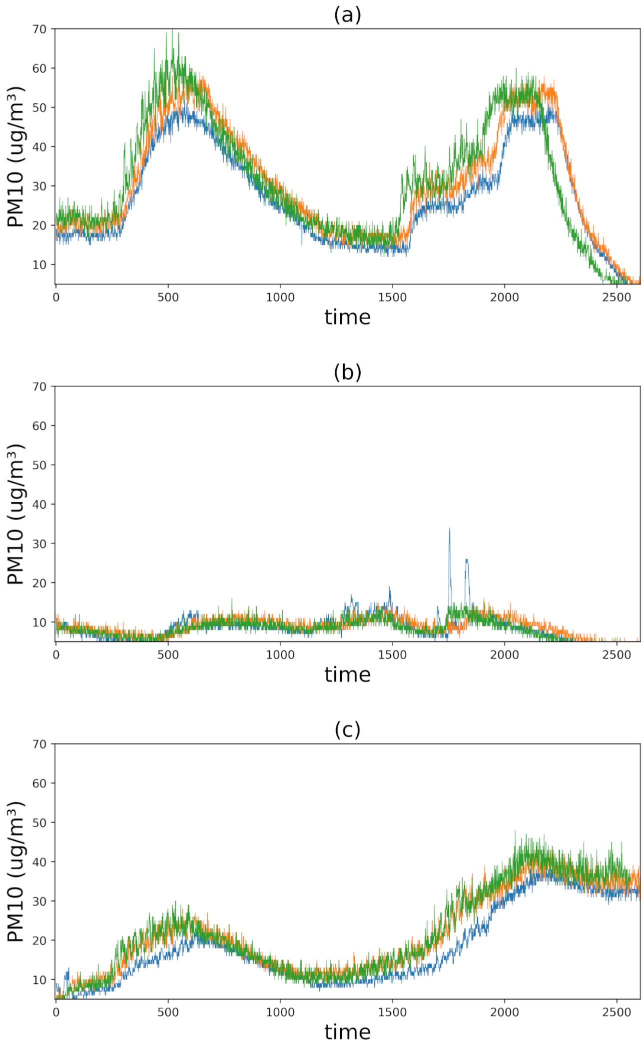

Fig. 8.7 Monitoring PM_{10}: the figure on the top (a) is the first assessment scenario, on middle (b) the second one and and the third scenario on the bottom (c)

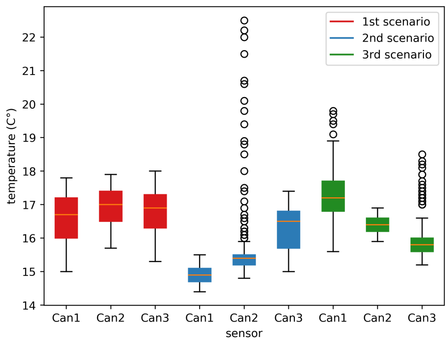

Fig. 8.8 Temperature values distribution for the three different assessment scenarios

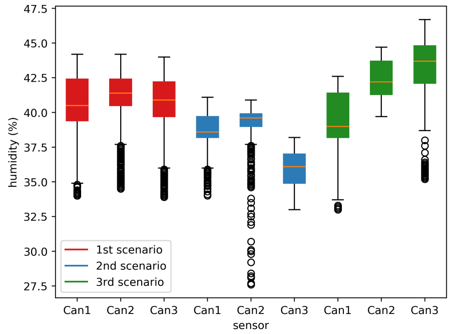

Fig. 8.9 Relative humidity values distribution for the three different assessment scenarios

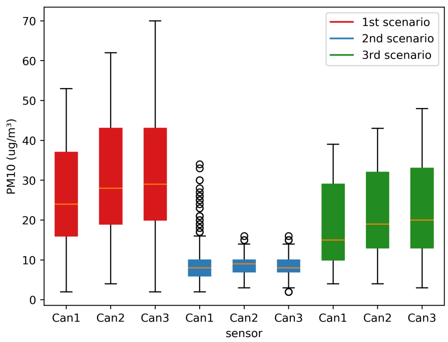

Fig. 8.10 PM_{10} values distribution for the three different assessment scenarios

Chapter 9

Results achieved

In this thesis, different relevant topics concerning Human-Computer Interaction, Smart Environments, Smart Buildings, and Smart Campus have been investigated and explored, by exploiting technologies and solutions based on edge-computing and IoT. This thesis focuses on the concept of comfort within environments such as the Smart Campus, and on how this can directly impact the efficiency of the occupants and indirectly on the energy saving of the building. Literature suggests that smart building design doesn't automatically guarantee that such buildings will be comfortable, ensuring occupants' well-being. For this reason, some of the principal open challenges have been faced, proposing a new conceptual framework, technologies, and tools to move forward the actual implementation of smart campuses. This chapter will summarise the most notable contributions of the thesis, on the basis of the research questions we presented in Chapter 1.

9.1 Discussion and contributions

In the opening chapter, the context of this thesis introduces at first, and then the motivations are given. It presents the definition of users' comfort and open issues and research questions are summarised. Lastly, the list of publications done during my PhD is listed.

The second chapter aims to answer the main research question (*RQ-MAIN*) of this thesis, a new conceptual framework enabling a Human-Centric and Comfort-oriented smart campus. The chapter includes the *design criteria* that should be reflected when deploying the emerging technologies on a smart campus and a *framework design* to demonstrate the multidisciplinary nature reflected in a smart campus.

The third chapter focuses on a known problem related to occupancy detection. Monitoring people flows and presence, counting individuals in indoor environments, including means of transport, detecting if persons are present in a building or in a specific place has always been strategic goals in different contexts. Inside a building, such as a University Campus, it's important information since it enables smart behaviors like understanding the best distribution of classrooms based on the number of students or lighting on the room when someone is inside or shutting the lights off when nobody is. Nowadays, a good occupancy detection technology, cheap but accurate at the same time, is still missing, making this one of the most relevant topics in smart campus conferences. With respect to this topic, which aims to answer the research questions *RQ-1a* and *RQ-1b*, in this third chapter, we have analyzed the usage of RGB and depth cameras on the edge in order to have a low-cost, accurate, and GDPR compliant device for human comfort.

The fourth chapter addresses one of the most serious and underestimated environmental problems: noise pollution. According to the World Health Organization, noise pollution from traffic and other human-activities, negatively impacting the population's health and life quality. Noise pollution can affect humans' comfort and performance both indoor and in outdoor environments, hence, it can play a significant role within the areas of a smart campus, involving its occupants. In this chapter, which aiming at the answer to the research question *RQ-2*, machine learning models are used to obtain predictions from low-cost devices as close as possible in terms of accuracy to calibrated sound level meter.

Interconnected computational devices in the Internet of Things (IoT) context make it possible to collect real-time data about a specific environment. Thus, the IoT paradigm can be exploited as a proof of concept of the importance of considering the community members as key players of a smart campus, not only as passive beneficiaries but also as active contributors. In the fifth chapter, it has been deployed an IoT infrastructure to gather data about different environmental conditions, concerning both indoor and outdoor phenomena, and it has designed and put available with a public installation a rich web-based interface, to let students interact with hyperlocal data. Hence, the platform, which is compliant with the main features of the HCSC (in particular with the context aware one), aiming to answer the research question *RQ-3* and can act as a tool to facilitate the participation of students and to increase the potential of hyperlocal data with the final goal of benefiting the comfort and performance of the whole campus community.

The sixth chapter is focused on methodologies and technologies to enable accessible smart moving across a university campus. Moving across a University campus could represent a barrier for students, in particular for those ones with disabilities, affecting their independence while they conduct their daily activities. In this sense, a system based on beacon technology has been designed and developed to equip the student with an indoor navigation system that supports campus occupants in finding classes, labs, libraries, and other significant places and with the aims to answer the research question *RQ-4*.

Air pollution is a phenomenon with negative effects on population health, and its monitoring can help the comfort of the occupants of a building such as a University Campus. The seventh chapter presents a study and a preliminary experiment done to identify potential problems and issues in setting up a testbed for air pollution measurement and modeling. Our preliminary experiment is based on a single line of environmental sensors such as temperature, humidity, air pressure, PM_1, $PM_{2.5}$ and PM_{10}. It shows interesting insights into the actual open challenge of air pollution modeling techniques validation, taking into account the effects of air pollutant emissions sources, meteorology, atmospheric concentrations and urban vegetation and with the aim to answer the research question *RQ-5*.

