Events Of Daily Living Classification on an Ambient Assisted Living Environment

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DIREITOS DE AUTOR E CONDIÇÕES DE UTILIZAÇÃO DO TRABALHO POR TERCEIROS

STATEMENT OF INTEGRITY

I hereby declare having conducted my thesis with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results in the process of the thesis elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

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”Considerai bem e medi bem os degraus, uns tão altos, outros tão baixos, por onde, tropeçando, ajoelhando e caindo, ou se perde a pretensão, ou se chega finalmente a tomar posse do lugar pretendido, vereis quanto mais custa o alcançar que o merecer.”

António Vieira SJ

Abstract

Population ageing is a global demographic challenge and countries all around the world are facing significant pressure on their health and social care systems in order to mitigate the effects of it.

The emerging social aspect introduced some crucial challenges to society and greater demands on the actual health care sector, which led to the emergence and increased integration of age-friendly innovative welfare technological-based care services for safe and independent ageing, including the assisted living technologies based on Ambient Intelligence (AmI) paradigm and Pervasive HealthCare. The Ambient Assisted Living (AAL) systems intend to provide caregivers with a detailed overview of their Events of Daily Living (EDL), which constitutes a clinical criteria to evaluate activity limitations.

This dissertation addresses these challenges and contributes to the Ambient Assisted Living research, by means of a holistic solution composed of a beyond the state-of-the-art AAL technologies, representing a novel approach to assist in the investigation and on the modeling of a subset of Events of Daily Living (EDL), for sustaining independent living and a continual naturalistic assessment of health.

The investigation was focused on 1) developing a multisensorial pervasive Research Data Acquistion (RDA) Platform with embedded Ambient Intelligence (AmI), 2) COTS to verify their validity and reliability for healthcare applications.

The proposed solution has been thoroughly evaluated in the Ambient Assisted Living Laboratory that showed its effectiveness classifying EDL through the application of the AAL paradigm in the real world.

Keywords: *Ambient Assisted living, Ambient Intelligence,Events Of Daily Living, Pervasive Healthcare*

Resumo

O envelhecimento populacional é um desafio demográfico global e os países em todo o mundo estão sob com enorme pressão nos seus sistemas de saúde a fim de mitigar os efeitos que poderão advir.

O aspecto social emergente introduziu alguns desafios cruciais para a sociedade e uma maior sobrecarga no setor de saúde, o que levou ao surgimento e aumento da integração de serviços inovadores de assistência social, de modo a que haja um envelhecimento seguro e independente, incluindo as tecnologias de assistência à vida com base no paradigma de Ambient Intelligence (AmI) e no Pervasive HealthCare, os sistemas de Ambient Assisted Living (AAL). Eles pretendem fornecer aos profissionais de saúde uma visão detalhada de seu Events of Daily Living (EDL), que constitui um critério clínico para avaliar as limitações da atividade.

Para enfrentar estes desafios, esta dissertação contribui para a pesquisa na área de Ambient Assisted Living, por meio de uma solução holística composta por uma tecnologia além das tecnologias state-of-the-art, representando uma nova abordagem para auxiliar na investigação e na modelação de um subconjunto de Events of Daily Living (EDL), para sustentar uma vida independente e uma avaliação naturalística contínua da saúde. A investigação foi focada em 1) desenvolver uma plataforma multisensorial pervasiva Research Data Acquistion (RDA) com Ambient Intelligence (AmI), 2) COTS para verificar a sua validade e fiabilidade para aplicações de assistência médica.

A solução proposta foi avaliada no Ambient Assisted Living Laboratory, que mostrou bastante eficácia ao classificar EDL através da aplicação do paradigma AAL no mundo real.

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Acronyms and Abbreviations

AAL Ambient Assisted Living.

AQMP Advanced Message Queuing Protocol.

AmI Ambient Intelligence.

AE Adverse Events.

ADL Activities of Daily Living.

AADL Advanced Activities of Daily Living.

ARS Activity Recognition Systems.

AR Activity Recognition.

API Application Programming Interface.

AP Activity Prediction.

BADL Basic Activities of Daily Living.

COTS Commercial Of-The-Shelf Sensors.

CN Clinically Normal.

CAR Circadian Activity Rythm.

DD Detection of Deviations.

DT Decision Tree.

EDL Events of Daily Living.

HMM lHidden Markov Model.

IoT Internet of Things.

ICT Information and Communication Technologies.

IADL Instrumental Activities of Daily Living.

ICU Intensive Care Unit.

JSON JavaScript Object Notation.

KNN K-Nearest Neighbour.

LTC Long-Term Care.

MCI Mild Cognitive Impairment.

MQTT Message Queue Telemetry Transport.

NB Naïve Bayes.

SSL Secure Sockets Layer.

PIR Passive Infrared Motion Sensor.

PADL Personal Activities of Daily Living.

QoL Quality of Life.

RDA Research Data Acquistion.

RFID lRadio-frequency identification.

SE Smart Environment.

SHC Smart Home Care.

WSNs Wireless Sensor Networks.

Reading Guide

The following reading guide provides the reader with a short introduction to the contents of the chapters in this dissertation.

Chapter 1 - Introduction	The Introduction provides a contextualization of the social transformations and demographic ageing to introduce the problem to be addressed. It also presents a set of hypotheses, research questions and objectives.
Chapter 2 – Background and Related Work	The Background and Related Work provides an overview of the current usage of AAL technologies, the concept of Events of Daily Living and the AAL Context-Awareness – activity recognition and long-term monitoring.
Chapter 3 - Methods	The Methods provides an overview of how the master thesis was structured together with a detailed description of the Research Data Acquisition Platform and the conducted studies.
Chapter 4 - Results	The Results presents the obtained results from the studies performed.
Chapter 5 - Discussion	The Discussion provides a discussion of the methods used, the obtained results and the limitations of the studies performed.
Chapter 6 - Conclusion	The Conclusion presents the conclusions drawn towards the hypothesis.

Chapter 1

Introduction

In this chapter, a contextualization of the problem to be investigated is presented, specifically focusing on the social transformations of the 21th century and the challenges in responding to demographic ageing. These transformations are creating strong pressure on the sustainability of health and social care systems to increase the quality of life for older people or for persons with disabilities. The chapter also adresses the purpose of this dissertation.

Following this, a set of hypothesis are described and as a way of investigating their feasibility, a set of research questions are defined.

1.1 Societal Challenges-Ageing Population

Population ageing is a global demographic challenge and countries all around the world are facing significant pressure on their health and social care systems in order to mitigate the effects of the increasing ageing population[1, 2]. According to data from World Health [3], as a result of both improved longevity and the aging of population cohorts (the "baby boomers") born during the years 1945-1964 post-World War II period in combination with other trends, including the increase in life expectency that occurred during the twentieth century is leading to witnessing a major demographic shift [3, 4, 5].

The peaks shown for the population in their 60 years or over in 2015-2020 and aged 80 years or over in 2030-2035 are the period where those borns during the post-Word War II baby boom reach older ages, Figure 1.1

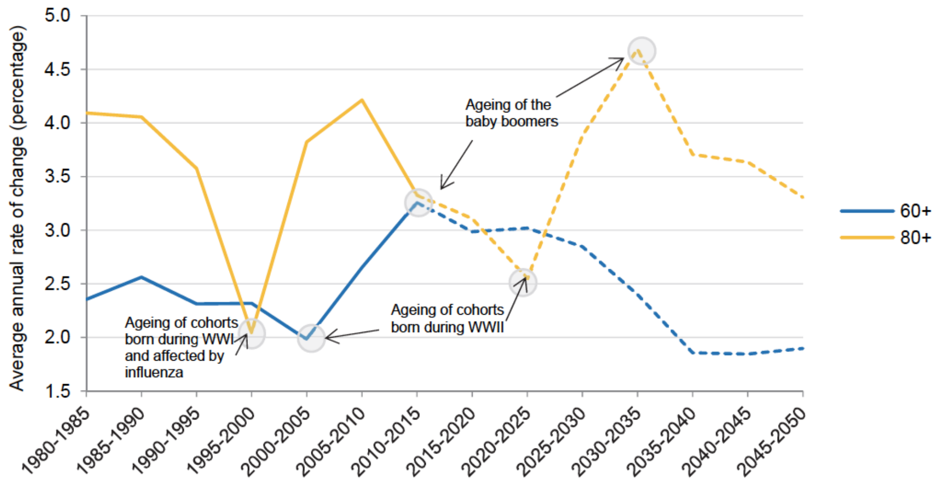


Figure 1.1: Average annual rate of change of the global population aged 60 years or over and aged 80 years or over, 1980-2050
[3]

Globally, the share of the older population that is aged 80 years old increased from 9 per cent in 1980 to 15 per cent in 2019, and it is projected to continue to grow. North America and Europe have the highest percentage, being closely followed by Oceania and Latin America, Figure 1.2 [6].

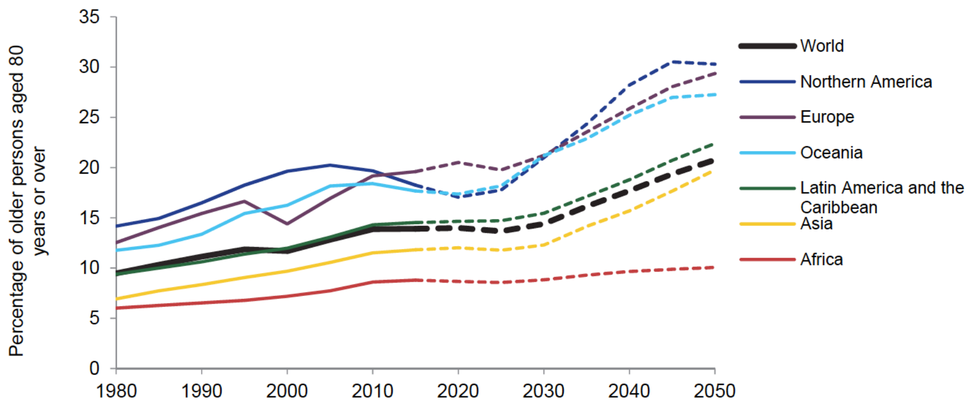


Figure 1.2: Percentage of older persons aged over 80 years or over
[3]

The process of ageing, despite the fact of being one of humanity's greatest achievements (longevity), brings to debate matters like the "Silver economy", since there is a enormous demand of new services and products for supporting personalized care to age-friendly technologies, creating better conditions of life as well as fostering industrial and business opportunities [7, 8].

However, this raise the question of "how are we going to pay for the quality care for the elderly" and "how are we going to deliver quality care to older adults due to their cognitive decline, chronic age-related diseases, as well as limitations in physical activity, vision, and hearing".

The emerging social aspect introduces some crucial challenges to society and greater demands on the actuals health care systems:

1. Increase in age related diseases, some of them with no current cure [9];

2. Increase in health care costs: senior citizens use a substancial portion of the health care budget and will continue to increases as the aging population increases, which could possibly lead to a decline of efficiency and quality of public health systems [10];

3. Shortage of caregivers: shortage of professionals to work with the aging population and increased caregiver burden, will lead to more family members have to take the role of informal caregivers, leading to emotional distress and fatigue of these [11];

4. Dependency: increasing age-related diseases will also increase the number of individuals that cannot live independently [9].

With adequate adjustments at a social, economic and demographic level to adress these and other related consequences, healthy ageing could be prometed by a set of evidence-based actions that strengthen the abilities of aging citizenz mantain their ability to manage various activities of daily living (ADL), such as personal hygiene, dressing, eating, maintaining continence and ambulating. These actions could start from:

1. Aligning health systems with the needs of older populations: Health systems need to be better organized around older people's needs and preferences, designed to enhance older people intrinsic capacity, and integrated across settings and care providers[12];

2. Developing systems for providing Long-Term Care (LTC). Systems of long-term care(including for pallative care or end-of-life) are needed in all countries to meet the needs of older people. It requires developing, sometimes from nothing, governance systems, infrastructure and workforce capacity [13];

3. Creating age-friendly environments.This will require actions to combat ageism, enable autonomy and support Healthy Ageing in all policies and at all levels of government [14];

4. Improving measurement, monitoring and understanding. Focused research, new metrics and analytical methods are needed for a wide range of ageing issues, namely chronic diseases [15].

1.2 Technological Solutions

This visible change focused on care is encouraging a shift in the healthcare sector [16], in which the delivery of health care could be within a person's own home.

This perspective is associated with the fact that 89% of the older adults prefer to stay in the comfort of their own homes[17]. However, this decentralized treatment from hospitals to home also bring several issues with it, mainly the fact that very few homes have been designed for the effective delivery of healthcare [18].

Taking all of these factors into consideration, led to the emergence and increased integration of several innovative welfare technological-based care services for safe and independent ageing, including the assisted living technologies based on Ambient Intelligence (AmI) paradigm, Pervasive HealthCare and Internet of Things (IoT) concepts, called Ambient Assisted Living (AAL) systems [18, 19, 20].

Ambient Assisted Living (AAL) systems will be vital in order to maintain the same high level of services in the future at similar or less cost and to meet the personal healthcare challenges and involve citizens in their healthcare in all stages of the life cycle through Information and Communication Technologies (ICT) [21].

When well integrated into people's homes and everyday lives, assistive technology could allow health care services to be delivered remotely in order to support the independence of elderly and prolong the period in which they can remain at home.

In AAL systems, the medical and ambient sensors are connected with the AAL applications and gateways for sending well-being and ambient data to the monitoring systems. The sensors rely on Wireless Sensor Networks (WSNs) for connecting with home gateways and information applications storing these data on databases, which are interconected to exchange data and provide services in this ambient assisted living environment[22, 23].

These systems should not rely on user's effort. They are the so called "zero-effort" technology, requiring no effort from the person that benefits from them on continuing monitoring his health behavior, allowing to build spatial information and a medical history around the person [24].

From the perspective of health care providers, digital care management systems provide caregivers with a detailed overview of their Events of Daily Living (EDL) as well as simple and accurate ways to improved and focus on the services that are really crucial to be provided [25, 26].

One of the key requirements for technological systems that are used to secure independent housing for seniors in their home environment is monitoring their EDL, their classification and recognition of routine daily patterns and habits of seniors in Smart Home Care (SHC).

With all of this being said, a high motivation exists and it is not about AAL replacing hospital and the health care system. The primary aim is to use these disruptive AAL technologies to monitor a subset of EDL for sustaining independent living and a continual naturalistic assessment of health as well as cognitive status, making the transparency and traceability a key factor for the quality of care in residence.

1.3 Problem Definition

Based on this motivation, the purpose of this dissertation would not be using AAL technologies to replace caregivers, doctors or even hospitals, but it would be a novel approach to assist in the investigation and on the modeling of events of daily living.

Futhermore, the aim is to develop and evaluate a multisensorial pervasive research platform that combined with several Commercial Of-The-Shelf Sensors (COTS) and embebbed inteligence is capable of monitoring senior citizens and patients under non-critical continuous care on a nursing home and classify their EDL.

1.4 Hypothesis

H1 It is feasiable to model and classify EDL based on the input of commercial off-the-shelf sensors;
H2 It is feasible to classify basic activities of daily living based on a basic sensor input from a single sensor;
H3 It is feasible to combining a broad range of ambient sensors (PIR, Bed, Chair and Co2) in a distributed home environment for monitoring EDL.

1.5 Research Questions

This dissertation contributes to addressing the need for context-awareness in AAL by developing unobtrusive solutions for activity recognition and modeling.

To guide the research on these topics and investigate the hypothesis described, the following research questions (RQ) were formulated:
RQ1 Which AAL technologies have been used to support the elderly and caregivers?
RQ2 Which methods have been used to monitor and classify EDL?

RQ3 To what specifity, sensitivity and accuracy does a single sensor perform classifying basic activities of daily living?