Collecting and measuring information about environmental conditions means that, after adequate analyses, specific actions can be decided and applied by policymakers in urban scenarios and in public smart buildings, with the aim of improving humans' comfort. In the last chapter, we present an investigation and a related experiment we have conducted with the aim of comparing sensed data obtained with different assessment scenarios, applied in library storage within a university campus, to answer the research question *RQ-6*. Hence, we exploit IoT and smart objects that can play a strategic role in equipping smart buildings with systems devoted to such monitoring activities.

References

[cam] Online etymology dictionary, "campus". https://www.etymonline.com/word/campus. Accessed: 2018-11-30.

[uni] The university from the 12th to the 20th century. https://www.unibo.it/en/university/who-we-are/our-history/university-from-12th-to-20th-century. Accessed: 2018-11-30.

[3] (2002). Cibse code for lighting. Standard, The Society of Light and Lighting, Rich Hill.

[4] (2007a). Indoor environmental input parameters for design and assessment of energy per-formance of buildings addressing indoor air quality, thermal environment, lighting and acoustics. Standard, European Committee for Standardization, Brussels.

[5] (2007b). Ventilation for non-residential buildings: Performance requirements for venti-lation and room-conditioning systems. Standard, European Committee for Standardization, Brussels.

[6] Abuarqoub, A., Abusaimeh, H., Hammoudeh, M., Uliyan, D., Abu-Hashem, M. A., Murad, S., Al-Jarrah, M., and Al-Fayez, F. (2017). A survey on internet of things enabled smart campus applications. In *Proceedings of the International Conference on Future Networks and Distributed Systems*, page 50. ACM.

[7] Adamko, A., Kadek, T., and Kosa, M. (2014). Intelligent and adaptive services for a smart campus. In *2014 5th IEEE Conference on Cognitive Infocommunications (CogInfoCom)*. IEEE.

[8] AG, A. (2006). European commission working group assessment of exposure to noise. *Position Paper (Final Draft) Good Practice Guide for Strategic Noise Mapping and the Production of Associated Data on Noise Exposure, Version*, 2:129.

[9] Aguiari, D., Delnevo, G., Monti, L., Ghini, V., Mirri, S., Salomoni, P., Pau, G., Im, M., Tse, R., Ekpanyapong, M., et al. (2018). Canarin ii: Designing a smart e-bike eco-system. In *2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 1–6. IEEE.

[10] Ahmetovic, D., Gleason, C., Ruan, C., Kitani, K., Takagi, H., and Asakawa, C. (2016). NavCog: A Navigational Cognitive Assistant for the Blind. *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '16*, pages 90–99.

[11] Aldowah, H., Rehman, S. U., Ghazal, S., and Umar, I. N. (2017). Internet of things in higher education: a study on future learning. In *Journal of Physics: Conference Series*, volume 892, page 012017.

[12] Alvear, O., Calafate, C. T., Zema, N. R., Natalizio, E., Hernández-Orallo, E., Cano, J.-C., and Manzoni, P. (2018). A discretized approach to air pollution monitoring using uav-based sensing. *Mobile Networks and Applications*, 23(6):1693–1702.

[13] Alvear, O., Zamora, W., Calafate, C. T., Cano, J.-C., and Manzoni, P. (2016). EcoSensor: Monitoring environmental pollution using mobile sensors. In *2016 IEEE 17th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*. IEEE.

[14] Alvear, O. A., Zema, N. R., Natalizio, E., and Calafate, C. T. (2017). A chemotactic pollution-homing uav guidance system. In *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 2115–2120. IEEE.

[15] Angeles, R. (2005). Rfid technologies: supply-chain applications and implementation issues. *Information systems management*, 22(1):51–65.

[16] Angelis, E. D., Ciribini, A., Tagliabue, L., and Paneroni, M. (2015). The brescia smart campus demonstrator. renovation toward a zero energy classroom building. *Procedia Engineering*, 118:735–743.

[17] Anwaar, W. and Shah, M. A. (2015). Energy efficient computing: a comparison of raspberry pi with modern devices. *Energy*, 4(02).

[18] Arenghi, A., Belometti, S., Brignoli, F., Fogli, D., Gentilin, F., and Plebani, N. (2018). Unibs4all: A mobile application for accessible wayfinding and navigation in an urban university campus. In *Smart Objects and Technologies for Social Good*, pages 1–6. ACM.

[19] Arunachalam, S., Valencia, A., Akita, Y., Serre, M. L., Omary, M., Garcia, V., and Isakov, V. (2014). A method for estimating urban background concentrations in support of hybrid air pollution modeling for environmental health studies. *International journal of environmental research and public health*, 11(10):10518–10536.

[20] Atthajariyakul, S. and Leephakpreeda, T. (2004). Real-time determination of optimal indoor-air condition for thermal comfort, air quality and efficient energy usage. *Energy and Buildings*, 36(7):720–733.

[21] Atzori, L., Iera, A., and Morabito, G. (2010). The internet of things: A survey. *Computer networks*, 54(15):2787–2805.

[22] Atzori, L., Iera, A., and Morabito, G. (2011). Siot: Giving a social structure to the internet of things. *IEEE communications letters*, 15(11):1193–1195.

[23] Atzori, L., Iera, A., and Morabito, G. (2014). From" smart objects" to" social objects": The next evolutionary step of the internet of things. *IEEE Communications Magazine*, 52(1):97–105.

[24] Awbi, H. B. (2003). *Ventilation of buildings*. Taylor & Francis.

[25] Babisch, W., Beule, B., Schust, M., Kersten, N., and Ising, H. (2005). Traffic noise and risk of myocardial infarction. *Epidemiology*, pages 33–40.

[26] Bansal, A. and Venkatesh, K. (2015). People counting in high density crowds from still images. *arXiv preprint arXiv:1507.08445*.

[27] Beauregard, S. and Haas, H. (2006). Pedestrian dead reckoning: A basis for personal positioning. *Positioning, Navigation and Communication*, pages 27–35.

[28] Belojevic, G., Jakovljevic, B., Slepcevic, V., et al. (2003). Noise and mental performance: Personality attributes and noise sensitivity. *Noise and Health*, 6(21):77.

[29] Bennani, A., Bahi, L., and Amgaad, S. (2017). Analysis of road noise in urban highway in casablanca using pca method.

[30] Bernardini, M., Fredianelli, L., Fidecaro, F., Gagliardi, P., Nastasi, M., and Licitra, G. (2019). Noise assessment of small vessels for action planning in canal cities. *Environments*, 6(3):31.

[31] Bluyssen, P. M. (2017). Health, comfort and performance of children in classrooms–new directions for research. *Indoor and Built Environment*, 26(8):1040–1050.

[32] Boerstra, A., Fitzner, K., Clements-Croome, D., Hanssen, S. O., and Anderson, J. (2007). *Indoor climate and productivity in offices: how to integrate productivity in life-cycle cost analysis of building services*. Rehva.

[33] Bolognese, M., Fidecaro, F., Palazzuoli, D., and Licitra, G. (2020). Port noise and complaints in the north tyrrhenian sea and framework for remediation. *Environments*, 7(2):17.

[34] Bondi, E., Seidenari, L., Bagdanov, A. D., and Del Bimbo, A. (2014). Real-time people counting from depth imagery of crowded environments. In *2014 11th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, pages 337–342. IEEE.

[35] Borgeson, S. and Brager, G. (2011). Comfort standards and variations in exceedance for mixed-mode buildings. *Building Research & Information*, 39(2):118–133.

[36] Boulos, M. N. K. and Berry, G. (2012). Real-time locating systems (rtls) in healthcare: a condensed primer. *International journal of health geographics*, 11(1):25.

[37] Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

[38] Breiman, L., Friedman, J., Stone, C. J., and Olshen, R. A. (1984). *Classification and regression trees*. CRC press.

[39] Brian, A. L. A., Arockiam, L., and Malarchelvi, P. (2014). An iot based secured smart library system with nfc based book tracking. *International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)*, 11(5).