RQ4 Is it feasible to use a broad range of sensors and the data acquired from those sensors be combined in a distributed home for monitoring EDL?

1.6 Objectives

Based on the research questions defined above the following Objectives (**O)** have been identified to guide the dissertation:

O1 Survey the state-of-art literature of the current usage and real-world deployement of AAL technologies;

O2 Survey the literature for studies to investigate which EDL technologies are essential to monitor and evaluate a decline in the user's health status;

O3 Evaluate ambient sensors to insight on their feasibility, reliability and the obstacles they pose towards remote monitoring applications;

O4 Propose and develop a research data acquistion platform for evaluating several sensors (PIR, Bed, Chair and Co2);

O5 Demonstrate the feasibility of this type of platforms concerning the integration and unification of different technologies used in healthcare;

O6 Classify EDL based on the acquired user's monitoring data.

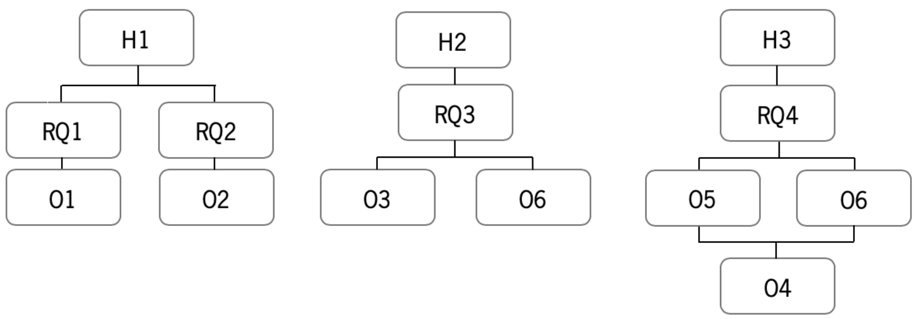


Figure 1.3: An overview of the relations between the Hypothesis (H), Research Questions (RQ), and Objectives (O).

Chapter 2

Background and Related Works

This Chapter introduces the background concepts and related works addressing the research questions described in Chapter 1 (**RQ1** and **RQ2**).

Regarding the **RQ1**, this chapter surveys a state-of-the-art literature of the current usage of and real-world deployment of AAL technologies and solutions that are being used in people's homes and nursing care homes (Smart Home Care) and how pervasive sensing technologies (ambient sensors) create an Ambient Intelligence (AmI) environement.

Regarding the **RQ2**, EDL are introduced in this dissertation as a category of events that include all events/activities a person could perform throughout a day. Three subcategories of events were identified: Activities of Daily Living (ADL), Instrumental Activities of Daily Living (IADL) and Adverse Events (AE) and were given an in depth review of all of them as methods to classify them.

Alongside it, we will focus on two pillars of AAL context-awareness based on the Ambient Intelligence (AmI) paradigm: activity recognition (AR, enumerating several AR classification methods, building a bridge to context-awareness services for elderly/his caregivers and long-term monitoring in AAL scenarios.

2.1 Ambient Assisted Living Solutions

AAL solutions and technologies are driven by societal challenges which arose in the last decade and the demands for new services aiming at compensating predominantly age-related functional limitations through technological information and communication support in a day to day basis.

The services may include supported living arrangements, care in a nursing home or at home. In this regard, the possibility to create an intelligent environment to reduce the use of dedicated nursing personnel or avoid the hospitalization represents a key factor in the adoption of AAL solutions [27, 28, 29].

In order to assist people in their homes, an AAL environment must provide useful services personalized on the user's needs. In table 2.1 are listed some of the main AAL areas of application:

Area	Applications
Cognitive Orthotics	Medication Reminders, Navigators, Wandering Prevention, Planning
Continuous Health Monitoring	Vital Signs, Sleep, and ADLs monitoring
Therapy	Tele-Health and Rehabilitation Systems
Emergency Detection	Fall, Medical Emergency, and Hazard Detection
Emotional Wellbeing	Social Inclusion, Facilitating Communication
Persuasive Applications	Medical and General Wellbeing Promotion

Table 2.1: AAL areas of application

These applications are made possible due to the recent advancements in key technological areas such as smart home care, as well as, mobile and wearable assistive sensors [29].

2.1.1 Smart Home Care (SHC)

A smart home is a regular home which has been augmented with various types of sensors and actuators [30]. It consists on a setup that converges embedded systems devices, real time analystics and appliances that support one or more common ecosystems controlled via Wireless Sensor Networks (WSNs), enabling the so called paradigm Internet of Things (IoT) [30].

The context-awareness information can be gathered through various types of sensor and then analyzed. The majority of smart environments use such knowledge for assessing the cognitive and physical health of the residents [30].

There are several SHC projects, table 2.2, aimed at Ambient Assisted Living (AAL). They provide two types of monitoring: preventative and responsive. The preventive model minimises patient risks using ADLs, by supporting tasks such as taking medications, eating and drinking. Responsive models on the other hand react to events like falls, alarms and patients leaving their home.

Project	Institutions	References
Aging in Place	U.Of Missouri	Ranz[35]
Aware Home	Georgia Tech	Abowd[37]
CareLab	Germany	Nick[45]
CASAS	Washington State U.	Cook[34]
DOMUS	U. Of Sherbrooke	Giroux[38]
Elite Care	OHSU	Adami[36]
ENABLE	Netherlands	Van Berlo[44]
HIS	Grenoble U., France	Noury[41]
MavHome	U. Of Texas	Perry[46]
Millenium Home	Brunel U.	Chan[47]
ProSAFE	LAAS, France	Nishida[43]
SELF	ETL, Japan	Allen[50]
Ubiquitous Home	UCG, Japan	Tamura[49]
WTH	JMITI, Japan	Celler[48]

Table 2.2: Smart Home Care (SHC) Projects

For instance, CASAS [31] project at Washington State University provides a non-invasive assistive environment for dementia patients at home. The "Aging in Place" project at the University of Missouri aims to provide a long-term care model for seniors in terms of supportive health [32]. Elite care is an assisted living facility equipped with sensors to monitor indicators such as time in bed, bodyweight, and sleep restlessness using various sensors [33]. The Aware Home project at Georgia Tech [34] employs a variety of sensors such as smart floor sensors, as well as assistive robots for monitoring and helping elderly. Other notable smart home testbeds include DOMUS [35] at the University de Sherbrooke and the Housen project at MIT [36].

Some smart home projects in Europe include iDorm [37], Grenoble Health Smart Home [38], Gloucester Smart House [39], PROSAFE [40], ENABLE [41], and CareLab [42]. There are also related joint initiatives such as the "Ambient Assisted Living Joint Programme", supported by the European commission with the goal of enhancing the quality of life of older people across Europe through the use of AAL technologies [43].

In America, the MavHome Project (Managing and Adaptive Versatile Home) is focused on conducting research in smart home technologies from the aspect of treating an environment as an intelligent agent. This project goes the home environment and encompasses all environments in which observations can be perceived through sensors, those observations can be reasoned about by the system, and actions can be taken to automate features of that environment [44].

Similar project is the Millenium home. It is a multimodal interface to a pervasive/ubiquitous computing system that supports independent living by older people in their own homes. The Millennium Home system involves fitting a resident's home with sensors. These sensors can be used to trigger sequences of interaction with the resident to warn them about dangerous events, or to check if they need external help [45].

In Asia, smart home projects have also been developed, such as the early "Welfare Techno House" project, which measured indicators such as ECG, body weight, and urinary volume using sensors placed in the bathroom and bathtub [46].

The Ubiquitous Home project [47] is another smart home project in Japan, which uses passive infrared (PIR) sensors, cameras, microphones, pressure sensors, and radio frequency identification (RFID) technology for monitoring the older adults.

Another two relevant projects are the SELF (Sensorized Environment for Life) and Smarter Safer Home [48]. SELF enables a person to maintain his or her health through "self-communication." The system externalizes a "self" by storing personal data such as physiological status, analyzing it, and reporting useful information to assist the person, in maintaining his or her health[49].

On the other hand, Smarter Safer Home reports this information to caregivers and clinical experts by the usage of a smart assistive living environment to make it easier for people to stay at home for long periods of time. Sensors were installed in the smart home to provide continuous data to a server. Analyzing this data, the machine learning help on the diagnosis and decision-making process of these medical professionals.[48]

In figure 2.1, it is represented a simple schematic setup of a smart apartment for behaviour monitoring of an elderly person based on different pervasive sensing technologies is despicted. The sensors placed in different places in the apartment, depending on the type of measurement pretended to be performed [48].

2.1.2 Pervasive Sensing Technologies

Sensor-based surveys have mostly focused on wearable sensors or have sometimes combined them with ambient sensors to facilitate independent living of the elderly. The process of data collection

Figure 2.1: Schematic setup for elderly care based on different sensing technologies

using wearable sensors is easier than that using ambient sensors. However, restrictions regarding wearable sensors on body could discourage the elderly people from adopting them. Usually, some wearables can cause an uncomfortable feeling during long-term skin attachment.

Hence, wearable sensor-based technologies, which are used to help elderly people live independently, may face a high risk of rejection. There is in contrast, extern or ambient sensors. Regarding these ones, it is important to verify whether the sensors collect accurate data from a distance.

Alongside it, wearable sensors may require professional adjustments on the body to collect accurate data, which indicates that complex processes may be necessary for installing the sensors. Hence, considering the drawbacks of wearable sensors, reliable ambient sensors are expected to be an appropriate choice for helping elderly. In table 2.3 some of the ambient sensors used in AAL are summarized [50].

In the next subsections, it will be summarized a description of some of the most used of this set of sensors as well as works in which they were applied to monitor patient´s behavior.

2.1.2.1 Passive Infrared (PIR) Motion Sensor

Many research works have applied passive infrared (PIR) motion sensors to detect the movements of individuals. PIR motion sensors are installed on walls or ceilings of the homes of elderly people, to

Sensor	Characteristics	Data format	Cost (€)
Infrared Motion Sensor	The binary-status-providing sensors detect motion in the coverage area.	Boolean	10±5
Temperature Sensor	The continuous-data-providing sensors detect the temperature of the ambient environment.	Numeric	9±2
Pressure Sensor	The sensors provide continuous pressure measurement at any surface.	Boolean	25±5
Magnetic Switch	The binary-status-providing sensors are easily installable. They are mainly used to detect the opening of doors, windows.	Boolean	5±1
Humidity Sensor	The sensor provides continuous humidity measurement.	Numeric	5±1
Sound Sensor	The sensor provides is mainly used to record sound samples	Sound	10±5
Video Sensor	The sensor is mainly used to record image samples	Image	60±5
Smoke Sensor	The status-providing sensors detect smoke in the environment.	Numeric	20±5

Table 2.3: Ambient sensors used in AAL
[51]

continuously collect motion data that are related to predefined activities in the scope of the sensors.

A PIR sensor capitalise on the heat properties of objects since all objects emit heat energy in the form of infrared radiation. However, it is not the actual heat that is measured but the infrared light emitted from objects. A PIR sensor is commonly used to detect movement of objects, where the radiation changes, when for instance a person enters or leaves the PIR sensors' field of view.

The motion data are collected and is interpreted for analysis of trends to detect changes in daily activities. The sensors can be adopted for various application such as detecting the degree of activity, detecting falls or other significant events. They can also be applied to analyze user location, time out of the home, sleeping patterns, and activities at night (night wandering) [51].

2.1.2.2 Pressure Sensor

Pressure sensors are applied to detect the presence of residents on chairs or in bed. They can be used to detect sit-to-stand transfers, stand-to-sit transfers and sleep. Some works reported the usage of this type of sensors, being the transfer duration time the main outcome [51].

2.1.2.3 Video Sensors

The most commonly used ambient sensors for eldercare are video sensors. Many research works have been carried out in AAL using video cameras for various applications, such as recognizing activities in their own homes. The cameras are installed on the walls or ceilings to detect activity through feature analysis and Machine Learning (ML). However, automatic activity recognition is difficult due to the intra-class variations in unconstrained scenarios. Therefore, they are often used as a way of evaluating other sensors by manually determine the actual activity - in other words, making unsupervised data to supervised data. Among the many applications, video monitoring technology has mostly been used to detect events of daily living, such as falls, despite the fact of being the most intrusive, because it can give people the feel of being watched [51].

2.1.2.4 Combined Ambient Sensors

Some works combined more than one monitoring technology, table 2.4. Using this multicomponent ambient sensor technologies, it increased the QoL being achieved within different target groups, such as residents and caregivers.

Sensor	Research Techniques	Outcomes
PIR Sensor	The work described probabilistic mixture model raw motion sensor data for recognition of different activities. Subjects were monitored for 65 days. Then, results were accumulated. The project utilized of a set of low-cost motion sensors. Two types of evaluations were performed: work and off - days.	The motion sensor data were grouped into 139 clusters. The experimental results showed that there were some frequent clusters that occurred consistently over time with low classification uncertainty.
	It was a pilot project with five months of monitoring the functional health status of the elderly at home. Parameters that are sensitive to changes in health were continuously recorded.	It was a pilot project with five months of monitoring the functional health status of the elderly at home. Parameters that are sensitive to changes in health were continuously recorded.
Pressure Sensor	Pressure sensor arrays were installed in a bed and floor. Then, pressure information over time was analyzed. The motion of the center of pressure was observed in the wavelet domain to determine whether a transfer occurred.	Older adults generated shorter sit-to-stand durations of approximately 2.88 s.
	Pressure sensors were installed in the toilet on the armrests of the commode. Clinical parameters were successfully obtained from several stand-to-sit and sit-to-stand transfers. Elderly people were included in the experiments as subjects.	Clinical parameters were successfully obtained for characterizing sit-to-stand and stand-to-sit transfer sequences. Older adults took longer and used less force in both cases.
	The work focused on the analysis of sit-to-stand and stand-to-sit transfers that were performed by the occupant in the bedroom and bathroom. Pressure sensors were installed in a bed and the grab bars of a toilet commode. Then, clinical feature extraction was performed to determine a warning level.	The clinically relevant features that were obtained from both bed-exits and grab bar usage showed differences between healthy adults and those with impaired mobility. The functionality of the proposed system in keeping track of potential warning signs was demonstrated.
Video Sensor	Two in-home fall trials were done in two real living rooms. For each trial, the users performed simulated falls and real daily living behaviors for seven days. For the second trial, the users were instructed to simulate falls only and 11 simulated falls were done for seven days.	100% sensitivity; 95% specificity.
	Motion information was extracted using motion history images and analyzed to detect three different actions for elderly people: walking, bending, and getting up. Shape deformations of the motion history images were investigated for different activities and used later for comparison in-room monitoring.	94% accuracy.
	Harris corner-based interest points and histogram-based features were applied with deep neural networks to recognize different human activities. The dataset consisted of six types of different activities: shake hands, hug, kick, point, punch, and push.	95% accuracy
Combined Sensors (PIR motion sensors, bed pressure sensor, video sensor)	Activities of daily living were monitored for 26 elderly residents and 25 caregivers over four months. A standard satisfaction-with-life scale instrument was used to assess the quality of life of the elderly people and the caregivers.	Once four months of monitoring were finished, there was no significant difference in the quality-of-life scores of the elderly users and the caregivers. The system seemed to be highly acceptable.
	Systems for detecting activities of daily living were installed in 15 assisted living units. The reports were sent to professional caregivers of the residents. Fifteen residents and six caregivers participated in the system. It was a pilot study in which monitoring was performed for three months. Quality of life was assessed using a standard satisfaction-with-life scale instrument.	There was a high acceptance rate of the system. The approach could be used for improved healthcare planning and detection of health status changes.

Table 2.4: List of research works conducted using ambient sensors [51]

2.2 Events of Daily Living (EDL)

This dissertation uses the concept of events of daily living. Events of Daily Living (EDL) are defined in this dissertation as a category of events that include all events or activities a person could perform throughout a day. EDL has been identified as a set of three subcategories of events, depicted in Figure 2.2.

ADL defined as the common, everyday self-care skills we all need to live safely and independently on a day-to-day basis that we initially learn as very young children [52, 53, 54].

IADL are more complex skills.They are, as the name says, very instrumental and performed by an individual on a day to day basis, but do not necessarily involve personal activities like self-care, but add quality of life (QoL) [55].These activities are not indispensable to a person's survival and fundamental functioning, but they do let someone live independently in society and function well as a self-reliant individual [55, 56].

AE defines unintended events like an incident that leads to negative health development.One of the most common of these events are falls [57, 58].

These three subcategories of EDL will be further elaborated in sections 2.2.1, 2.2.2 and 2.2.3 to adress research question **RQ2** and objective **O2**.

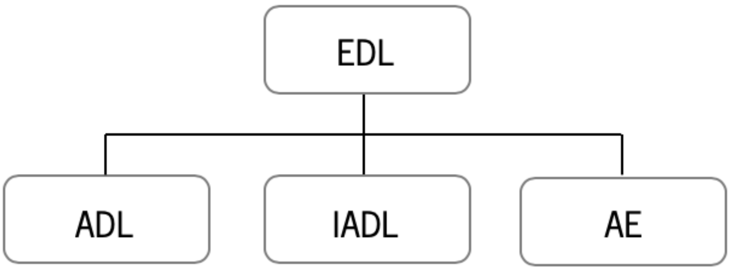


Figure 2.2: An overview of Events of Daily Living

2.2.1 Activities of Daily Living (ADL)

The Activities of Daily Living (ADL), often termed physical ADLs or basic ADLs, include the fundamental skills needed to manage basic physical needs, comprised the following areas: grooming/personal hygiene, dressing, toileting/continence, transferring/ambulating, and eating [53, 54]. These functional skills are mastered early in life and are relatively more preserved in light of declined cognitive functioning when compared to higher level tasks. These ADL are often referred to as Personal Activities of Daily Living (PADL) or Basic Activities of Daily Living (BADL).

Activities of daily living are traditionally assessed with questionnaires like the Katz Index of Independence in Activities of Daily Living [59], Stanford Health Assessment Questionnaire [60] and the Barthel ADL Index [61].

Questionnaire based ADL assessments are challenging as they rely on informant information. In addition, such self-reported data are subject to bias and errors due to cognitive impairments or lack of insight.

The elderly who need help from other people or appliances in these basic daily activities will be treated as disabled. Disability will not only lead to a sharp deterioration in the living conditions of the elderly, but also increase the burden of care. Disability refers to the state of losing the ability on performing daily activities, in most of the cases driven by chronic diseases, physical injury, or psychological imbalance.

2.2.2 Instrumental Activities of Daily Living (IADL)

Instrumental Activities of Daily Living (IADL) refers to a category of activities that are more complex than ADL and often requires use of executive functions, social skills, and more complex environmental interactions. IADL is often referred to as Advanced Activities of Daily Living (AADL) or extended Activities of Daily Living (ADL). The Lawton Instrumental Activities of Daily Living Scale (IADL) is an instrument to assess independent living skills [62].

Among several tasks, IADL involves tasks such as: ability to use telephone, shopping, food preparation, housekeeping, laundry, mode of transportation, responsibility for own medications and ability to handle finances.

Impairment in instrumental activities of daily living (IADL) may occur in the earliest stages of mild cognitive impairment (MCI), which can adversely impact the abilities of intensive care unit (ICU) to live independently [63].

2.2.2.1 Instrumental Activities of Daily Living Measures

Since the assessment of functional abilities after critical illness is crucial, several studies were performed all over the world with the use of two different IADL questionnaires: the Lawton IADL questionnaires and the Pfeffer Functional Activities Questionnaire (FAQ).

The Lawton IADL is an eight-item questionnaire that assesses several IADL, it scores range from 0 to 8, with lower scores indicating greater dependence [64].

The FAQ is a 10-item questionnaire that assesses tasks needed to live independently, including managing finances, working on a hobby, remembering current events, paying attention to and understanding television or a book. Items are scored 0 (“independence”), 1 (“difficulty, but can complete without assistance”), 2 (“difficulty requiring assistance”), or 3 (“complete dependence”).

2.2.2.2 Change in Instrumental Activities of Daily Living Dependency

From different studies performed around the world table 2.5, an increase in IADL dependency from the pre- to post-ICU period.Interestingly, no studies demonstrated a return in post-ICU IADL dependencies to pre-ICU levels.

These studies also demonstrated that a large number of individuals experienced new or worsening IADL dependencies after critical illness.Although a majority of studies report new post-ICU IADL dependencies there was significant variability in the incidence and definitions of IADL dependency despite use of the same instruments across studies.

The wide range of definitions of IADL disability, variability in follow-up times, and lack of reporting actual scores, including domain scores, are problematic, being few reliable measures of IADL in MCI or that have a sufficient range of scores in clinically normal (CN) elderly [63].

Study	IADL Instrument	Change in IADL Dependency over Time	Results
Abelha(Portugal, 2013)	Lawton IADL	Pre-ICU: 7% had at least 1 IADL dependency 6 mo: 19% had at least 1 IADL dependency	Increase in IADL dependencies compared with pre-ICU
Bienvenu(USA,2012)	Lawton IADL	IADL, >2 dependencies: 3 mo: 64% 6 mo: 53% 12 mo: 43% 24 mo: 45% Remission vs. no remission: Remission in IADL dependency z1 in follow-up No remission in IADL dependency >4 in follow-up	IADL dependencies decreased over time but are still present in many patients
Broslawski(USA,1995)	Lawton IADL	Change from pre-ICU to 6 mo 6 patients, scores declined 21 patients, score stated the same or improved	Majority of patients had no change or decrease in IADL dependencies compared with pre-ICU; some patients had increased IADL dependencies over time
Brummel(USA,2014)	FAQ	3 mo: 3 IADL deficiencies (range, 0–6); disability in IADL in 17% 2 mo: 1 IADL deficiency (range, 0–5); disability in IADL in 5%	Decrease in IADL dependence over 12 mo
Cox(USA,2007)	Lawton IADL	Pre-ICU admission: mean, 2.1; SD, 2.7 2 mo: mean, 5.7; SD, 2.1 6 mo: mean, 5.2; SD, 2.4 12 mo: mean, 4.8; SD, 2.6	Increase in IADL dependencies initially post-ICU compared with pre-ICU: Slight, but not significant decrease over time
Daubin(France,2011)	Lawton IADL	No significant change from pre-ICU to 3-mo follow-up Pre-ICU: 40% completely independent and 7% completely dependent Number of IADL dependencies: Pre-ICU: mean, 1.1; SD, 1.3 vs. 3-mo follow-up: mean, 2.9; SD, 1.4 (P = 0.62)	Increase in IADL dependencies compared with pre-ICU early after ICU discharge, with no change over time
Jackson(USA,2007)	FAQ	3 mo: 56% of patients with prior IADL disability had disability versus 23% with new IADL disability (9.5 vs. 2.2 IADLs) 12 mo: 62% of patients with prior IADL disability had disability versus 20% with new IADL disability (10.0 vs. 2.0 IADLs)	New disability in IADL compared with pre-ICU for some patients; no significant change over time
Quality of Life after Mechanized Ventilation in the Elderly Study Investigators(USA,2002)	Lawton IADL	Pre-ICU IADL scores: Median = 1 for overall group (survivors and nonsurvivors) Median = 4 for nonsurvivors Post-ICU IADL scores: Median = 4 for patient interview (n = 132) Median = 7 for proxy interview (n = 98)	Increase in IADL dependencies compared with pre-ICU
Sacanella(Spain,2011)	Lawton IADL	IADL scores: Pre-ICU: mean, 6.7; SD, 1.7 3 mo: mean, 5.2; SD, 1.7 6 mo: mean, 5.6; SD, 1.6 12 mo: mean, 5.3; SD, 2.6	Slight decrease in IADL dependencies compared with pre-ICU; still significantly disabled in IADL dependencies; no change over time
Van Pelt(USA,2017)	Lawton IADL	Pre-ICU functional dependency: 42% 2 mo: 91% with functional dependency 6 mo: 78% with functional dependency at 6 mo 12 mo: 70% had functional dependency at 12 mo	Increase in IADL dependency compared with pre-ICU with some decrease over time

Table 2.5: Change in IADL dependency over time
[63]

2.2.3 Adverse Events (AE)

An adverse event results in unintended harm to the patient by an act of commission or omission rather than by the underlying disease or condition of the patient [57]

AEs are sometimes defined as any event following or during medical treatment with consequences for a patient in such way that adjustment of the treatment is necessary, or even worse, that the patient becomes temporarily or permanently disabled [57, 58, 65].

Older patients are particularly prone to suffering from AE, but also to their consequences. It lead more frequently to hospitalization,permanent disability and death in older than in younger patients[66, 67].

On table 2.6 is shown some information on patient that were admited through the emergency department to the department of internal medicine facility [66]. The characteristics, such as age, sex, number of medications, admission cause, length of hospital stay, comorbidity, cognitive functioning, performance in Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL).

N (%) or median (range)	AE group (n = 105)	Control group (n =156)
Age in years	76.1 (65.2–100.6)	77.5 (65.0–100.0)
Cognitive impairment	14 (13.2)	39 (25.0)
Number of medications	8 (1–20)	6(0–21)
ADL-dependent	62 (58.5)	92 (59.0)
IADL-dependent	69 (65.1)	114 (73.1)
Assisted living	17 (16.0)	34 (21.8)
Length of hospital stay (days)	5 (1–44)	8 (1–48)

Table 2.6: Characteristics of patients admitted because of an AE and controls
[66]

Interestingly, being IADL dependent and ADL depedent was a key consideration to take into account in this experiment.It was possible to draw conclusions about the direct connection of not being indepent and the fact of suffer from an adverse event even in the group of patients hospitalized without having suffered an adverse event (Control Group) [66].

2.3 Context Aware

In literature, the term context is described as location, identities of nearby people, objects and changes to those objects of the users environment that the computer knows about [68, 69, 70]. For our purposes, one of the most accurate definitions is given in [71]. The authors refer to context as :

"any information that can be used to characterize the situation of entities (i.e., whether a person, place or object) that are considered relevant to the interaction between a user and an application, including the user andthe application themselves" [71]

In our field of investigation, we embrace this definition and refine it, considering context as any information that can be used to charecterize the current situation of an entity, where an entity is in this case of study a person. The information gathered can include physical gestures, relationship between the people and objects in the environment, features of the physical environment, identity and location of people and objects in the environment.

The research works on the area of context-aware can be decomposed into four main dimensions: Activities Discovery (AD), Activities Recognition (AR), Detection of Deviations (DD) and Activities Prediction (AP).

The goal of AD is to create one or several model activities. These models can be built automatically from sensor data. It is only performed off-line and mainly depends on the quality of the data available.

The goal of AR, which contrary to activity discovery is performed online, is to detect which activity is performed by the person.

Detection of deviations and activity predicition follow activity discovery and activity recognition. Once an activity is detected, the aim of DD is to determine whether there is or not a deviation from the habitual behaviour, taking into account the activities modeled by AD Considering AD, its aim is to determine the next activity that should be performed by using past events and the current detected activity. On figure 2.3 it is represented the links between these different dimensions:

Among the several dimensions of context-aware presented ,we will focus on the AR.

Regarding the context-aware information, the most frequently used is the location information [72, 73]. However, when dealing with AAL scenarios, together with the position of the user in the Smart Environment (SE), it is important as well to characterize the activities performed by the user [74, 75, 76].

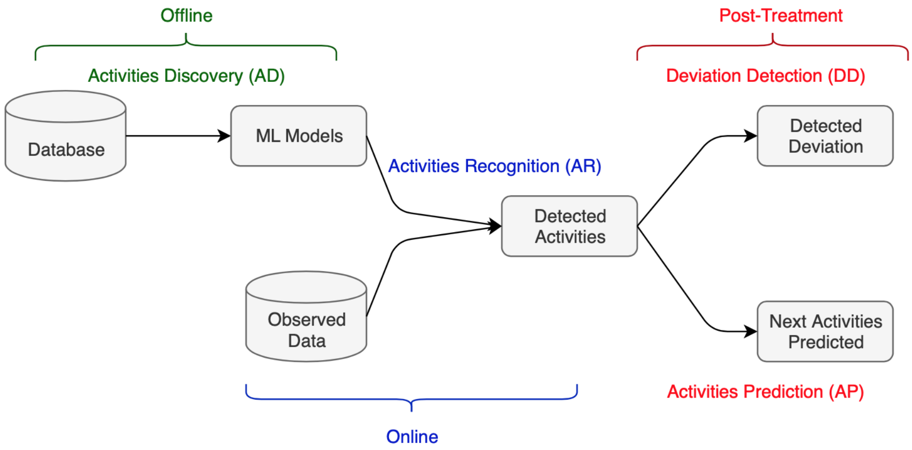


Figure 2.3: Context-Awareness Links

In [77], the author also suggests that for some activities, more sensors improve the recognition. The use of ambient sensors has been analyzed in the literature (e.g. [78],[79]). In these solutions, a network of ambient sensors was used to model activities in the environment, as a sequence of sensor events.

The main concern relies on the assumption of consistent predefined activities as a sequence of events that might not happen in reality, due to several physical, cognitive, cultural, and lifestyle differences, not all individuals perform the same set of tasks in similar sequences [80].

With this in mind, the next subsections survey the state-of-art Machine Learning (ML) models and activity recognition systems (ARS) used in the area of recognition of EDL. Simple actions such as walking, sleeping, seating can be represented in the form of periodic time-series patterns, the activity maps, which will be elaborated further.

2.3.1 Activity Recognition (AR)

One of the main mechanisms of AR is the recognition of human activities.The representation of the activity itself can be done at different resolutions, such as a single movement/action or even an activity/group activity. The degree of the resolution should be chosen properly, according to the particular application to be deployed.

In the case of tools assisting the elderly, a higher resolution is needed in order to recognize the particular activity they are perfoming. Within the broader context of a long-term monitoring AAL system, it is expected to be up and running all day long and over long periods of time in order to prevent cognitive or physical deterioration of the user. In this scenario, a system able to recognize simple activities(e.g. lying, sitting, standing, walking,bathing) instead of a single movement or action, is a good compromise between the possibility of inferring high-level activities (i.e. to infer ADL).

Recently, machine Learning (ML) techniques have found wide applications in building human activity recognition systems based on data generated from sensors. Depending on the treated data nature regarding the scenario considered and of the admissible trade-off among efficiency, exibility and performance, different (ML) methods have been applied in this application area [51].

2.3.2 EDL Classification Methods

From a learning perspective, human activity recognition problems often involve computational learning tasks. In this sense, the various estimations to be provided in relation to specific activities can be considered to be discernible basing on specific patterns of activations from a typically heterogeneous set of possibly noisy sensor sources and based on the temporal order of such series.

Irrespective of the sensor-type, all sensor systems require processing and classification of massive amount of collected data to derive information regarding the EDL.

The patterns of input data are associated with activities (classes) under consideration. In general, the classification task requires learning a decision rule or a function associating idata inputs to the classes. There are two main directions in machine learning techniques: supervised and unsupervised approaches [81, 82]. Unsupervised learning mainly deals with unlabelled data and is often used to find unknown patterns. On the other hand, supervised learning uses labelled existing or produced data to predict output for a given input through a model.

Focusing on supervised learning models for human activity recognition applications, most of them are train-based methods, which include the family of Naïve Bayes classifiers ,Hidden Markov Model (HMM) [83], K- Nearest Neightbour (KNN), Decision Tree (DT), which have been applied to recognize EDL (e.g. [84, 85, 86]).