[40] Brumitt, B., Meyers, B., Krumm, J., Kern, A., and Shafer, S. (2000). EasyLiving: Technologies for intelligent environments. In *Handheld and Ubiquitous Computing*, pages 12–29. Springer Berlin Heidelberg.

[41] Buckman, A. H., Mayfield, M., and Beck, S. B. (2014). What is a smart building? *Smart and Sustainable Built Environment*.

[42] Bujari, A., Ciman, M., Gaggi, O., Marfia, G., and Palazzi, C. E. (2015). Paths: Enhancing geographical maps with environmental sensed data. In *Proceedings of the 2015 Workshop on Pervasive Wireless Healthcare*, pages 13–16.

[43] Bujari, A., Ciman, M., Gaggi, O., and Palazzi, C. E. (2017). Using gamification to discover cultural heritage locations from geo-tagged photos. *Personal and Ubiquitous Computing*, 21(2):235–252.

[44] Bujari, A., Furini, M., Mandreoli, F., Martoglia, R., Montangero, M., and Ronzani, D. (2018). Standards, security and business models: key challenges for the iot scenario. *Mobile Networks and Applications*, 23(1):147–154.

[45] Bunn, F. and Zannin, P. H. T. (2016). Assessment of railway noise in an urban setting. *Applied acoustics*, 104:16–23.

[46] Caivano, D., Fogli, D., Lanzilotti, R., Piccinno, A., and Cassano, F. (2018). Supporting end users to control their smart home: design implications from a literature review and an empirical investigation. *Journal of Systems and Software*, 144:295–313.

[47] Calafate, C. T., Lino, C., Diaz-Ramirez, A., Cano, J.-C., and Manzoni, P. (2013). An integral model for target tracking based on the use of a wsn. *Sensors*, 13(6):7250–7278.

[48] Cano, J.-C., Manzoni, P., and Toh, C.-K. (2006). Ubiqmuseum: A bluetooth and java based context-aware system for ubiquitous computing. *Wireless Personal Communications*, 38(2):187–202.

[49] Cantuna, J. G., Solórzano, S., and Clairand, J.-M. (2017). Noise pollution measurement system using wireless sensor network and ban sensors. In *2017 Fourth International Conference on eDemocracy & eGovernment (ICEDEG)*, pages 125–131. IEEE.

[50] Carfagni, M., Furferi, R., Governi, L., Volpe, Y., and Tennirelli, G. (2012). Tactile representation of paintings: An early assessment of possible computer based strategies. *Progress in Cultural Heritage Preservation*, pages 261–270.

[51] Casini, L., Delnevo, G., Roccetti, M., Zagni, N., and Cappiello, G. (2019). Deep water: Predicting water meter failures through a human-machine intelligence collaboration. In *International Conference on Human Interaction and Emerging Technologies*, pages 688–694. Springer.

[52] Caţă, M. (2015). Smart university, a new concept in the internet of things. In *RoEduNet International Conference-Networking in Education and Research (RoEduNet NER), 2015 14th*, pages 195–197. IEEE.

[53] Cerf, V. G. (2019). Libraries considered hazardous. *Communications of the ACM*, 62(2):5–5.

[54] Chan, A. B., Liang, Z.-S. J., and Vasconcelos, N. (2008). Privacy preserving crowd monitoring: Counting people without people models or tracking. In *2008 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–7. IEEE.

[55] Chan, A. B. and Vasconcelos, N. (2012). Counting people with low-level features and bayesian regression. *IEEE Transactions on Image Processing*, 21(4):2160–2177.

[56] Chaudhuri, T., Soh, Y. C., Li, H., and Xie, L. (2019). A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings. *Applied energy*, 248:44–53.

[57] Chen, A. and Chang, V. W.-C. (2012). Human health and thermal comfort of office workers in singapore. *Building and Environment*, 58:172–178.

[58] Chen, D., Liu, Z., Wang, L., Dou, M., Chen, J., and Li, H. (2013). Natural disaster monitoring with wireless sensor networks: a case study of data-intensive applications upon low-cost scalable systems. *Mobile Networks and Applications*, 18(5):651–663.

[59] Chen, M., Ebert, D., Hagen, H., Laramee, R. S., van Liere, R., Ma, K.-L., Ribarsky, W., Scheuermann, G., and Silver, D. (2009). Data, information, and knowledge in visualization. *IEEE Computer Graphics and Applications*, 29(1):12–19.

[60] Chen, N.-S., Cheng, I.-L., Chew, S. W., et al. (2016). Evolution is not enough: Revolutionizing current learning environments to smart learning environments. *International Journal of Artificial Intelligence in Education*, 26(2):561–581.

[61] Chianese, A. and Piccialli, F. (2014). Designing a smart museum: When cultural heritage joins iot. In *2014 eighth international conference on next generation mobile apps, services and technologies*, pages 300–306. IEEE.

[62] Clements-Croome, D. (2011). Sustainable intelligent buildings for people: A review. *Intelligent Buildings International*, 3(2):67–86.

[63] Coccoli, M., Guercio, A., Maresca, P., and Stanganelli, L. (2014). Smarter universities: A vision for the fast changing digital era. *Journal of Visual Languages & Computing*, 25(6):1003–1011.

[64] Cueto, J. L., Petrovici, A. M., Hernández, R., and Fernández, F. (2017). Analysis of the impact of bus signal priority on urban noise. *Acta Acustica united with Acustica*, 103(4):561–573.

[65] Daisey, J. M., Angell, W. J., and Apte, M. G. (2003). Indoor air quality, ventilation and health symptoms in schools: an analysis of existing information. *Indoor air*, 13(LBNL-48287).

[66] Daly, A. and Zannetti, P. (2007). Air pollution modeling–an overview. *Ambient air pollution*, pages 15–28.

[67] Darcy, S., Buhalis, D., et al. (2011). Introduction: from disabled tourists to accessible tourism. *Accessible tourism: Concepts and issues*, pages 1–20.

[68] De Dear, R. J. and Brager, G. S. (2002). Thermal comfort in naturally ventilated buildings: revisions to ashrae standard 55. *Energy and buildings*, 34(6):549–561.

[69] Deepesh, P., Rath, R., Tiwary, A., Rao, V. N., and Kanakalata, N. (2016). Experiences with using ibeacons for indoor positioning. In *Proceedings of the 9th India Software Engineering Conference*, pages 184–189. ACM.

[70] del Mar Castilla, M., Alvarez, J. D., Berenguel, M., Pérez, M., Guzmán, J. L., and Rodríguez, F. (2010). Comfort optimization in a solar energy research center. *IFAC Proceedings Volumes*, 43(1):36–41.

[71] Del Pizzo, L., Foggia, P., Greco, A., Percannella, G., and Vento, M. (2016). Counting people by rgb or depth overhead cameras. *Pattern Recognition Letters*, 81:41–50.

[72] Delnevo, G., Monti, L., Vignola, F., Salomoni, P., and Mirri, S. (2018). Almawhere: A prototype of accessible indoor wayfinding and navigation system. In *2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 1–6. IEEE.

[73] Djahel, S., Doolan, R., Muntean, G.-M., and Murphy, J. (2014). A communications-oriented perspective on traffic management systems for smart cities: Challenges and innovative approaches. *IEEE Communications Surveys & Tutorials*, 17(1):125–151.

[74] Dounis, A. I. and Caraiscos, C. (2009). Advanced control systems engineering for energy and comfort management in a building environment—a review. *Renewable and Sustainable Energy Reviews*, 13(6-7):1246–1261.

[75] Dratva, J., Phuleria, H. C., Foraster, M., Gaspoz, J.-M., Keidel, D., Künzli, N., Liu, L.-J. S., Pons, M., Zemp, E., Gerbase, M. W., et al. (2012). Transportation noise and blood pressure in a population-based sample of adults. *Environmental health perspectives*, 120(1):50–55.

[76] Enescu, D. (2017). A review of thermal comfort models and indicators for indoor environments. *Renewable and Sustainable Energy Reviews*, 79:1353–1379.

[77] Fanger, P. O. et al. (1970). Thermal comfort. analysis and applications in environmental engineering. *Thermal comfort. Analysis and applications in environmental engineering.*

[78] Feige, A., Wallbaum, H., Janser, M., and Windlinger, L. (2013). Impact of sustainable office buildings on occupant's comfort and productivity. *Journal of Corporate Real Estate*, 15(1):7–34.

[79] Fekri-Ershad, S. (2018). A review on image texture analysis methods. *arXiv preprint arXiv:1804.00494*.

[80] Fernandez-Rincon, A., Fuentes-Jimenez, D., Losada-Gutierrez, C., Romera, M. M., Luna, C. A., Guarasa, J. M., and Mazo, M. (2017). Robust people detection and tracking from an overhead time-of-flight camera. In *VISIGRAPP (4: VISAPP)*, pages 556–564.

[81] for Standardization, E. C. (2011). Light and lighting—lighting of work places—part 1: indoor work places. *BSI Standard Publication, page 10. EN*, 12464.

[82] Fredianelli, L., Gallo, P., Licitra, G., and Carpita, S. (2017). Analytical assessment of wind turbine noise impact at receiver by means of residual noise determination without the wind farm shutdown. *Noise Control Engineering Journal*, 65(5):417–433.

[83] Fredianelli, L., Nastasi, M., Bernardini, M., Fidecaro, F., and Licitra, G. (2020). Pass-by characterization of noise emitted by different categories of seagoing ships in ports. *Sustainability*, 12(5):1740.

[84] Frontczak, M. and Wargocki, P. (2011). Literature survey on how different factors influence human comfort in indoor environments. *Building and environment*, 46(4):922–937.

[85] Gagliardi, P., Teti, L., and Licitra, G. (2018). A statistical evaluation on flight operational characteristics affecting aircraft noise during take-off. *Applied acoustics*, 134:8–15.

[86] Gamba, M., Gonella, A., and Palazzi, C. E. (2015). Design issues and solutions in a modern home automation system. In *2015 International Conference on Computing, Networking and Communications (ICNC)*, pages 1111–1115. IEEE.

[87] GhaffarianHoseini, A., Dahlan, N. D., Berardi, U., GhaffarianHoseini, A., Makaremi, N., and GhaffarianHoseini, M. (2013). Sustainable energy performances of green buildings: A review of current theories, implementations and challenges. *Renewable and Sustainable Energy Reviews*, 25:1–17.

[88] Ghayvat, H., Mukhopadhyay, S., Gui, X., and Suryadevara, N. (2015). Wsn-and iot-based smart homes and their extension to smart buildings. *Sensors*, 15(5):10350–10379.

[89] Gretzel, U., Sigala, M., Xiang, Z., and Koo, C. (2015). Smart tourism: foundations and developments. *Electronic Markets*, 25(3):179–188.

[90] Group, B. et al. (2010). Ergonomics of human-system interaction: Human-centred design for interactive systems: Iso 9241-210. *BSI Standards Publication*, 4:32.

[91] Guillén, M. A., Llanes, A., Imbernón, B., Martínez-España, R., Bueno-Crespo, A., Cano, J.-C., and Cecilia, J. M. (2020). Performance evaluation of edge-computing platforms for the prediction of low temperatures in agriculture using deep learning. *JOURNAL OF SUPERCOMPUTING*.

[92] Guo, B., Yu, Z., Zhou, X., and Zhang, D. (2012). Opportunistic iot: Exploring the social side of the internet of things. In *Proceedings of the 2012 IEEE 16th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 925–929. IEEE.

[93] Ha, H. and Haryanti, M. (2019). Tva discomfort during teaching and learning process in malaysian classroom. *International Journal of Innovation, Creativity and Change*, 9.

[94] Hagler, L. and Goiner, L. (2007). Noise pollution: a modern plague. *Southern Medical Journal.[Online]*, 100(3):287–293.

[95] Halawa, E. and Van Hoof, J. (2012). The adaptive approach to thermal comfort: A critical overview. *Energy and Buildings*, 51:101–110.

[96] Harrison, A., Loe, E., and Read, J. (2005). *Intelligent buildings in south East Asia*. Taylor & Francis.

[97] Helmer, R. (1999). Guidelines for community noise. *World Health Organization (WHO)*.

[98] Hewson, E. W. and Olsson, L. E. (1967). Lake effects on air pollution dispersion. *Journal of the Air Pollution Control Association*, 17(11):757–761.

[99] Hirsch, B. and Ng, J. W. (2011). Education beyond the cloud: Anytime-anywhere learning in a smart campus environment. In *2011 international conference for internet technology and secured transactions*, pages 718–723. IEEE.

[100] Holnicki, P. and Nahorski, Z. (2015). Emission data uncertainty in urban air quality modeling—case study. *Environmental Modeling & Assessment*, 20(6):583–597.

[101] Idrees, H., Saleemi, I., Seibert, C., and Shah, M. (2013). Multi-source multi-scale counting in extremely dense crowd images. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2547–2554.

[102] Iglesias-Merchan, C., Diaz-Balteiro, L., and Soliño, M. (2015). Transportation planning and quiet natural areas preservation: Aircraft overflights noise assessment in a national park. *Transportation Research Part D: Transport and Environment*, 41:1–12.

[103] Iguernaissi, R., Merad, D., and Drap, P. (2018). People counting based on kinect depth data. In *ICPRAM*, pages 364–370.

[104] ISO 7730:2005(en) (2005). Ergonomics of the thermal environment — analytical determination and interpretation of thermal comfort using calculation of the pmv and ppd indices and local thermal comfort criteria. Standard, ISO/TC 159/SC 5 Ergonomics of the physical environment.

[105] Jain, P., Srivastava, A., Hazela, B., Singh, V., and Asthana, P. (2020). Customization of learning environment through intelligent management system. In *Proceedings of First International Conference on Computing, Communications, and Cyber-Security (IC4S 2019)*, pages 619–631. Springer.

[106] Jariwala, H. J., Syed, H. S., Pandya, M. J., and Gajera, Y. M. (2017). Noise pollution & human health: A review. *Noise and Air Pollutions: Challenges and Opportunities. Ahmedabad: LD College of Engineering*.

[107] Kampa, M. and Castanas, E. (2008). Human health effects of air pollution. *Environmental pollution*, 151(2):362–367.

[108] KARABIBER, Z. (2003). Michel vallet: Classroom acoustics politics-an overview. *Euronoise Naples 2003*.

[109] Kaushik, A., Mohammed, A., Tumula, P., and Ebohon, J. (2020). Effect of thermal comfort on occupant productivity in office buildings: response surface analysis. *Building and Environment*, page 107021.

[110] Kay, R. and Mattern, F. (2004). The design space of wireless sensor networks. *IEEE Wireless communications*, 11(6):54–61.

[111] Kim, M., Kim, W., and Kim, C. (2011). Estimating the number of people in crowded scenes. In *Visual Information Processing and Communication II*, volume 7882, page 78820L. International Society for Optics and Photonics.

[112] Ko, J., Lu, C., Srivastava, M. B., Stankovic, J. A., Terzis, A., and Welsh, M. (2010). Wireless sensor networks for healthcare. *Proceedings of the IEEE*, 98(11):1947–1960.

[113] Kocakulak, M. and Butun, I. (2017). An overview of wireless sensor networks towards internet of things. In *2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC)*, pages 1–6. IEEE.

[114] Kodialam, M. and Nandagopal, T. (2006). Fast and reliable estimation schemes in rfid systems. In *Proceedings of the 12th annual international conference on Mobile computing and networking*, pages 322–333. ACM.

[115] Kolokotsa, D., Tsiavos, D., Stavrakakis, G., Kalaitzakis, K., and Antonidakis, E. (2001). Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal–visual comfort and indoor air quality satisfaction. *Energy and buildings*, 33(6):531–543.

[116] Kuflik, T., Lanir, J., Dim, E., Wecker, A., Corra, M., Zancanaro, M., and Stock, O. (2011). Indoor positioning: challenges and solutions for indoor cultural heritage sites. In *Proceedings of the 16th international conference on Intelligent user interfaces*, pages 375–378. ACM.

[117] Landau, S., Wiener, W., Naghshineh, K., and Giusti, E. (2005). Creating accessible science museums with user-activated environmental audio beacons (ping!). *Assistive Technology*, 17(2):133–143.

[118] Landström, U., Åkerlund, E., Kjellberg, A., and Tesarz, M. (1995). Exposure levels, tonal components, and noise annoyance in working environments. *Environment International*, 21(3):265–275.