To automatically classify routine activities and identify regular patterns of behavior, Circadian Activity Rythm (CAR) is frequently used. It was proven by the investigation [87], that this specific classifier was able to recognize EDL via Wireless Sensor Networks (WSNs). Despite being relatively simple, they often deliver good results, making them a good state-of-the art classifiers for first data assessments and to be used alongside a wireless sensor system to acquire environmental data.

In the following sections, it is briefly described the ML classification techniques used in this dissertation and another two classification techniques worth of mention.

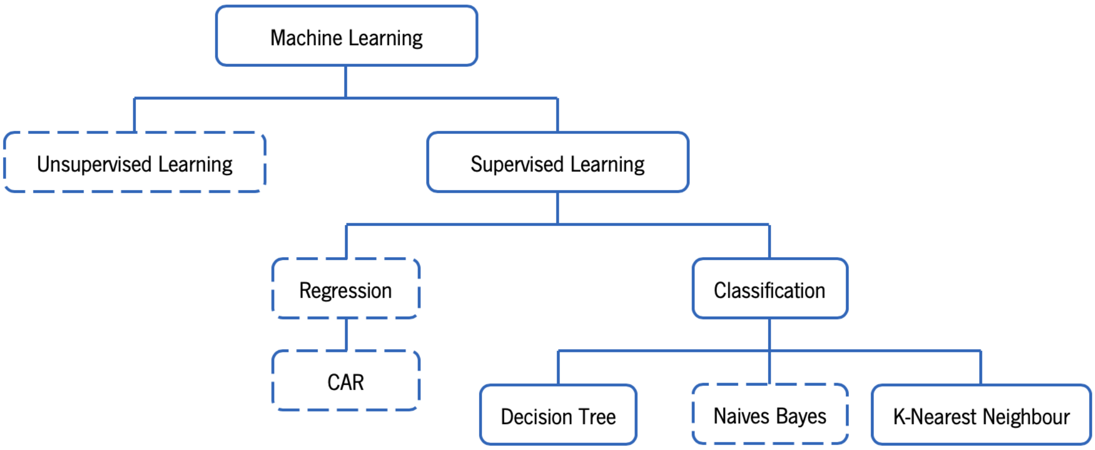


Figure 2.4: Grouping of machine learning algorithms used in this dissertation.

2.3.2.1 Naïve Bayes (NB) Classifier

This classifier is based on Bayes theorem, which assumes that the features are independent. Bayes conditional probability model is then combined with a decision rule, which picks the most probable hypothesis. This is done by maximising the posterior probability, and thereby assigning a class-label to a given input vector [88].

The algorithm on figure 2.5 provides a way of calculating the posterior probability- P(c|x), from P(c), P(x), and P(x|c). It is assumed that the effect of the value of a predictor (x) on a given class (c) is independent of values of other predictors. This assumption is called class conditional independence [88].

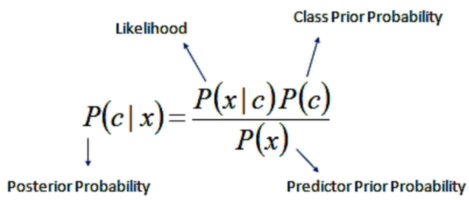


Figure 2.5: NB algorithm [88]

- P(c|x) is the posterior probability of class (target) given predictor (attribute);
- P(c) is the prior probability of class;
- P(x|c) is the likelihood which is the probability of predictor given class;
- P(x) is the prior probability of predictor;

Compared to other classifiers, NB is simple, computationally efficient, requires relatively little data for training, does not have lot of parameters and is naturally robust to missing and noise data. It has been largely and sucessfully used to data mining patient´s medical data [89],[90],[91], due to the fact that the available information is used to explain the classification, seeming to be natural for its usage on medical diagnostics [92].

2.3.2.2 K-Nearest Neighbour (KNN) Classifier

K-nearest neighbor (KNN) [93] is an algorithm, which stores all cases and classify new cases based on similarity measure. Nearest neighbor classification is used mainly when all the attributes are continuous. Simple K nearest neighbor algorithm consists at two steps:

1. Find the K training instances which are closest to unknown instance;
2. Pick the most commonly occurring classification for these K distances.

Regarding 1), k is the number of nearest neighbors. The number of neightbors is the core deciding factor. K is generally an odd number if the number of classes is 2. When K=1, then the algorithm is known as the nearest neighbor algorithm. This is the simplest case.

Regarding 2), find the k closest point to P and then classify points by majority vote of its K neighbors. Each object votes for their class and the class with the most votes is taken as the prediction. For finding closest similar points, we find the distance between points using distance measures such as Euclidean distance, Hamming distance and Minkowski distance. On figure 2.6, is given a visual description of the classification algorithm.

KNN has proved to be quite effective regarding human activity classification [94], showing a high level of accuracy and satisfactory segmentation results. It is also used in diagnosing some diseases, having as a input a vast storage of patient's data in order to be able to perform a diagnosis based on the patient´s profile [95]. By analysing multiple variables it was able to link a strong connection between the evidences recorded and the variables that commonly are associated with chronic diseases [96].

2.3.2.3 Decision Tree (DT) Classifier

Decision Tree (DT) is a prediction classification model that uses a decision tree to go from conjunctions of features (branches) to conclusions about the class labels (leaves). Classification trees are

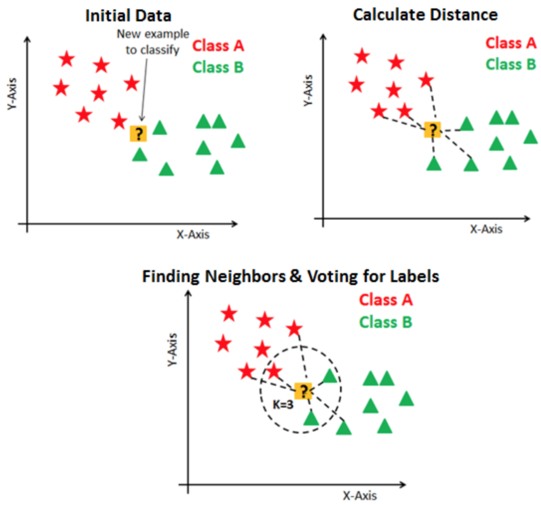


Figure 2.6: KNN Classification Algorithm
[93]

tree models where the target variable can take a discrete set of values and where the predicted output is where the class belongs.

The C4.5 is an algorithm used to generates decision tree from a set of training data, which is already classified. The decision rules of the algorithm are found based on entropy and information gain ratio pair of each feature. The decision rule in each level is the feature having the maximum gain ratio. Pruning reduces the size of the decision tree by removing sections that provide little power to classify, which can lead to less overfiting [97].

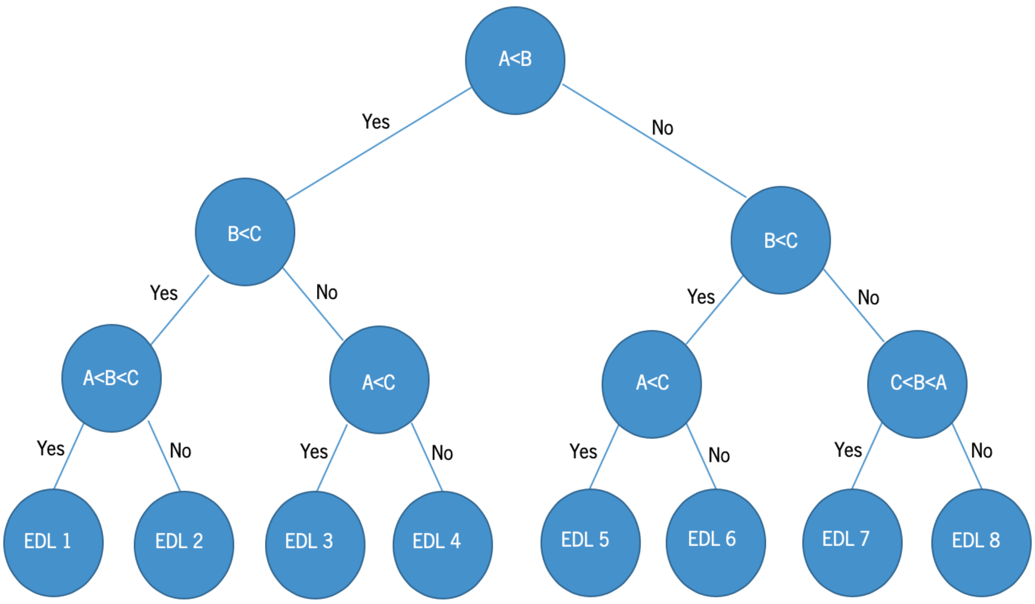


Figure 2.7: DT Classification Algorithm

2.3.2.4 Circadian Activities Rhythm (CAR) Classifier

Circadian rhythms are mainly based on daylight and are characterized by their amplitude, period and phase. The daily activities of humans also periodically fluctuate and are dependent on the circadian rhythms. The CAR classifier is based on measuring the circadian variability of an activity by recognizing rhythmic patterns with small fluctuations for an activity.It is used on the assumption that irrespective of the daily routine of the subject, specific patterns with specific duration and timing occur every day figure 2.8 [98].

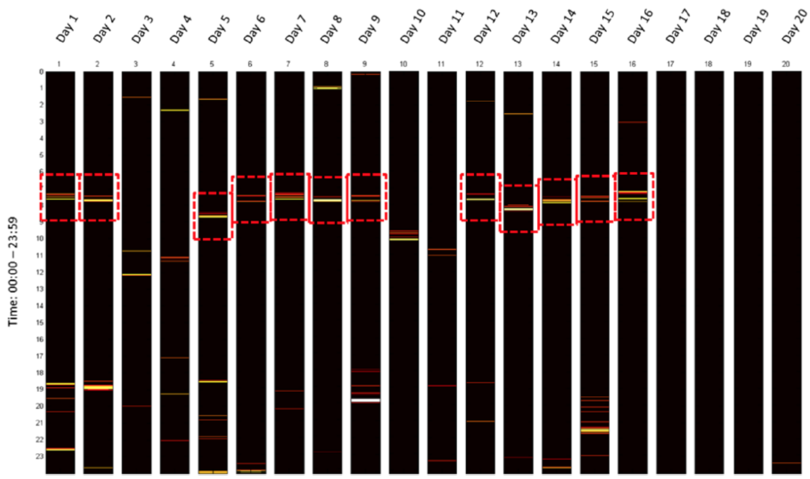


Figure 2.8: Activity Map - Daily Patterns
[98]

The classifier is built on the idea of pattern recognition with a core algorithm, which analyses sequences of ambient value matrices (Si). Figure 2.9 [98] shows the sequence of data processing and analysis of the CAR classifier [98].

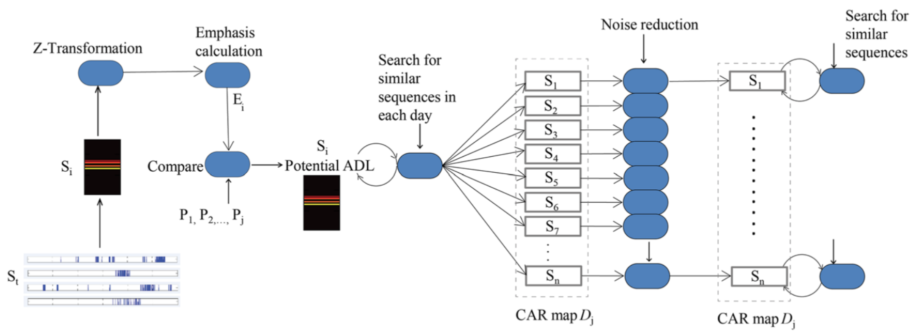


Figure 2.9: CAR classifier schematic

2.4 Long-Term Monitoring

A key parameter when developing an AAL monitoring system is the time of intervention. Among all the user's conditions by a monitoring system, the most relevants are emergency situations and chronic diseases. In order to detect an abnormal behaviour, we first need to create a behavioral profile of the user.This can be done recognizing recurrent behavioral patterns from mobility traces over a long period of time (Activity Map).Once we have a behavioral profile, we can detect anomalies in order to be aware of possible behavioral deviations that can lead to emergency situations related to emerging diseases. It could be labeled as situation-awareness.

2.4.1 Activity Maps

The activity map is a visualization technique which makes it possible to analyze the complete whole data at once. It is both a visual technique which can make use of the human eye's ability to recognize patterns and a quantitative one, in the sense that it introduces colored sequences which quantify the information contained in the data patterns. It constitutes a good benchmark regarding the physical and cognitive abilities of patients.

In figure 2.10 is presented one example of the recognized EDL for each subject were plotted against the time period of 20 days to generate an activity map [98].

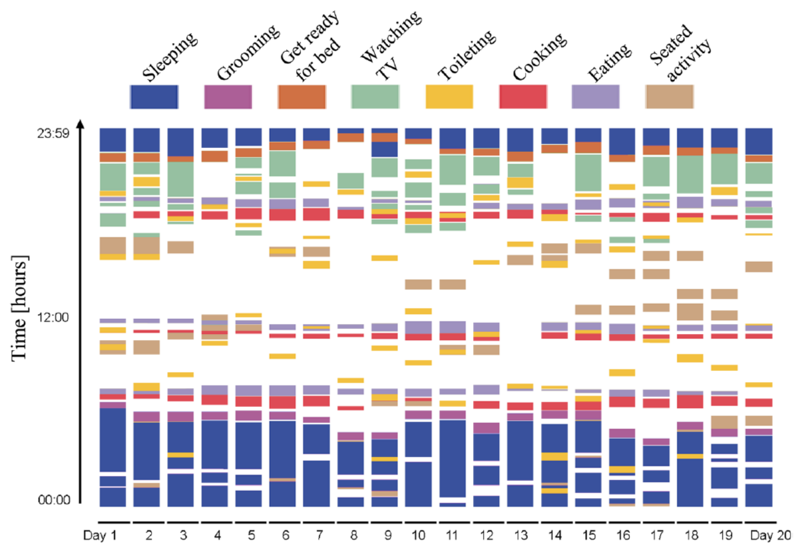


Figure 2.10: This activity map visualizes the EDL recognized

Firstly the patterns on the data allow us to create a representarion from the low-level, raw sensor data capture the resident´s activities and behaviours of daily living and then to assemble EDL activities into personalized daily and weekly profiles. Secondly, these activity profiles are analyzed to enable both the identification of changing trends in the patient's activities over time [98].

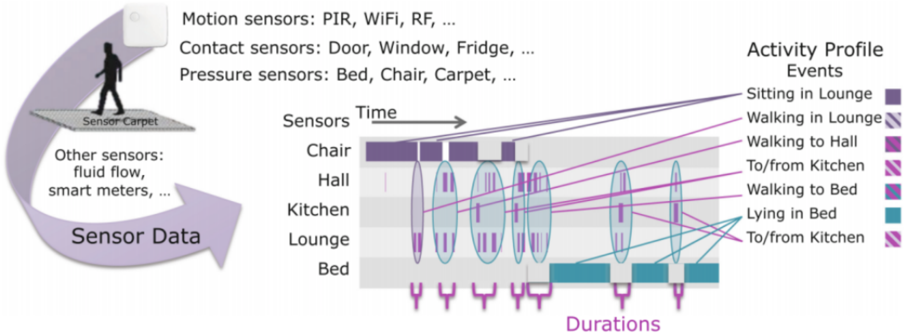


Figure 2.11: Identifying activities from sensor acitivations
[98]

Figure 2.12 shows an example of sensor activations for motion sensors and for pressure sensors. Simple events can be infered from this data to generate activities, in form of time-stamped events identified by sensors, being transformed into a daily user profile. In this case, the profile is a set of EDL, with mixed data types: binary- movement; counts- number of room transistions or stand up from seat count; cumulative daily time spans- time sitting or in bed.