[119] Leyten, J. L., Kurvers, S. R., and Raue, A. K. (2013). Temperature, thermal sensation and workers' performance in air-conditioned and free-running environments. *Architectural Science Review*, 56(1):14–21.

[120] Li, K., Yuen, C., Kanhere, S. S., Hu, K., Zhang, W., Jiang, F., and Liu, X. (2018). Understanding crowd density with a smartphone sensing system. In *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*, pages 517–522. IEEE.

[121] Li, T. and Fong, S. (2018). Counting passengers in public buses by sensing carbon dioxide concentration: System design and implementation. In *Proceedings of the 2018 2nd International Conference on Big Data and Internet of Things*, pages 218–221. ACM.

[122] Licitra, G., Cerchiai, M., Teti, L., Ascari, E., Bianco, F., and Chetoni, M. (2015). Performance assessment of low-noise road surfaces in the leopoldo project: comparison and validation of different measurement methods. *Coatings*, 5(1):3–25.

[123] Licitra, G., Fredianelli, L., Petri, D., and Vigotti, M. A. (2016). Annoyance evaluation due to overall railway noise and vibration in pisa urban areas. *Science of the total environment*, 568:1315–1325.

[124] Licitra, G., Gallo, P., Rossi, E., and Brambilla, G. (2011). A novel method to determine multiexposure priority indices tested for pisa action plan. *Applied acoustics*, 72(8):505–510.

[125] Lin, Y., Dong, W., and Chen, Y. (2018). Calibrating low-cost sensors by a two-phase learning approach for urban air quality measurement. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(1):1–18.

[126] Liu, H., Darabi, H., Banerjee, P., and Liu, J. (2007). Survey of wireless indoor positioning techniques and systems.

[127] Lloret, J., Tomas, J., Canovas, A., and Parra, L. (2016). An integrated iot architecture for smart metering. *IEEE Communications Magazine*, 54(12):50–57.

[128] Lombardi, P., Giordano, S., Farouh, H., and Yousef, W. (2012). Modelling the smart city performance. *Innovation: The European Journal of Social Science Research*, 25(2):137–149.

[129] Longo, S. and Cheng, B. (2015). Privacy preserving crowd estimation for safer cities. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers - UbiComp '15*. ACM Press.

[130] Lopes, S. I., Vieira, J. M., Reis, J., Albuquerque, D., and Carvalho, N. B. (2015). Accurate smartphone indoor positioning using a WSN infrastructure and non-invasive audio for TDoA estimation. *Pervasive and Mobile Computing*, 20:29–46.

[131] Lou, M. (2018). Interactive 3D Mall Map. https://tympanus.net/codrops/2016/04/13/interactive-3d-mall-map/. [Online; accessed 19-July-2018].

[132] Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, 6:1–10.

[133] Lull, W. P. (1995). *Conservation environment guidelines for libraries and archives*. Canadian Council of Archives.

[134] Luna, C. A., Losada-Gutierrez, C., Fuentes-Jimenez, D., Fernandez-Rincon, A., Mazo, M., and Macias-Guarasa, J. (2017). Robust people detection using depth information from an overhead time-of-flight camera. *Expert Systems with Applications*, 71:240–256.

[135] Maisonneuve, N., Stevens, M., Niessen, M. E., and Steels, L. (2009). Noisetube: Measuring and mapping noise pollution with mobile phones. In *Information technologies in environmental engineering*, pages 215–228. Springer.

[136] Mangano, S., Saidinejad, H., Veronese, F., Comai, S., Matteucci, M., and Salice, F. (2015). Bridge: Mutual reassurance for autonomous and independent living. *IEEE Intelligent Systems*, 30(4):31–38.

[137] Marjanović, M., Grubeša, S., and Žarko, I. P. (2017). Air and noise pollution monitoring in the city of zagreb by using mobile crowdsensing. In *2017 25th International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, pages 1–5. IEEE.

[138] Martin, M., Tarrero, A., González, J., and Machimbarrena, M. (2006). Exposure–effect relationships between road traffic noise annoyance and noise cost valuations in valladolid, spain. *Applied acoustics*, 67(10):945–958.

[139] Mattoni, B., Pagliaro, F., Corona, G., Ponzo, V., Bisegna, F., Gugliermetti, F., and Quintero-Nunez, M. (2016). A matrix approach to identify and choose efficient strategies to develop the smart campus. In *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*. IEEE.

[140] Mead, M. N. (2007). Noise pollution: the sound behind heart effects.

[141] Mehdi, M. R., Kim, M., Seong, J. C., and Arsalan, M. H. (2011). Spatio-temporal patterns of road traffic noise pollution in karachi, pakistan. *Environment international*, 37(1):97–104.

[142] Mehmood, Y., Ahmad, F., Yaqoob, I., Adnane, A., Imran, M., and Guizani, S. (2017). Internet-of-things-based smart cities: Recent advances and challenges. *IEEE Communications Magazine*, 55(9):16–24.

[143] Melikov, A. K., Skwarczynski, M., Kaczmarczyk, J., and Zabecky, J. (2013). Use of personalized ventilation for improving health, comfort, and performance at high room temperature and humidity. *Indoor Air*, 23(3):250–263.

[144] Melis, A., Mirri, S., Prandi, C., Prandini, M., Salomoni, P., and Callegati, F. (2016). Crowdsensing for smart mobility through a service-oriented architecture. In *2016 IEEE International Smart Cities Conference (ISC2)*, pages 1–2. IEEE.

[145] Mellert, V., Baumann, I., Freese, N., and Weber, R. (2008). Impact of sound and vibration on health, travel comfort and performance of flight attendants and pilots. *Aerospace Science and Technology*, 12(1):18–25.

[146] Michaud, D. S., Feder, K., Keith, S. E., Voicescu, S. A., Marro, L., Than, J., Guay, M., Denning, A., McGuire, D., Bower, T., et al. (2016). Exposure to wind turbine noise: perceptual responses and reported health effects. *The Journal of the Acoustical Society of America*, 139(3):1443–1454.

[147] Miedema, H. and Oudshoorn, C. (2001). Annoyance from transportation noise: relationships with exposure metrics dnl and denl and their confidence intervals. *Environmental health perspectives*, 109(4):409–416.

[148] Miedema, H. and Oudshoorn, C. (2002). Position paper on dose response relationships between transportation noise and annoyance. *EU's Future Noise Policy, WG2–Dose/Effect*, 20.

[149] Mighali, V., Del Fiore, G., Patrono, L., Mainetti, L., Alletto, S., Serra, G., and Cucchiara, R. (2015). Innovative iot-aware services for a smart museum. In *Proceedings of the 24th international conference on world wide web*, pages 547–550. ACM.

[150] Milicchio, F. (2016). Disabilità e turismo: un caso di creatività digitale in italia. *Turismo creativo e identità culturale*.

[151] Mirri, S., Prandi, C., Roccetti, M., and Salomoni, P. (2017a). Handmade narrations. *Journal on Computing and Cultural Heritage*, 10(4):1–17.

[152] Mirri, S., Prandi, C., Roccetti, M., and Salomoni, P. (2017b). Walking under a different sky: Urban colored routes for creative engagement and pleasure. *International Journal of Human–Computer Interaction*, 33(12):1010–1021.

[153] Mirri, S., Prandi, C., and Salomoni, P. (2016a). Personalizing pedestrian accessible way-finding with mpass. In *Consumer Communications & Networking Conference (CCNC), 2016 13th IEEE Annual*, pages 1119–1124. IEEE.

[154] Mirri, S., Prandi, C., Salomoni, P., Callegati, F., Melis, A., and Prandini, M. (2016b). A service-oriented approach to crowdsensing for accessible smart mobility scenarios. *Mobile Information Systems*, 2016.

[155] Mirri, S., Prandi, C., Salomoni, P., and Monti, L. (2016c). Social location awareness: A prototype of altruistic iot. In *2016 8th IFIP International Conference on New Technologies, Mobility and Security (NTMS)*, pages 1–5. IEEE.

[156] Mirri, S., Roccetti, M., and Salomoni, P. (2018). Collaborative design of software applications: the role of users. *Human-centric Computing and Information Sciences*, 8(1).

[157] Mirri, S., Salomoni, P., and Prandi, C. (2011). Augment browsing and standard profiling for enhancing web accessibility. In *Proceedings of the International Cross-Disciplinary Conference on Web Accessibility*, page 5. ACM.

[158] Mohammadmoradi, H., Munir, S., Gnawali, O., and Shelton, C. (2017). Measuring people-flow through doorways using easy-to-install ir array sensors. In *2017 13th International Conference on Distributed Computing in Sensor Systems (DCOSS)*, pages 35–43. IEEE.

[Montani] Montani, R. Un museo per tutti è per ciascuno. verso una cultura museale inclusiva a partire dai documenti internazionali sui diritti umani.

[160] Monti, L., Mirri, S., Prandi, C., and Salomoni, P. (2019a). Preservation in smart libraries: An experiment involving iot and indoor environmental sensing. In *2019 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6. IEEE.

[161] Monti, L., Mirri, S., Prandi, C., and Salomoni, P. (2019b). Smart sensing supporting energy-efficient buildings: On comparing prototypes for people counting. In *Proceedings of the 5th EAI International Conference on Smart Objects and Technologies for Social Good*, pages 171–176.

[162] Monti, L., Prandi, C., and Mirri, S. (2018). Iot and data visualization to enhance hyperlocal data in a smart campus context. In *Proceedings of the 4th EAI International Conference on Smart Objects and Technologies for Social Good*, pages 1–6. ACM.

[163] Monti, L., Vincenzi, M., Mirri, S., Pau, G., and Salomoni, P. (2020). Raveguard: A noise monitoring platform using low-end microphones and machine learning. *Sensors*, 20(19):5583.

[164] Moreno, M. V., Zamora, M. A., and Skarmeta, A. F. (2014). User-centric smart buildings for energy sustainable smart cities. *Transactions on emerging telecommunications technologies*, 25(1):41–55.

[165] Morley, D., De Hoogh, K., Fecht, D., Fabbri, F., Bell, M., Goodman, P., Elliott, P., Hodgson, S., Hansell, A., and Gulliver, J. (2015). International scale implementation of the cnossos-eu road traffic noise prediction model for epidemiological studies. *Environmental pollution*, 206:332–341.

[166] Muhamad, W., Kurniawan, N. B., Suhardi, and Yazid, S. (2017). Smart campus features, technologies, and applications: A systematic literature review. In *2017 International Conference on Information Technology Systems and Innovation (ICITSI)*. IEEE.

[167] Müller, J., Wilmsmann, D., Exeler, J., Buzeck, M., Schmidt, A., Jay, T., and Krüger, A. (2009). Display blindness: The effect of expectations on attention towards digital signage. In *International Conference on Pervasive Computing*, pages 1–8. Springer.

[168] Muzet, A. (2007). Environmental noise, sleep and health. *Sleep medicine reviews*, 11(2):135–142.

[169] Namiot, D. and Sneps-Sneppe, M. (2015). The physical web in smart cities. In *Advances in Wireless and Optical Communications (RTUWO), 2015*, pages 46–49. IEEE.

[170] Nässén, J., Holmberg, J., Wadeskog, A., and Nyman, M. (2007). Direct and indirect energy use and carbon emissions in the production phase of buildings: an input–output analysis. *Energy*, 32(9):1593–1602.

[171] Navarro, J. M., Martínez-España, R., Bueno-Crespo, A., Martínez, R., and Cecilia, J. M. (2020). Sound levels forecasting in an acoustic sensor network using a deep neural network. *Sensors*, 20(3):903.

[172] Nie, X. (2013). Constructing smart campus based on the cloud computing platform and the internet of things. In *proceedings of the 2nd International Conference on Computer Science and Electronics Engineering*. Atlantis Press.

[173] Nowak, D. J., McHale, P. J., Ibarra, M., Crane, D., Stevens, J. C., and Luley, C. J. (1998). Modeling the effects of urban vegetation on air pollution. In *Air pollution modeling and its application XII*, pages 399–407. Springer.

[174] Ogden, S. (1999). Temperature, relative humidity, light, and air quality: basic guidelines for preservation. *Preservation of Library and Archival Materials*.

[175] Omer, A. M. (2008). Energy, environment and sustainable development. *Renewable and sustainable energy reviews*, 12(9):2265–2300.

[176] Omidvari, M. and Nouri, J. (2009). Effects of noise pollution on traffic policemen.

[177] Organization, W. H. (2018). 9 out of 10 people worldwide breathe polluted air, but more countries are taking action. http://www.who.int/news-room/detail/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-coun\tries-are-taking-action. [Online; accessed 19-June-2018].

[178] Ormandy, D. and Ezratty, V. (2012). Health and thermal comfort: From who guidance to housing strategies. *Energy Policy*, 49:116–121.

[179] Pagliaro, F., Mattoni, B., Gugliermenti, F., Bisegna, F., Azzaro, B., Tomei, F., and Catucci, S. (2016). A roadmap toward the development of sapienza smart campus. In *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*. IEEE.

[180] Parsons, K. (2014). *Human thermal environments: the effects of hot, moderate, and cold environments on human health, comfort, and performance*. CRC press.

[181] Perles, A., Perez-Marin, E., Mercado, R., Segrelles, J. D., Blanquer, I., Zarzo, M., and Garcia-Diego, F. J. (2018). An energy-efficient internet of things (iot) architecture for preventive conservation of cultural heritage. *Future Generation Computer Systems*, 81:566–581.

[182] Pope, C. A., Thun, M. J., Namboodiri, M. M., Dockery, D. W., Evans, J. S., Speizer, F. E., Heath, C. W., et al. (1995). Particulate air pollution as a predictor of mortality in a prospective study of us adults. *American journal of respiratory and critical care medicine*, 151(3):669–674.

[183] Popoola, S. I., Atayero, A. A., Badejo, J. A., John, T. M., Odukoya, J. A., and Omole, D. O. (2018). Learning analytics for smart campus: data on academic performances of engineering undergraduates in nigerian private university. *Data in brief*, 17:76–94.

[184] Poria, Y., Reichel, A., and Brandt, Y. (2009). People with disabilities visit art museums: an exploratory study of obstacles and difficulties. *Journal of Heritage Tourism*, 4(2):117–129.

[185] Powell, J. (1990). Intelligent design teams design intelligent buildings. *Habitat International*, 14(2-3):83–94.

[186] Prandi, C., Melis, A., Prandini, M., Delnevo, G., Monti, L., Mirri, S., and Salomoni, P. (2018a). Gamifying cultural experiences across the urban environment. *Multimedia Tools and Applications*, pages 1–24.

[187] Prandi, C., Monti, L., Ceccarini, C., and Salomoni, P. (2019). Smart campus: Fostering the community awareness through an intelligent environment. *Mobile Networks and Applications*, pages 1–8.

[188] Prandi, C., Nisi, V., and Nunes, N. (2018b). On exploring a pervasive infrastructure to foster citizens participation and sustainable development. In *British HCI 2018*. BCS Learning and Development Ltd.

[189] Puteh, M., Adnan, M., Ibrahim, M. H., Noh, N. M., and Che'Ahmad, C. N. (2014). An analysis of comfortable teaching and learning environment: Community response to climate change in school. *Procedia-Social and Behavioral Sciences*, 116:285–290.

[190] Quinlan, J. (2014). *C4. 5: programs for machine learning*. Elsevier.

[191] Raw, G. and Oseland, N. (1994). Why another thermal comfort conference. In *Thermal comfort: past, present and future, Proceedings of a conference held at the Building Research Establishment, Garston*, pages 9–10.

[192] Raykov, Y. P., Ozer, E., Dasika, G., Boukouvalas, A., and Little, M. A. (2016). Predicting room occupancy with a single passive infrared (PIR) sensor through behavior extraction. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp '16*. ACM Press.

[193] Reda, R., Piccinini, F., and Carbonaro, A. (2018). Towards consistent data representation in the iot healthcare landscape. In *Proceedings of the 2018 International Conference on Digital Health*, pages 5–10.

[194] Redin, D., Vilela, D., Nunes, N., Ribeiro, M., and Prandi, C. (2017). ViTFlow: A platform to visualize tourists flows in a rich interactive map-based interface. In *2017 Sustainable Internet and ICT for Sustainability (SustainIT)*. IEEE.