With the comparison of these profiles with previous similar profiles labbeled as at risk or proviles showing a big difference in how the activities are performed may constitute a good indicator to identify risk or deteriorating behaviour [98].

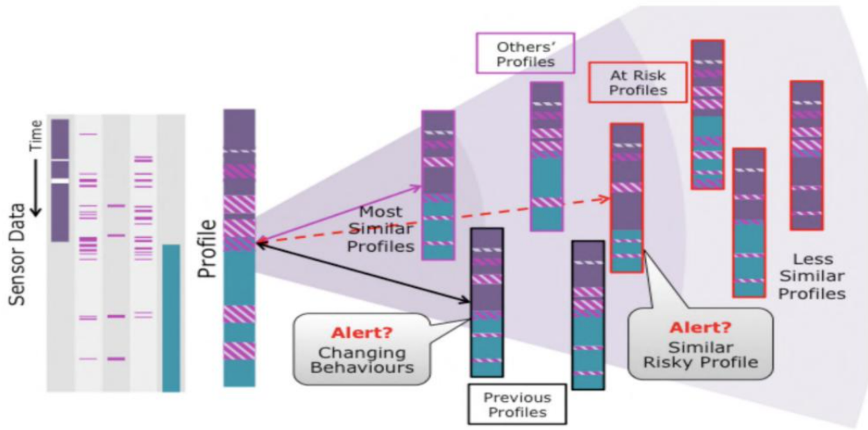


Figure 2.12: Identifying abnormal behaviours
[98]

Chapter 3

Methods

This chapter introduces the research methodology throughout the dissertation. It is the starting point in an overall process description after which a description of the technology used for the Research Data Acquisition (RDA) Platform that will be presented alongside with a description of the RDA Platform, adressing the research question **RQ4** and objective **O4**.

Furthermore, the chapter seeks to describe how experiments were conducted and how results were analysed and evaluated. The studies performed were:

- Study 1 - **Validity & Reliability** adressing the research question **RQ3** and obecjtive **O3**;
- Study 2 - **EDL Classification** adressing the research question **RQ4** and objectives **O5** and **O6**.

Some of the events have specific time to be conducted (Static Events) and some do not have a specific time (Dynamic Events).

3.1 Process Descripton

Figure 3.1 shows the overall process of this dissertation. It is an adaptation of the Waterfall Methodology in a way that it a straightforward process, thanks in large part due to the step-by-step nature of the method itself. The main differences are in the numbers and descriptions of the steps involved in a waterfall method.

Regardless, the concepts are all the same and encompass the broad scope of what it takes to start with an investigation topic and develop a full-scalle exploratory research around it.

The whole process can be divided in separate phases to be adressed. The outcome of one phase acts as the input for the next phase sequentially. This means that any phase in the development process begins only if the previous phase is complete.

The **Conception Phase** has started with an idea and a baseline assesment through a definition of a set of hypothesis as well as a set of research questions to guide the research on these topics, evaluating their feasibility to meet the objectives proposed.

The **Analysis Phase** consisted on a review focused on the state-of-art of Healthcare Systems, Smart Home Care (SHC)/ Nursing Care Homes and Pervasive Sensing Technologies used in AAL Environments to support the well-being of an elderly. With some insight on these concepts, was built a bridge to the concepts of EDL mainly on the methods and technologies currently used to evaluate them.

The **Design Phase** covered the technical design the specifications, namely the software and hardware specifications of the Research Data Acquisition Platform,data organization and interoperability between different modules alongside the actions needed to get there. This phase also consists on designing the studies:

- Study 1: Validity & Reliability Study - The purpose of this study is to investigate the accuracy, specificity and sensitivity of the several sensors as a stand-alone system. These study will contribute to identify potential problems with the sensors in a simple setting before using them in a more complex setting (Study 2). It will also investigate the classification of basic activities of daily living based on the input of these sensors;

- Study 2: EDL Classification - The purpose of this study is to investigate the relationship between combinations of sensors and EDLs and thereby investigate if sensors sensitivity and specificity than a single-sensor system when monitoring EDLs (Experimental Setup-Ambient Assisted Living Lab).

This phase will also adress the case scenarios and test protocols which will be performed in the last phase of the project (Experimental Phase).

The **Development Phase** consist on the development of the Research Data Acquisition Platform according to the design specification defined already defined on the design phase.

The **Experimental Phase** the research platform is ready to be deployed to a live environment (Ambient Assisted Living Lab). In this phase is also important to give subsequent support and maintenance that may be required to keep it functional and up-to-date.

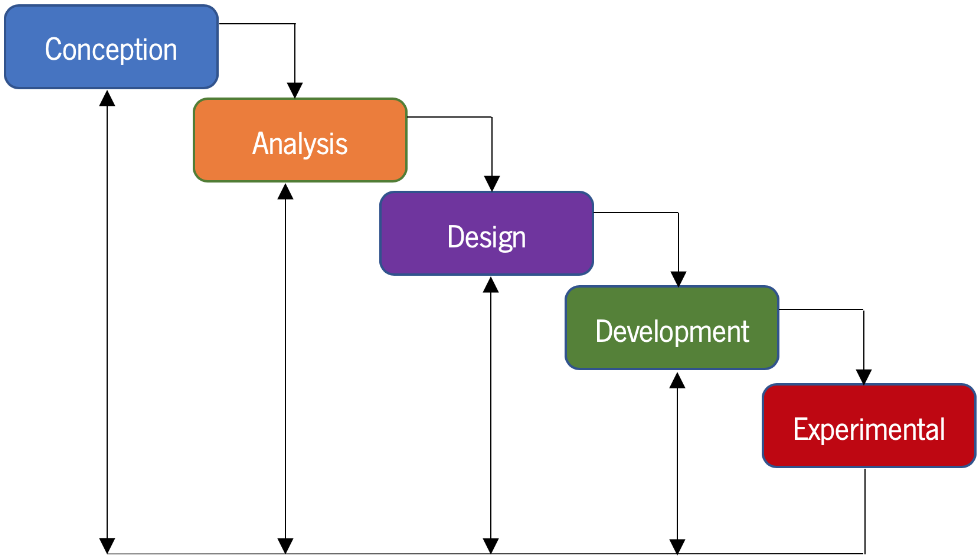


Figure 3.1: Process overview showing the different phases

3.2 Research Data Acquisition (RDA) Platform

In AAL a key role is played by infrastuctures, able to adapt their behavior to the current context without explicit request. The context information may be retrieved in a variety of ways, such as ambient sensors, retrieving network information and device status (hard data), or using user profiles (soft data).In an AAL environment scenario, a context-aware platform faces several challenging issues.

Firstly, it employs multiple networked sensor nodes. Coordination and management of such a large number of sensors are non-trivial task, sensors may suffer frquent failures, due to energy depletion or processing power and memory size limitation.

Secondly, the sensors continuously keep sampling large amounts of raw data about the user actions. For this reason, managing huge sets of raw data, storing and processing them, are also non-trivial tasks to perform. Moreover, the raw data need to be processed and reasoned properly in order to capture meaningful context information about the user.The development of an effective research data acquisition platform addresses the research question **(RQ4)** and objective **(O4)**. An overview of the RDA platform is depicted in figure 3.2:

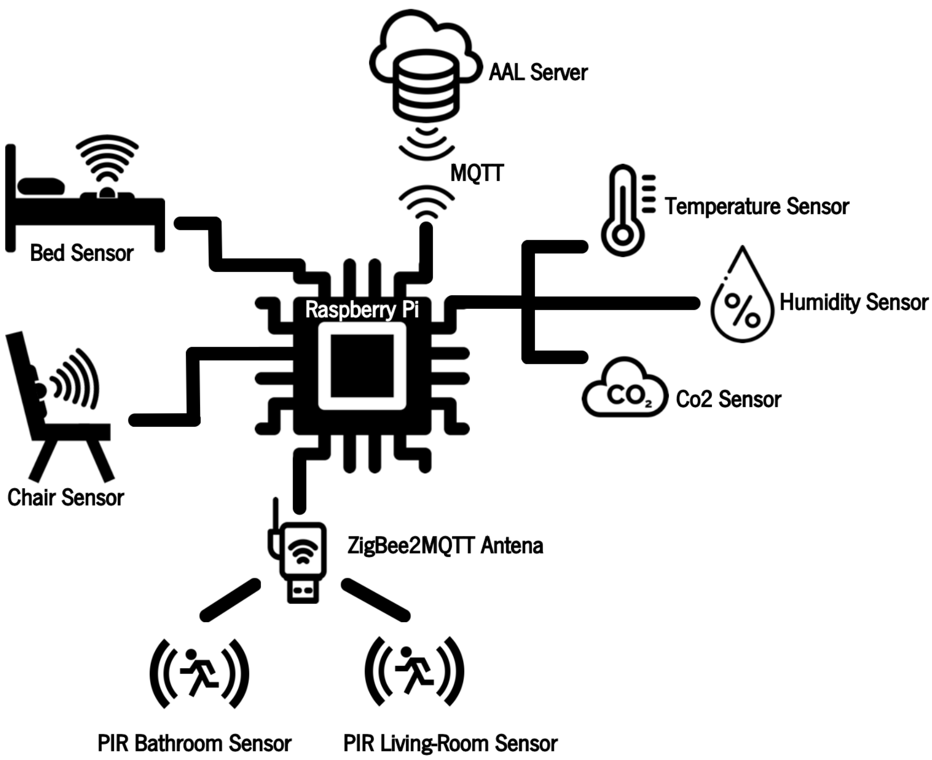


Figure 3.2: RDA Overview

3.2.1 RDA Platform Stack

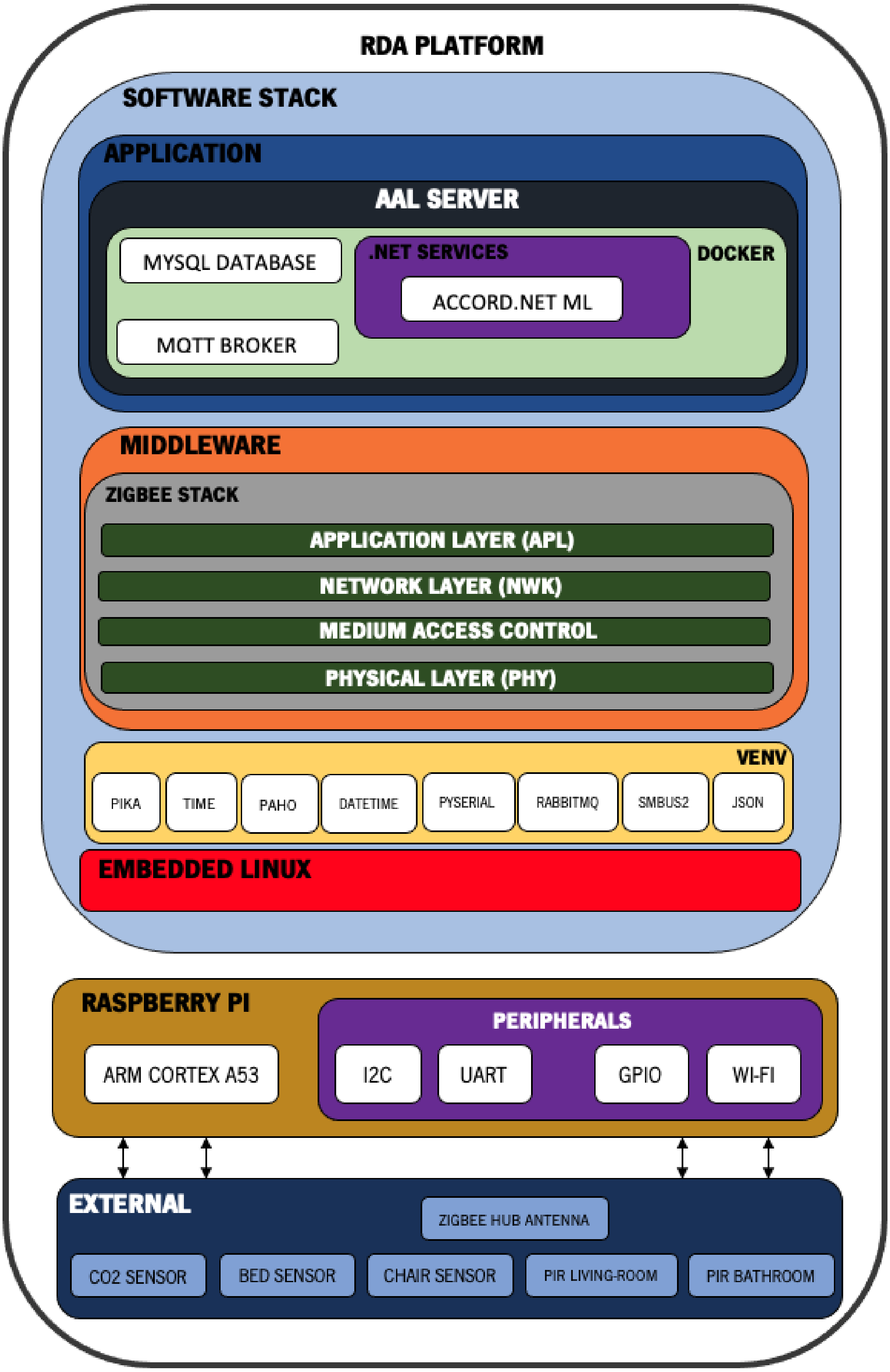


Figure 3.3: RDA Platform Stack

A system stack is crucial to understand in a graphic way, how the different layers can interact and what APIs should be developed to pass data through the diferent layers.

In the **Hardware Layer** of the system stack, the external peripherals, sensors and communication modules (Co2 Sensor, Chair Sensor, Bed Sensor and PIR Sensors) are represented. The data will be collected through them and the main board that interact with the "real world" and receive the data converting it into digital to be able to be processed and analyse in the other layers. In this layer the board Raspberry PI 3 Model B+ will be the development board where all the modules are physically connected.

In the **Software Layer** of the system stack, three layers are represented:

- The first layer is composed by the Embedded Linux Operating System. Here, there are the drivers developed to interpret the data provided by its Modules in the Hardware layer.To ease the configuration of the board's peripherals, we will use Standard Peripheral Drivers APIs as an interface to the microcontroller registers, hiding this way the needless complexity of some functionalities;
- **Python Virtual Environment** (venv), isolated from the system directories. This venv has its own Python binary (which matches the version of the binary that was used to create this environment) and have its own independent set of installed Python packages in its site directories (Pika, Datetime, Smbus2, Time, Pyserial);
- The middleware layer that will support our platform development are:
  1. **RabbitMQ** - is a messaging broker - an intermediary for messaging, which takes messages and sends them to other places. It has the great advantage of running on all major operating systems in this case Linux and supports a large number of developer platforms and it will be used in a Python platform and .NET.
  2. **ZigBee to MQTT** - allows the usage of zigbee devices without the vendors bridge or gateway. It bridges events and allows the control of Zigbee devices via MQTT. In this way, it is possible to get devices to be auto-discovered.

3.3 Hardware Specification

Each of the previously mentioned hardware needs to be specified before the implementation. The next key items will provide a brief specification of what the hardware will be, as much as the communication protocol and the features.

3.3.1 Raspberry Pi 3 Model B+

As development board, the Raspberry Pi 3 Model B+, Figure 3.4. It will be the project core, since it will be in it that all software to interface with the senors will be develloped. It consists of a small single-board computer that can be practically used in terms of embedded systems.

The sensors used will be all connected to the board, transmitting the data captured from the real world (analog), which are passed to digital data and in this way are processed later.