[195] Redmon, J. and Farhadi, A. (2018a). Yolov3: An incremental improvement. *arXiv*.

[196] Redmon, J. and Farhadi, A. (2018b). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.

[197] Roccetti, M., Delnevo, G., Casini, L., and Cappiello, G. (2019). Is bigger always better? a controversial journey to the center of machine learning design, with uses and misuses of big data for predicting water meter failures. *Journal of Big Data*, 6(1):70.

[198] Roccetti, M., Marfia, G., and Palazzi, C. E. (2011). Entertainment beyond divertissment. *Computers in Entertainment*, 9(2):1–9.

[199] Rocha, P., Siddiqui, A., and Stadler, M. (2015). Improving energy efficiency via smart building energy management systems: A comparison with policy measures. *Energy and Buildings*, 88:203–213.

[200] Rodriguez-Sanchez, M., Martinez-Romo, J., Borromeo, S., and Hernandez-Tamames, J. (2013). Gat: Platform for automatic context-aware mobile services for m-tourism. *Expert Systems with applications*, 40(10):4154–4163.

[201] Rodriguez-Sanchez, M., Moreno-Alvarez, M., Martin, E., Borromeo, S., and Hernandez-Tamames, J. (2014). Accessible smartphones for blind users: A case study for a wayfinding system. *Expert Systems with Applications*, 41(16):7210–7222.

[202] Ruiz-Padillo, A., Ruiz, D. P., Torija, A. J., and Ramos-Ridao, Á. (2016). Selection of suitable alternatives to reduce the environmental impact of road traffic noise using a fuzzy multi-criteria decision model. *Environmental Impact Assessment Review*, 61:8–18.

[203] Salomoni, P., Mirri, S., Ferretti, S., and Roccetti, M. (2007). Profiling learners with special needs for custom e-learning experiences, a closed case? In *Proceedings of the 2007 international cross-disciplinary conference on Web accessibility (W4A) - W4A '07*. ACM Press.

[204] Santini, S., Ostermaier, B., and Vitaletti, A. (2008). First experiences using wireless sensor networks for noise pollution monitoring. In *Proceedings of the workshop on Real-world wireless sensor networks*, pages 61–65.

[205] Sanz, N. and Bergan, S. (2002). *The Heritage of European Universities*. Number v. 548 in Cultural heritage. Council of Europe Pub.

[206] Savale, P. (2014). Effect of noise pollution on human being: Its prevention and control. *Journal of Environmental Research and Development*, 8(4):1026–1036.

[207] Seaman, N. L. (2000). Meteorological modeling for air-quality assessments. *Atmospheric environment*, 34(12-14):2231–2259.

[208] Seco, F., Jim, A. R., Prieto, C., Roa, J., and Koutsou, K. (2009). A survey Mathematical Methods for for Indoor A survey of of mathematical methods indoor Localization localization. *WISP 2009 • 6th IEEE International Symposium on Intelligent Signal Processing*, pages 9–14.

[209] Seto, E. Y. W., Holt, A., Rivard, T., and Bhatia, R. (2007). Spatial distribution of traffic induced noise exposures in a us city: an analytic tool for assessing the health impacts of urban planning decisions. *International journal of health geographics*, 6(1):24.

[210] Seyedzadeh, S., Rahimian, F. P., Glesk, I., and Roper, M. (2018). Machine learning for estimation of building energy consumption and performance: a review. *Visualization in Engineering*, 6(1):5.

[211] Shabha, G. (2006). A critical review of the impact of embedded smart sensors on productivity in the workplace. *Facilities*.

[212] Shah, S. H. and Yaqoob, I. (2016). A survey: Internet of things (iot) technologies, applications and challenges. In *2016 IEEE Smart Energy Grid Engineering (SEGE)*, pages 381–385. IEEE.

[213] Shaikh, P. H., Nor, N. B. M., Nallagownden, P., Elamvazuthi, I., and Ibrahim, T. (2014). A review on optimized control systems for building energy and comfort management of smart sustainable buildings. *Renewable and Sustainable Energy Reviews*, 34:409–429.

[214] Shi, W., Cao, J., Zhang, Q., Li, Y., and Xu, L. (2016). Edge computing: Vision and challenges. *IEEE internet of things journal*, 3(5):637–646.

[215] Shirehjini, A. A. N. and Semsar, A. (2017). Human interaction with iot-based smart environments. *Multimedia Tools and Applications*, 76(11):13343–13365.

[216] Singh, J. (1996a). Health, comfort and productivity in the indoor environment. *Indoor and Built Environment*, 5(1):22–33.

[217] Singh, J. (1996b). Impact of indoor air pollution on health, comfort and productivity of the occupants. *Aerobiologia*, 12(1):121–127.

[218] Singh, N. and Davar, S. C. (2004). Noise pollution-sources, effects and control. *Journal of Human Ecology*, 16(3):181–187.

[219] Smith, S. (2007). Intelligent buildings. In *Design and Construction*, pages 60–82. Routledge.

[220] Snyder, E. G., Watkins, T. H., Solomon, P. A., Thoma, E. D., Williams, R. W., Hagler, G. S., Shelow, D., Hindin, D. A., Kilaru, V. J., and Preuss, P. W. (2013). The changing paradigm of air pollution monitoring.

[221] Sørensen, M., Andersen, Z. J., Nordsborg, R. B., Jensen, S. S., Lillelund, K. G., Beelen, R., Schmidt, E. B., Tjønneland, A., Overvad, K., and Raaschou-Nielsen, O. (2012). Road traffic noise and incident myocardial infarction: a prospective cohort study. *PloS one*, 7(6).

[222] Sørensen, M., Lühdorf, P., Ketzel, M., Andersen, Z. J., Tjønneland, A., Overvad, K., and Raaschou-Nielsen, O. (2014). Combined effects of road traffic noise and ambient air pollution in relation to risk for stroke? *Environmental research*, 133:49–55.

[223] Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., and Bonavitacola, F. (2014). Calibration of a cluster of low-cost sensors for the measurement of air pollution in ambient air. In *SENSORS, 2014 IEEE*, pages 21–24. IEEE.

[224] Srivastava, A. and Rao, B. P. S. (2011). Urban air pollution modeling. In *Air Quality-Models and Applications*. InTech.

[225] Sundstrom, E., Town, J. P., Rice, R. W., Osborn, D. P., and Brill, M. (1994). Office noise, satisfaction, and performance. *Environment and behavior*, 26(2):195–222.

[226] Sutjarittham, T., Gharakheili, H. H., Kanhere, S. S., and Sivaraman, V. (2019). Experiences with iot and ai in a smart campus for optimizing classroom usage. *IEEE Internet of Things Journal*, 6(5):7595–7607.

[227] Sykes, E. R., Pentland, S., and Nardi, S. (2015). Context-aware mobile apps using ibeacons: towards smarter interactions. In *Proceedings of the 25th Annual International Conference on Computer Science and Software Engineering*, pages 120–129. IBM Corp.

[228] Symeonaki, E. G., Arvanitis, K. G., and Piromalis, D. D. (2019). Current trends and challenges in the deployment of iot technologies for climate smart facility agriculture. *International Journal of Sustainable Agricultural Management and Informatics*, 5(2-3):181–200.

[229] Tianbo, Z. (2012). The internet of things promoting higher education revolution. In *2012 Fourth International Conference on Multimedia Information Networking and Security*, pages 790–793. IEEE.

[230] Torrado, J. C., Montoro, G., and Gomez, J. (2016). Easing the integration: A feasible indoor wayfinding system for cognitive impaired people. *Pervasive and Mobile Computing*, 31:137–146.

[231] Tse, R., Aguiari, D., Chou, K.-S., Tang, S.-K., Giusto, D., and Pau, G. (2018a). Monitoring cultural heritage buildings via low-cost edge computing/sensing platforms: the biblioteca joanina de coimbra case study. In *Proceedings of the 4th EAI International Conference on Smart Objects and Technologies for Social Good*, pages 148–152.

[232] Tse, R., Monti, L., Im, M., Mirri, S., Pau, G., and Salomoni, P. (2020). Deepclass: edge based class occupancy detection aided by deep learning and image cropping. In *Twelfth International Conference on Digital Image Processing (ICDIP 2020)*, volume 11519, page 1151904. International Society for Optics and Photonics.