This board comes with the follow specifications:

- Broadcom BCM2837B0 64-bit SoC, quad core ARM Cortex-A53 with 1.2 GHz clock;
- 2.4GHz and 5GHz IEEE 802.11.b/g/n/ac wireless LAN;
- Extended 40-pin GPIO header;
- Bluetooth 4.2, BLE-Bluetooth Low Energy;

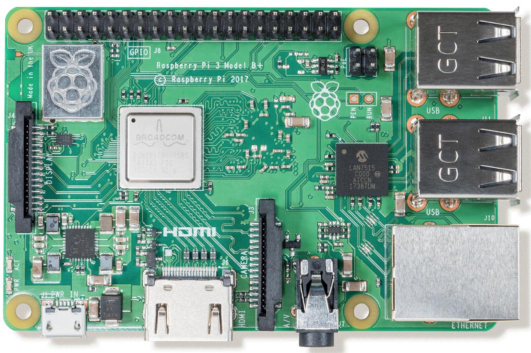


Figure 3.4: Raspeberry PI 3 Model B+

3.3.2 TRÅDFRI Wireless Motion Sensor

TRÅDFRI Wireless Motion Sensor, Figure 3.5, is a IoT sensor that transmits data using the Zigbee technology. It has a maximum range of 10 metres to the light source when not blocked by walls. For reaction to movement, the maximum range is 5 metres and a 120° angle. The sensor transmit data whenever the sensor is stimulated with a change in infrared radiation. When the PIR sensor is stimulated the sensor goes to sleep mode to conserve power. The sleep time is 1:30 minutes.

Figure 3.5: TRÅDFRI Wireless Motion Sensor

3.3.3 CozIR-A CO_2 Sensor

Cozir-A in figure 3.6, is a CO_2 sensor and it will be used to measure the CO_2 concentration (ppm).It was designed for measuring low levels of CO_2 ranging from 0-2000ppm, the sensor offers optional temperature and humidity sensing, and optional analogue (voltage) output. The sensor communicates via UART and it suits very good in wireless IoT networks, such as Zigbee and Enocean. This sensor comes with the following specifications:

- Low power/energy consumption - 3.5mW;
- Measures up to 1% CO_2 concentration;
- Serial communication 9600 bps/ 8 data bits/ 1 stop bit/ non parity;
- Accuracy: $50\,\mathrm{ppm} \pm 3\,\%$ of reading;
- Low noise measurement (<10ppm)

(a) (b)

Figure 3.6: CozIR-A CO2 Sensor

3.3.4 Cypress CapSense controller CY8CMBR3102

The Cypress CapSense controller CY8CMBR3102 in figure 3.7 is a capacitive touch sensing sensor. It communicates via I2C with up to 400khz, in which the raspberry pi is the master and the capsense is the slave. The sensitivity of each capsense is configurable , ranging from 0.1pF to 0.4pF.

The capacitive sensor can be used as a button, slidder or proximity sensor. The purpose is to use it as a proximity sensor is to detect presence when a person is nearby.The sensor has low power consumption, operating between 1.71V to 5.5V. However, the conditions of application require the usage of an advanced noise community algorithm for a stable sensor operation.

The threshold makes the sensor wake-up on interrupt (approach event). A low pass filter is applied in order to have low noise attenuation.

The sensor, depicted in figure 3.7, has two loops and the output is determined by the difference count between those two.

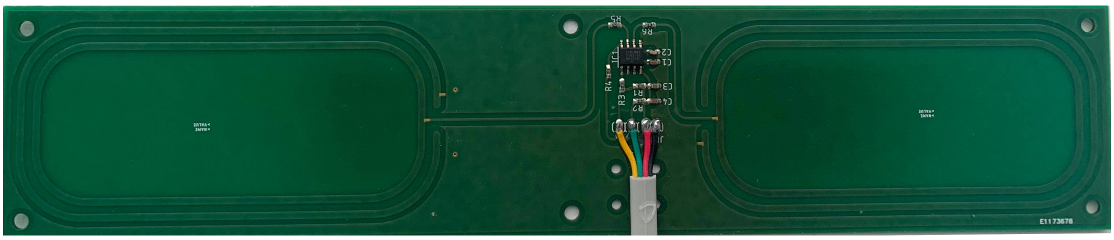


Figure 3.7: Cypress CapSense controller CY8CMBR3102

3.4 Software Specification

In figure 3.8, the UML diagram of the research platform is represented. Being a top-level view, it does not include all the details to be executed until the very end. It simply constitutes a forward design, where is possible to analyse all the workflows before start coding.

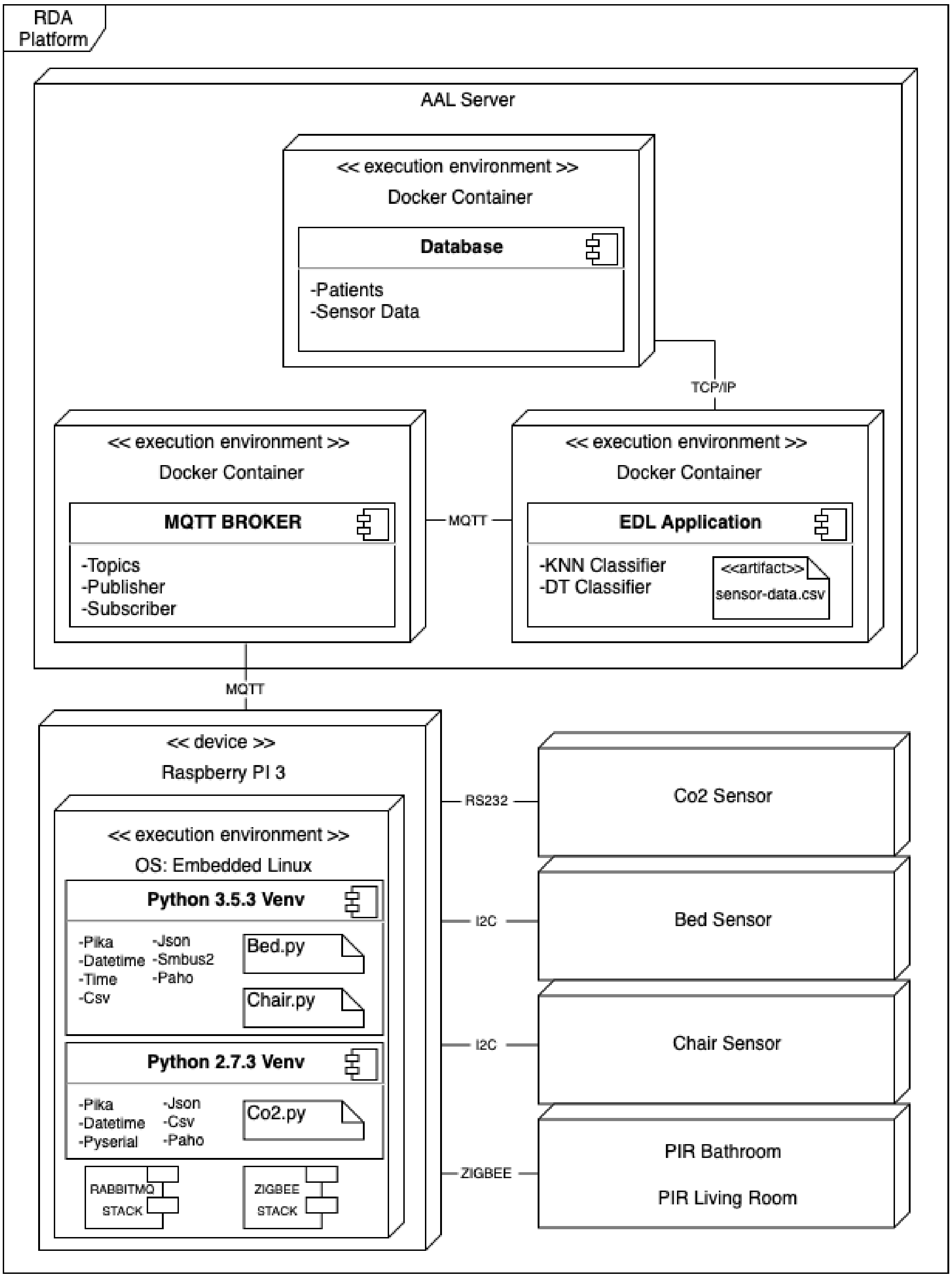


Figure 3.8: RDA UML Diagram

3.4.1 AAL Server

3.4.1.1 Docker Deployment

Running applications in containers comes with the advantages of isolation, portability and scalability. Isolation means that the containers run independently where different software versions will not affect each other, and all dependencies are handled in one place. Containerised applications are portable when it can be deployed on different systems and be expected to perform similarly. In this case, it is relevant because of the resource-demanding machine learning algorithms. Given the advantages, the application isolation was develloped with Docker and the components were placed in Docker containers and deployed on a CentOS Linux server.

Docker uses images, which are read-only templates with instructions for creating Docker containers. Containers are runnable instances of images.The containers can be started and stopped using the Docker Application Programming Interface (API) or the command-line interface.

Each component contains a Dockerfile, located in the root of the application folder which tells Docker how to build and run the respective application and which image to download and use. The application with all the included Docker containers is defined in a YAML file which configures names, ports, volumes and relationships.

3.4.1.2 EDL Application

The purpose of the EDL Application is twofold: detect and classify EDL based on the ambient sensor data collected, used as the input of the ML model; and secondly, persist the received sensor data in the Sensor Database. EDL Application is developed as an ASP.NET Core application and runs in a Docker container, as described in Docker Deployment.

EDL Application implements two supervised ML classification models: DT and KNN, using the Accord.NET framework. Accord.NET is a machine learning framework written in C#, including a set of support libraries and classification models. The feature vector was used for both ML classsification models. The sensors can be divided into four categories: PIR, Co2, Bed and Chair. All the sensor features are booleans which means that they can either be ”0” or ”1”. In order to accommodate the perspective of time and context, one additional features is used. The Last Class feature contains the information of the last class classified by the respective ML classification models.

The outcomes of the classification schemes can be interpreted as user states and are divided into the following classes: In bed, in chair , bathroom movement, living-room movement, living-room to bathroom movement, bathroom to living room movement and ”unknown”. The classification schemes predict the user state once every second and transmit the results to the MQTT broker on the topic EDLClass. The training data for the classification schemes was created with an Excel script that generated input for the feature vector based on simulated activitys within the AAL Lab.

3.4.1.3 AAL Server Database

To allow persistence of data, a self-hosted MS SQL database is used. An entity-relationship model of the database is illustrated in figure 3.9.

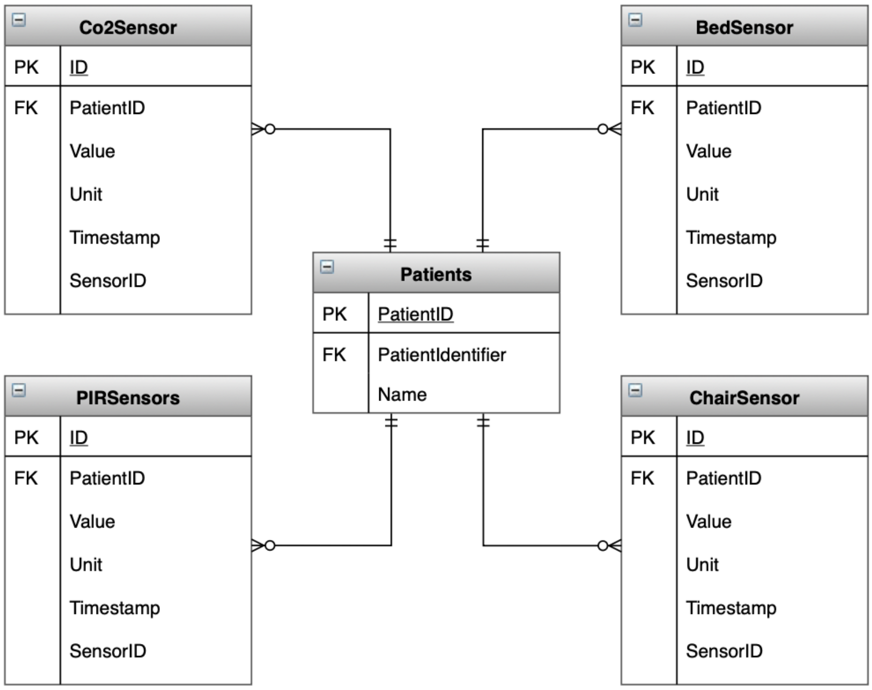


Figure 3.9: Entity-relationship model of the database with tables containing data from the sensors. There is a one-to-many relationship from Patients to each table.

This diagram iilustrates the relation between the five entities that come into "play". The five entities are: the Patient, Co2Sensor, ChairSensor, BedSensor and PIRSensors. The Patient will have a lot of data associated with it, which can be seen by having its primary key (PK) as a foreign key (FK) in the other tables.

The database consists of a Patients table and four data tables which correspond to the sensors used in the platform. The Patients table has a primary key identifier, a free text identifier and a name field. Each sensor data table consists of the columns Value, Unit, Timestamp, SensorID and PatientID. The value column represents the state of the sensor, which it can be a integer, float and a boolean.

The Unit column enables the database to store the unit of the received data, which can be relevant if sensors measuring continues values are added. The Timestamp column contains time information of the data, and the SensorID column makes it possible to distinguish between sensors. The PatientID column contains a foreign key to the Patients table so that each row of the sensor data tables refers to a specific user or patient.

The database uses the Entity Framework to connect to the database, which allows for automated database related activities by working on C# objects instead of the underlying database directly. With this approach, additional sensors are simply added to the system by creating new data models and map them to the database in the Entity Framework.

3.4.1.4 MQTT Broker

The internet of things network will work through a specialised messaging protocol - Message Queue Telemetry Transport (MQTT). It hosts a MQTT broker, which consists a server that mediates messages between subscribers and publishers and thereby decouples the MQTT clients of the system which are never directly connected. Communication via MQTT is based on topics where subscribers subscribe to a specific topic.

A publisher publishes a message on the topic, the broker forwards the message to any client subscribing to it. MQTT relies on the TCP/IP protocol for data transmission. A description of topics used to communicate is shown in table 3.1

Topic	Publisher	Description
BedSensor	RDA	Message with the chair occupancy
PIRSensor	RDA	Message containing the presence status in the bedroom and bathroom
Co2Sensor	RDA	Message indicating the carbon dioxide concentration (ppm)
ChairSensor	RDA	Message with the chair occupancy
EDLClass	EDL Application	Message with the latest classification by KNN and DT

Table 3.1: Topics used in the MQTT protocol with the description of usage and publisher.

JSON(JavaScript Object Notation) is the chosen data format for the payload. The fields to send are encapsulated in a Javascript object and then each individual parameter value is acessed and it is generated JSON-format data. An example is seen in listing in figure 3.10, which shows the payload of an MQTT message.

Timestamp is the time of the report, patientID is the ID of the Patient, sensorID is the ID of the sensor, and value is a boolean, float or integer. RDA Platform implements the MQTT broker Mosquitto running in a Docker container [99].

{“timestamp”: 1583918968852, “patientID”: 1, “sensorID”: “PIRLivingRoom”, “value”: True}

Figure 3.10: MQTT message Payload

Security

The broker is self-hosted to ensure full control of the data flow. The broker supports client authentication where a username and password from the client are required before a connection is permitted. This prevents intruders from simply subscribing to a topic and thus receive data sent across the platform. Furthermore, self-signed certificates are used to ensure transport encryption of personal data with Secure Sockets Layer (SSL).