[233] Tse, R., Monti, L., Prandi, C., Aguiari, D., Pau, G., and Salomoni, P. (2018b). On assessing the accuracy of air pollution models exploiting a strategic sensors deployment. In *Proceedings of the 4th EAI International Conference on Smart Objects and Technologies for Social Good*, pages 55–58. ACM.

[234] Tse, R. and Pau, G. (2016). Enabling street-level pollution and exposure measures: a human-centric approach. In *Proceedings of the 6th ACM International Workshop on Pervasive Wireless Healthcare*, pages 1–4. ACM.

[235] Tse, R., Xiao, Y., Pau, G., Fdida, S., Roccetti, M., and Marfia, G. (2016). Sensing pollution on online social networks: A transportation perspective. *Mobile Networks and Applications*, 21(4):688–707.

[236] Tsirmpas, C., Rompas, A., Fokou, O., and Koutsouris, D. (2014). An indoor navigation system for visually impaired and elderly people based on Radio Frequency Identification (RFID).

[237] UNION, P. et al. (2008). Directive 2008/50/ec of the european parliament and of the council of 21 may 2008 on ambient air quality and cleaner air for europe. *Official Journal of the European Union*.

[238] Vallero, D. A. (2016). Air pollution monitoring changes to accompany the transition from a control to a systems focus. *Sustainability*, 8(12):1216.

[239] Van Hoof, J. (2008). Forty years of fanger's model of thermal comfort: comfort for all? *Indoor air*, 18(3):182–201.

[240] Vapnik, V. (1963). Pattern recognition using generalized portrait method. *Automation and remote control*, 24:774–780.

[241] Vapnik, V. (1964). A note one class of perceptrons. *Automation and remote control*.

[242] Vapnik, V. N. (1999). An overview of statistical learning theory. *IEEE transactions on neural networks*, 10(5):988–999.

[243] Veronese, F., Saidinejad, H., Comai, S., and Salice, F. (2016). Elderly monitoring and aal for independent living at home: human needs, technological issues, and dependability. In *Optimizing Assistive Technologies for Aging Populations*, pages 154–181. IGI Global.

[244] Vilcekova, S., Meciarova, L., Burdova, E. K., Katunska, J., Kosicanova, D., and Doroudiani, S. (2017). Indoor environmental quality of classrooms and occupants' comfort in a special education school in slovak republic. *Building and Environment*, 120:29–40.

[245] Wang, F., Feng, Q., Chen, Z., Zhao, Q., Cheng, Z., Zou, J., Zhang, Y., Mai, J., Li, Y., and Reeve, H. (2017a). Predictive control of indoor environment using occupant number detected by video data and CO 2 concentration. *Energy and Buildings*, 145:155–162.

[246] Wang, Y., Saez, B., Szczechowicz, J., Ruisi, J., Kraft, T., Toscano, S., Vacco, Z., and Nicolas, K. (2017b). A smart campus internet of things framework. In *2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*. IEEE.

[247] Wargocki, P., Sundell, J., Bischof, W., Brundrett, G., Fanger, P. O., Gyntelberg, F., Hanssen, S., Harrison, P., Pickering, A., Seppänen, O., et al. (2002). Ventilation and health in non-industrial indoor environments: report from a european multidisciplinary scientific consensus meeting (euroven). *Indoor air*, 12(2):113–128.

[248] Wigginton, M. and Harris, J. (2013). *Intelligent skins*. Routledge.

[249] Wong, J. K., Li, H., and Wang, S. (2005). Intelligent building research: a review. *Automation in construction*, 14(1):143–159.

[250] Wu, L., Kaiser, G., Solomon, D., Winter, R., Boulanger, A., and Anderson, R. (2012). Improving efficiency and reliability of building systems using machine learning and automated online evaluation. In *2012 IEEE Long Island Systems, Applications and Technology Conference (LISAT)*, pages 1–6. IEEE.

[251] Yahya, S., Ahmad, E., and Abd Jalil, K. (2010). The definition and characteristics of ubiquitous learning: A discussion. *International Journal of Education and Development using ICT*, 6(1).

[252] Yaik, O. B., Wai, K. Z., Tan, I. K., and Sheng, O. B. (2016). Measuring the accuracy of crowd counting using wi-fi probe-request-frame counting technique. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, 8(2):79–81.

[253] Yang, L., Yan, H., and Lam, J. C. (2014). Thermal comfort and building energy consumption implications–a review. *Applied energy*, 115:164–173.

[254] Yun, G. Y. (2018). Influences of perceived control on thermal comfort and energy use in buildings. *Energy and Buildings*, 158:822–830.

[255] Yun, J. and Lee, S.-S. (2014). Human movement detection and identification using pyroelectric infrared sensors. *Sensors*, 14(5):8057–8081.

[256] Zacarías, F. F., Molina, R. H., Ancela, J. L. C., López, S. L., and Ojembarrena, A. A. (2013). Noise exposure in preterm infants treated with respiratory support using neonatal helmets. *Acta Acustica united with Acustica*, 99(4):590–597.

[257] Zambrano, J. L., Calafate, C. T., Soler, D., Cano, J.-C., and Manzoni, P. (2016). Using real traffic data for its simulation: Procedure and validation. In *2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld)*, pages 161–170. IEEE.

[258] Zambrano-Martinez, J. L., Calafate, C. T., Soler, D., Cano, J.-C., and Manzoni, P. (2018). Modeling and characterization of traffic flows in urban environments. *Sensors*, 18(7):2020.

[259] Zamora, W., Calafate, C. T., Cano, J.-C., and Manzoni, P. (2017a). Accurate ambient noise assessment using smartphones. *Sensors*, 17(4):917.

[260] Zamora, W., Calafate, C. T., Cano, J.-C., and Manzoni, P. (2017b). Noise-sensing using smartphones: Determining the right time to sample. In *Proceedings of the 15th International Conference on Advances in Mobile Computing & Multimedia*, pages 196–200.

[261] Zamora, W., Calafate, C. T., Cano, J.-C., and Manzoni, P. (2017c). Smartphone tuning for accurate ambient noise assessment. In *Proceedings of the 15th International Conference on Advances in Mobile Computing & Multimedia*, pages 115–122.

[262] Zamora, W., Vera, E., Calafate, C. T., Cano, J.-C., and Manzoni, P. (2018). Grc-sensing: an architecture to measure acoustic pollution based on crowdsensing. *Sensors*, 18(8):2596.

[263] Zannin, P. H. T. and Marcon, C. R. (2007). Objective and subjective evaluation of the acoustic comfort in classrooms. *Applied Ergonomics*, 38(5):675–680.

[264] Zhao, T., Nevatia, R., and Wu, B. (2008). Segmentation and tracking of multiple humans in crowded environments. *IEEE transactions on pattern analysis and machine intelligence*, 30(7):1198–1211.

[265] Zhu, L. and Wong, K.-H. (2013). Human tracking and counting using the kinect range sensor based on adaboost and kalman filter. In *International Symposium on Visual Computing*, pages 582–591. Springer.

[266] Zhu, Z.-T., Yu, M.-H., and Riezebos, P. (2016). A research framework of smart education. *Smart learning environments*, 3(1):4.

[267] Zimmerman, N., Presto, A. A., Kumar, S. P., Gu, J., Hauryliuk, A., Robinson, E. S., Robinson, A. L., and Subramanian, R. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. *Atmospheric Measurement Techniques*, 11(1).

[268] Zuckerwar, A. J., Herring, G., and Elbing, B. R. (2006). Calibration of the pressure sensitivity of microphones by a free-field method at frequencies up to 80 khz. *The Journal of the Acoustical Society of America*, 119(1):320–329.

[269] Zuo, F., Li, Y., Johnson, S., Johnson, J., Varughese, S., Copes, R., Liu, F., Wu, H. J., Hou, R., and Chen, H. (2014). Temporal and spatial variability of traffic-related noise in the city of toronto, canada. *Science of the Total Environment*, 472:1100–1107.

[270] Zuo, J. and Zhao, Z.-Y. (2014). Green building research–current status and future agenda: A review. *Renewable and sustainable energy reviews*, 30:271–281.