3.4.2 Python Virtual Environment (Venv)

It consists on a a self-contained directory tree that contains a Python installation for a particular version of Python, plus a number of additional packages.The main propose of creating a venv was to build a lightweight virtual environment in order to isolate their own site directories from system site directories. Since for some python packages it is needed some different python versions, each environemt is designed for its own application/sensor with its own Python binary (which matches the version of the binary that was used to create this environment) and have its own independent set of installed Python packages in its site directories. All of this will help in particular solving some:

- Resolve dependency issues, allowing different python version 2.7.3 and 3.5.3;
- Make it self-contained and reproducible by capturing all package dependencies in a requirements file;

The site-packages(third-party librarys to use) are:

- **Pika**- is an implementation of the AQMP (Advanced Message Queuing Protocol) 0-9-1 protocol, enables application to connect to an AQMP broker and publishing/subscribing messages using this protocol;
- **Datetime**- provides classes for manipulating dates and times;
- **Json**- is used to work with json data;

- **Pyserial**-is a module that encapsulates the acess for the serial port;
- **Time**- it provides various time related functions;
- **Paho**- it implements the mqtt protocol, which enables applications to connect to an MQTT broker to publish messages, and to subscribe to topics and receive published messages. It also provides some helper functions to make publishing one off messages to an MQTT server very straightforward;
- **SMBus**- allows SMBus access through the I2C /dev interface on Linux hosts, regarding that the host kernel must have I2C support.

3.5 Study 1 - Validity & Reliability

The purpose of this study is to test each sensor as a stand-alone solution to validate the performance and reliability of the sensor. This was done to ensure that each sensor performed as expected before being combined in a multi-sensor platform.

3.5.1 Experimental Setup

The study will be carried out in a laboratory setting at the Ambient Assisted Living Laboratory at Aarhus University-Department of Engineering. Figure 3.2 shows the experimental setup and placement of each sensor in the laboratory where three artificial rooms were created: living-room, bedroom and bathroom.

The laboratory setting contains one door and it will be used as the entry door to simulate a standard space in a nursing care home.

3.5.2 Experimental Evaluation

Each sensor will be evaluated according to accuracy, sensitivity, and specificity. An accuracy of 100% refers to a sensor only firing when it is suppose to, which is what is always aimed at. If the accuracy is below 100% it could either mean that the sensor is firing when it is suppose to or when it is not suppose to.

Nevertheless, the accuracy can not tell us which one of the above cases it is and therefore, the sensitivity and specificity are great measures. If the sensitivity is 100% it implies that the sensor catches all the events that occur however, it does not tell us how many times the sensor fired when

Table 3.2: Experimental Setup AAL lab

it was not supposed to - that is the specificity. Specificity is the amount of times the sensor did not fire when an event did not occur divided by the amount of times an event did not occur in total.

The folowing equations show to to calculate the accuracy equation (3.1), sensitivity equation (3.2) and specificity equation (3.3).

$$Accuracy = \frac{TruePositives + TrueNegatives}{All} \tag{3.1}$$

$$Sensitivity = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{3.2}$$

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives} \tag{3.3}$$

As it can be seen in table 3.3, it is explained the concepts needed to understand the equations.

True Positives	The amount of times an event is observed when the event did occur
True Negatives	The amount of times an event is not observed when the event did not occur
False Positives	The amount of times an event is observed when the event did not occur
False Negatives	The amount of times an event is not observed when the event did occur

Table 3.3: Definition of True Positives, True Negatives, False Positives and False Negatives

3.5.3 Experimental Methods

In the experimental methods, the tasks to be performed will be splitted into two categories:

- Measurement (recording data via the RDA platform).
- Operational (changing system parameters, for e.g sensivity, triggering time, etc).

Each one of the tasks will be carried out in series(one after each other) and in parallel (tasks occurring at the same time). For each one of the sensor procedures, a test protocol was defined to ensure its reliability,consistency,reproducability and to allow the possiblity of making objectivily observations not subjectivily, in other words, observations based on specific events that have already happened and can be verified by others.

3.5.3.1 PIR Sensor

For the PIR Sensor, the purpose of testing it, is to evaluate the performance of the sensor under different circumstances and to expose possible errors and pit falls connected to the sensor. To evaluate the sensor, a TRÅDFRI Wireless motion sensor will be setup in a room.

To ensure that the test is reliable,consistent and reproducible, the test protocol in Table 3.4 was designed. The PIR sensor has one triggering timeout of 1 min.

Test Protocol for TRÅDFRI Wireless Motion Sensor

Step 1	Enter the room
Step 2	Wait stimuli seconds
Step 3	Leave the room
Step 4	Wait interstimuli seconds

Table 3.4: Test Protocol - TRÅDFRI Wireless Motion Sensor

For each trial a stimuli time is defined as the time between stimuli, e.g. the time between lying and getting out of bed , and an interstimuli time that defines the time between each repetition. The stimuli and interstimuli times for the PIR sensor can be seen in Table 3.5.

Experimental Tests

Test ID	True Positive	Stimuli[m]	Interstimuli[m]
1P	20	2	2
2P	20	4	3
3P	20	Walk By	2

Table 3.5: PIR sensor tests. Each test has a Test ID, a number of repetitions, a stimuli time [m], and an interstimuli time [m]

When the test subject enter the room or leave the room an 'enter' or 'leave' marker is set. This is the interval in which the sensor is suppose to trigger and thereby, any sensor firings outside this interval will be classified as a false positive.

To evaluate the PIR sensor, in test 1P, 2P and 3P, the definitions in Table 3.6 has been defined. Test 3P is a little different due to the fact that the purpose of this test is to test the behaviour of the sensor by walking past it and not by staying in a room like the others tests.

True Positives	The sensor fires while in the room
True Negatives	The sensor does not fire while not in the room
False Positives	The sensor fires while not in the room
False Negatives	The sensor does not fire while in the room

Table 3.6: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity and specificity of the PIR sensor

3.5.3.2 Bed Sensor

To evaluate the sensor Bed Sensor- Cypress CapSense controller CY8CMBR3102, the sensor wil be setup in a hospital bed. From the output of this sensor, should be possible to identify two events (In/Out of Bed). The purpose of this evaluation is to investigate the validity of the Bed Sensor, regarding the accuracy, sensitivity and is to detect the presence or absence of a person in bed as well as the person sleep time.

As was preveously defined with the PIR sensor, to ensure that the test is reliable,consistent and reproducible, the test protocol in Table 3.7 has been designed. Being the bed sensor fully configurable, we choose the trigger time of 1s.

Test Protocol for Cypress Capsense CY8CMBR3102

Step 1	Lie down in bed
Step 2	Lie in bed for stimuli time
Step 3	Leave the bed
Step 4	Wait interstimuli seconds

Table 3.7: Test Protocol - Cypress Capsense CY8CMBR3102 - Bed

To evaluate how the bed sensor perform under different time frames, several combinations of stimuli time and interstimuli time were defined, Table 3.8.

Experimental Tests

Test ID	Repetitions	Stimuli[s]	Interstimuli[s]
1B	10	30	30
2B	10	60=1min	30
3B	10	120=2min	60=1min
4B	10	180=3min	60=1min
5B	10	300=5min	60=1min
6B	5	600=10min	300=5min

Table 3.8: Bed sensor tests. Each test has a Test ID, a number of repetitions, a stimuli time [s], and an interstimuli time [s]

The definitions in Table 3.9 was defined to classify the obtained data and to calculate accuracy, sensitivity and specificity for the bed sensor.

True Positives	The Bed Sensor detects when a person is present in bed
True Negatives	The Bed Sensor detects when a person is absent in the bed
False Positives	The Bed Sensor detects presence of a person or fails to detect absence when the person is absent in the bed
False Negatives	The Bed Sensor detects absence of a person or fails to detect presence of a person when the person is present in the bed

Table 3.9: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity and specificity of the Bed sensor

3.5.3.3 Chair Sensor

To evaluate the Chair Sensor, will be used the same sensor used in the bed setup - CapSense Express controller CY8CMBR3102, with different settings, so that their behavior is appropriate to the way of use and the function it will have to perform. The sensor wil be setup in a resting chair and from the output of the sensor is possible to identify two events (In/Out of Chair). To investigate the validity of this sensor when setting up as a chair sensor, the test protocol in Table 3.10 has been designed.

Test Protocol for Cypress Capsense CY8CMBR3102	
Step 1	Sitting down in chair
Step 2	Sitting for stimuli time
Step 3	Getting up from the chair
Step 4	Wait interstimuli seconds

Table 3.10: Test Protocol - Cypress Capsense CY8CMBR3102 - Chair

As in the previous trials, a stimuli time is defined as the time between stimuli, the interstimuli time, e.g. the time between sitting and getting out of the chair, and the interstimuli time defined as the time between each iteration. These times can be seen in Table 3.11.

Experimental Tests

Test ID	Repetitions	Stimuli[s]	Interstimuli[s]
1C	10	30	30
2C	10	60=1min	30
3C	10	120=2min	60=1min
4C	10	180=3min	60=1min

Table 3.11: Chair sensor tests. Each test has a Test ID, a number of repetitions, a stimuli time [s], and an interstimuli time [s]

The definitions in Table 3.12 was defined to classify the obtained data and to calculate accuracy, sensitivity and specificity for the chair sensor.

3.5.3.4 CO_2 Sensor

For the CO_2 Sensor -CozIR-A, the purpose of testing it , is to evaluate the behaviour of the sensor under different circunstances, namely with a scenario where the number of people inside the setup will change during time. The sensor will be setup in the wall area and from the output of the sensor should be possible to identify (0, 1 or >1 person in the room).

True Positives	The chair sensor detects when a person is seated on chair
True Negatives	The chair sensor detects when a person is absent chair
False Positives	The chair sensor detects presence of a person or fails to detect absence when the person is absent chair
False Negatives	The chair sensor detects absence of a person or fails to detect presence of a person when the person is seated on chair

Table 3.12: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity and specificity of the chair sensor

To ensure that the test is reliable, consistent and reproducible, the test protocol in table 3.13 has been designed. Being the CO_2 sensor fully configurable.

Test Protocol for CozIR-A Co2 Sensor	
Step 1	Enter the room
Step 2	Stay in the room
Step 3	Leave the room
Step 4	Wait interstimuli seconds

Table 3.13: Test Protocol - CO_2 Sensor CozIR-A

To evaluate what the reponse time of the sensor, how this time influenciates the output of the sensor, it was defined several combinations of stimuli time and interstimuli time between each iteration, table 3.14.

Experimental Tests

Test ID	Repetitions	Stimuli[m]	Interstimuli[m]
1CO	5	4	2
2CO	5	8	4
3CO	5	20	10
4CO	5	30	15

Table 3.14: Co2 sensor tests. Each test has a Test ID, a number of repetitions, a stimuli time [m], and an interstimuli time [m]

The definitions in Table 3.15 was defined to classify the obtained data and to calculate accuracy, sensitivity and specificity for the CO_2 sensor.

True Positives	The CO_2 sensor increases the CO_2 concentration (ppm) when a person has entered the room
True Negatives	The CO_2 sensor decreases CO_2 concentration (ppm) when a person has left the room
False Positives	The CO_2 sensor increases CO_2 concentration (ppm) or fails to decrease when a person has left the room
False Negatives	The CO_2 sensor decreases CO_2 concentration (ppm) or fails to increase when a person has entered the room

Table 3.15: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity and specificity of the CO_2 sensor

3.6 Study 2 - EDL Classification

The purpose of this study is to investigate the usage of a broad range of sensors and the data acquired from those sensors to be combined in a distributed home for monitoring EDLs adressing research question **RQ4** and objective **O4**.

This study is conducted by using the previous described RDA system to collect data from the sensors while participants are performing different EDLs. Hereafter, the collected data was analysed with ML models in a .Net ML application-EDL Application, section 3.4.1.2, adressing the research question **RQ4** and objectives **O5** and **O6**.

3.7 EDL Scenarios

3.7.1 Scenario 1-Sleeping Activity

3.7.1.1 Scenario 1A

The test subject lies down in bed the and decide to sleep for the next hour.

Expected Result

- The test subject lies completely still on the back in the bed;
- The bed sensor signals that a person is in the bed;
- The test subject remains completely still on the back for the next hour;
- The bed sensor signals that a person is in the bed for the next hour;
- The test subject wakes up and gets out of bed;
- The bed sensor signals that a person is no longer in the bed.

3.7.1.2 Scenario 1B

The test subject lies down bed for a little recovery.

Expected Result

- The test subject lies the back in the bed;
- The bed sensor signals that a person is in the bed;
- The test subject is resting in the bed for the next 10 minutes;
- The bed sensor signals that a person is in the bed for the next 10 minutes;
- The test subject gets out of bed;
- The bed sensor signals that a person is no longer in the bed;
- The test subject waits standing for the next two minutes;
- The test lies the back again in the bed;
- The test subject is resting in the bed for the next 10 minutes;
- The bed sensor signals that a person is in the bed for the next 10 minutes;
- The test subject gets out of bed;
- The bed sensor signals that a person is no longer in the bed.

3.7.2 Scenario 2-Seated Activity

The test subject seats down on the chair for a bit of rest.

Expected Result

- The test subject sits completely upright in the chair;
- The chair sensor signals that a person is in the chair;
- The test subject remains completely upright on the chair for the next 10 minutes;
- The chair sensor signals that a person is on the chair for the next 10 minutes;
- The test subject gets up from the chair;
- The chair sensor signals that a person is no longer on the chair.

3.7.3 Scenario 3-Walking Activity

The test subject walks around is living room area.

Expected Result

- The test subject enters in the Living-Room;
- The test subject walks to the Living-Room for the next 3 minutes;
- The PIR sensor named "PIR Living-Room" signals activity in the living room for the next 3 minutes;
- The test subject leaves the Living-Room;
- The PIR sensor named "PIR Living-Room" is not triggered again.

3.7.4 Scenario 4 - Fall

The test subject wakes up during the night and goes to the toilet. Falls on the way to the bathroom and cannot get up again. Lies on the floor for 1 hour.

Expected Result

- The Bed Sensor signals that a person is in the bed;
- The Bed Sensor signals that a person is no longer in the bed;
- The PIR Sensor named "PIR Living-Room" signals activity in the living room for the next minute;
- The PIR Sensor named "PIR Bathroom" signals activity in the bathroom for the next two minutes;
- The PIR Sensor named "PIR Living-Room" signals activity in the living room;
- No sensors triggered for the next hour.

3.7.5 Experimental Procedure

Each scenario defined requires two persons; one participant and one supervisor. The participant is the test subject of the test and has to perform BADL throughout the different scenarios.The supervisor has to ensure that the test subject understand the given scenario before performing each scenario.

During the study the supervisor also has the responsibility of manually noting the start and end of each iteration in each scenario. Each scenario has to be performed five times by each test subject. Figure 3.11 illustrates the test protocol for Study 2 - EDL Classification.

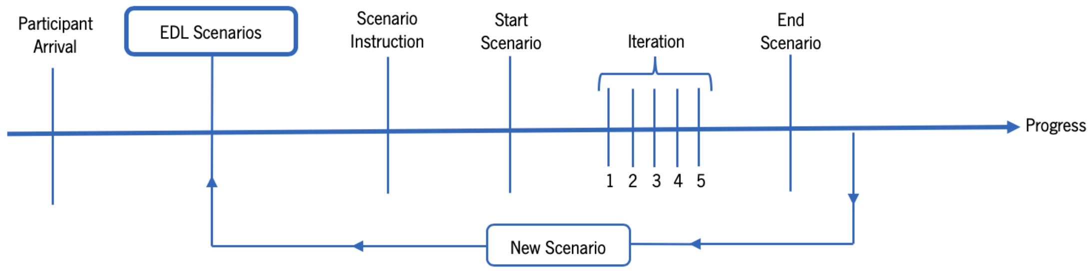


Figure 3.11: Study 2 - EDL Classification: protocol progress

3.7.6 Data Handling

In order to apply a ML model, the data from the sensors is needed. This data should be complete and later should be analysed to identify possible outliers or even missing data. This data is called dataset and it is collection of data. These sets of data will be extracted from the sensors, through the realization of the test protocols previously defined.

The dataset created will correspond to the contents of a single database table where every column of the table represents a specific variable (or feature), and each row corresponds to a sample. The data set will list values for each of the variables, such as the proximity or temperature measured by a sensor. The data sets will consist of a test and train sets..

Regarding this, the data will be splitted in these two sets (also known as holdout split). These sets are normally split in 80/20 of all the data. The 80% of the train data will be also used for training validation purposes.

The next step will be to go in depth in data visualization. The test set should be set aside and only the training set should be used. The data will be visualized graphically , by experimenting combination of features in different axis. This could tell how the features correlate with each other since this will affect the model, most of the time, negatively for classifcation.

3.7.6.1 Feature Extraction

Features are sets of variables that carry discriminating and characterizing information about an object which are usually measurements or observations. There is no specific number of features to be extracted.

Extracting large numbers of features normally provide high classification accuracy because the features contain most of the values about a particular class, but require considerable computational resources.Extracting low number of features requires small computation resources but provide low classification accuracy because the features contain a small number of values for certain classes.

The ideal process would be to extract a low number of very representative features from raw sensor data. This is helpful to improve the accuracy of advanced processing algorithms or further information processing stages while reducing at the same time the computational cost of activity inference. The process of finding useful hidden information from the raw data, which helps in eliminating the noisy data and reduce the amount of time and memory required in classification process, is called feature extraction.

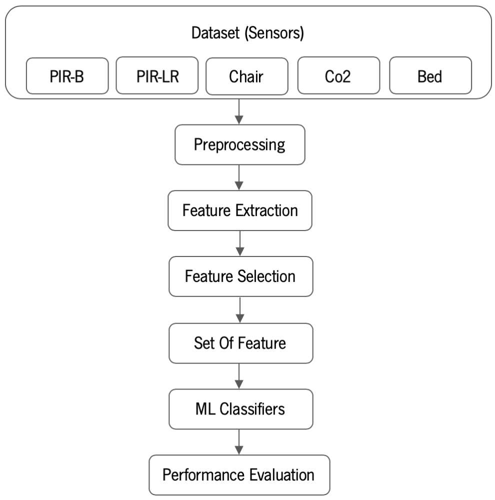
Feature extraction process transforms the raw dataset into a set of features vectors, which should contain proper information to be the input of the activities discrimination and learning algorithms. The most commonly used approaches of feature extraction operate in three domains: time domain, frequency domain and discrete domain [144].

3.7.6.2 Feature Selection

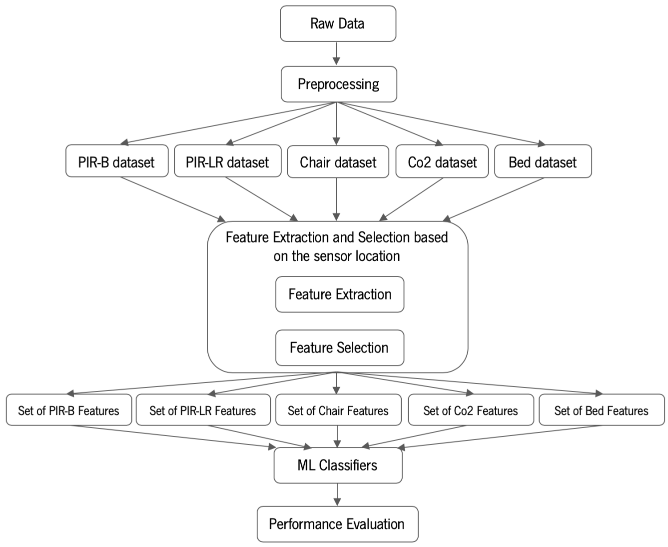
Features extracted from raw sensor data may contain redundant and irrelevant information, which can negatively affect system performance. It is important to produce a new reduced set of features from the extracted set of features to reduce dimensionality, redundancy or irrelevant features that might negatively affect the results of subsequent analysis.

Feature selection plays an effective role in selecting more discriminative features and reducing the dimensionality of feature vector. This way, the main task of the feature selection process is to find a more relevant subset of features from within a high dimensional feature vector, in order to reduce computational expense and noise, and to benefit the application of learning models.

Regarding the feature selection, this dissertation propose a different approach different from the standard one, Figure 3.12a and Figure 3.12b, in which are illustrated respectively the proposed and standard approaches to classify EDLs using our set of sensors.



(a) Standard Approach



(b) Proposed Approach

Figure 3.12: Process description to classify EDLs

In the proposed architecture, the feature selection layer is different from that of the standard approach. In this layer, the proposed method separately performs feature selection on each sensor, whereas the standard method considers all extracted features at once.

The main advantage of the proposed method is that each sensor has a different feature. Moreover, the computation requirement of feature selection is significantly decreased compared with the standard approach.

3.7.6.3 Feature Vector

The data from each repetition in each scenario is then transformed into a feature vector which describes what happens within the given time period. The purpose of transforming the data into a feature vector is to make the data easily comparable. The feature vector contain features from all the sensors included in the study as shown on Figure 3.13.

The sensors can be divided into four categories namely, PIR, CO_2 , Bed/Chair and Last Class. Each sensor within the same category is defined by the same features.

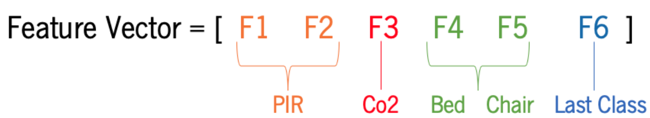


Figure 3.13: Structure of the feature vector

Figure 3.14, shows the features of each PIR sensor. Each sensor has 2 dimensions where each dimension describes activity observed by the sensor within a one and half minute interval. The feature space for the PIR sensors cover the entire duration of that scenario. The dimension is boolean which means that it can either be "1"/ "True" or "0"/"False". 1" indicates that activity has been observed within the given time period and "0" indicates that no activity was observed.

$$\text{PIR} = \begin{cases} \text{Activity between 0 – 90 secs} & \text{Boolean: True} \\ \text{No Activity between 0 – 90 secs} & \text{Boolean: False} \end{cases}$$

Figure 3.14: PIR sensor features in the feature vector

Figure 3.15 shows the features of the Bed and Chairsensor. The sensor reports an activity measure between 0 - 4096 (12 bits output chosen) ,which has been divided into two dimensions-presence and absence. Furthermore, dimensions for presence and absence events has been defined together with the observed activity before and after these events and if a presence prior to absence has been observed in vice versa-Last Class feature.

$$\text{Bed/Chair} = \begin{cases} \text{Activity 0} & \text{Boolean} \\ \text{Activity 1 – 4095} & \text{Boolean} \\ \text{Presence} & \text{Boolean} \\ \text{Absence} & \text{Boolean} \\ \text{Activity before presence} & \text{Boolean} \\ \text{Activity before absence} & \text{Boolean} \\ \text{Absence before presence} & \text{Boolean} \\ \text{Presence before absence} & \text{Boolean} \end{cases}$$

Figure 3.15: Bed and Chair sensor features in the feature vector

3.8 Model Selection

After the problem was framed and all the data available and explored, it is possible to select and train a machine learning model. However, before selecting the model, the problem must be categorized. This will help on the identification of the model to be used. It will be categorized in the following way:

- If the output of the model is a number, it's a regression problem;
- If the output of the model is a class, it's a classification problem;
- If the output of the model is a set of input groups, it's a clustering problem.

Assessing the performance of different learning algorithms on a dataset is at the core of machine learning. If this task is done properly, the best algorithm can be selected and the problem of generalization is partially solved. In this case, it will be used K-nearest neighbors (KNN) and Decision Tree (DT).

A way to evaluate it, will consist in spliting the training set into smaller training set and a test set, then train the models against the smaller training set and evaluate them against the test set. This is called cross-validation. It is a very useful technique for assessing the effectiveness of the models used, particularly in cases where it is need to mitigate overfitting. The most common form of this type of this validation is K-fold cross-validation and the Leave-P-Out Cross Validation.

3.8.0.1 K-Fold Cross-Validation

When evaluating a machine learning model one need to distinct between validation error and training error. The validation error is the average error that results from using a statistical model on observations that were not used to train the model [100]. The training error can be calculated by applying the statistical model on the data it was trained on. The training error can be used as an estimate for the validation error, however it can be quite different from the validation error and it often underestimates the validation error.

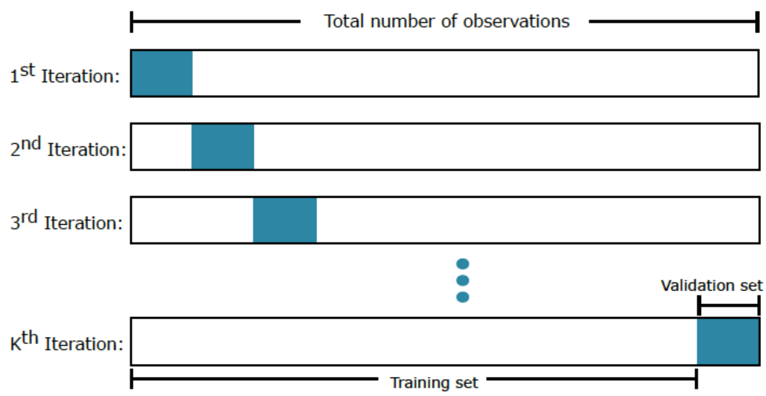


Figure 3.16: K-fold cross-validation with K folds. Fold marked blue - the validation.Remain-training set.

One way of estimating the validation error is by using k-fold cross-validation. This method randomly splits the training set into K distinct subsets called folds, then it trains and evaluates the model K times, picking a different fold for evaluation and training on the other K-1 folds, every iteration. The first fold is treated as the validation set and the model is trained on the remaining K-1 folds of observations. This procedure is done K times, where a new fold is the validation set in each iteration. This process is illustrated in Figure 3.16.

3.8.0.2 Leave-P-Out Cross Validation

The leave-p-out method is a particular instance of cross-validation. This approach leaves p data points out of training data, i.e. if there are n data points in the original sample then, n-p samples are used to train the model and p points are used as the validation set. This is repeated for all combinations in which original sample can be separated this way, and then the error is averaged for all trials, to give overall effectiveness [101].

It is exaustive in the sense that it has to validate all the possible combinations, depending on the value of p. In this dissertation, this method will be used with the particular case of p=1. This is known as Leave one out cross validation. This method is generally preferred over the previous one because it does not suffer from the intensive computation, as number of possible combinations is equal to number of data points in original sample or n.

Figure 3.17: Testing set - orange and Training set - blue

3.8.0.3 Evaluation Criteria

In [102], it was found that using accuracy alone as the only reporting metric often results in a poor reporting. If the accuracy is not 0 % or 100 %, it can not tell whether it is the true positives or the true negatives that is causing the issue. Making a conclusion exclusively on the accuracy metric can cause to misleading conclusions especially if the data has an unequal class proportion which is the case in Study 2.

Most of the times classification accuracy is used to measure the performance of the model, however it is not enough to truly judge it. The most common methods to evaluate model are:

- Classification accuracy;
- Confusion Matrix;
- F1 Score;
- Mean Absolute Error;
- Mean Squared Error.

Depending of the type of model, classification or regression this methods apply differently. The first five methods are for classification, while the last two are for regression. To evaluate the performance of our proposed approach and model, it will be used three metrics: classification accuracy, precision, recall and F1-Score.

Classification accuracy is the ratio of number of correct predictions to the total number of input samples, following equation 3.4. It works well only if there are equal number of samples belonging to each class.

$$Accuracy = \frac{NumberofCorrectPredicitions}{TotalofPredictions} \tag{3.4}$$

The confusion matrix is a handy presentation of the accuracy of a model with two or more classes. The table presents the prediction classes on the x-axis and the true class on the y-axis. The cells of the table are the number of predictions made by the model.

After choosing a model that suits our research, testing it and evalutating it, comes the solution presentation and maintenance of the platform. This maintenance means human analysis to evaluate the new predictions, evaluating input data quality and even retraining the models with freash data on a regular basis.

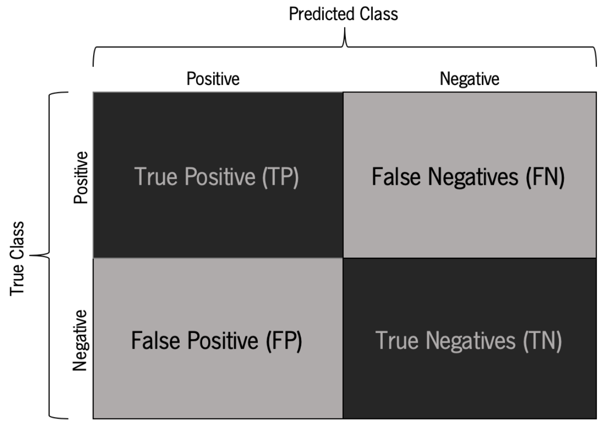


Figure 3.18: Confusion Matrix

F1 Score is the harmonic mean between precision and recall. The range for F1 Score is [0, 1]. It tells how precise the classifier is (how many instances it classifies correctly),as well as how robust it is (does not miss a significant number of instances). High precision but lower recall, gives an extremely accurate, but it then misses a large number of instances that are difficult to classify. The greater the F1 Score, the better is the performance of the model. Mathematically, it can be expressed as:

$$F1 = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \tag{3.5}$$

where precision is:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{3.6}$$

and Recall is:

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{3.7}$$

Chapter 4

Results

This chapter presents the results obtained from Study 1 - Validity & Reliability and Study 2- EDL Classification. The purpose of Study 1 was to evaluate the performance of the Bed Sensor, Chair Sensor, PIR Sensor and CO_2 Sensor as a stand-alone system (**RQ3**). The purpose of Study 2 was to investigate the usage of a broad range of sensors and the data acquired from those sensors to be combined in a distributed home for monitoring EDLs (**RQ4**).

4.1 Study 1 -Validity & Reliability

This section presents the results from Study 1 - Validity & Reliability. The purpose of the study was to test and validate the performance of each sensor (RQ3) as a stand-alone solution and thereby reveal potential problems before combining them into a multi-sensor system in Study 2 - EDL Classification. The results from each sensor will be presented with the number of True Positives, True Negatives, False Positives, and False Negatives from which the accuracy, sensitivity, and specificity are calculated.

4.1.1 PIR Sensors

4.1.1.1 PIR Sensor Living Room

The definitions of True Positives, True Negatives, False Positives, and False Negatives used in the PIR Living-Room sensor setup is showed in Table 4.1

True Positives	The PIR Living Room triggers while in the living room
True Negatives	The PIR Living Room does not trigger while not in the living room
False Positives	The PIR Living Room triggers while not in the living room
False Negatives	The PIR Living Room does not trigger while in the living room

Table 4.1: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity, and specificity of the Pir Living-Room Sensor.

Based on the definitions in Table 4.1 the observations were labelled as shown in Table 4.2. This labelling were used to calculate the accuracy, sensitivity, and specificity as shown in Table 4.3.

Test ID	True Positive	True Negative	False Positive	False Negative	Stimuli[m]	Interstimuli[m]
1PLR	20	20	0	0	2	2
2PLR	20	20	0	0	4	4
3PLR	20	0	0	0	Walk By	4
4LPR	10	0	0	10	Walk By	1

Table 4.2: Trial data from the PIR Living Room (PLR) labelled as True Positives, True Negatives, False Positives, and False Negatives.

It was not possible to calculate the sensitivity and the specificity in test 3PLR and 4LPR due to the definition of the test scenario. Test 3PLR differed from the others by not specifying an interval in which the sensor had to trigger between. The test just checked whether or not the sensor did fire after it was stimulated. In test 4AP the sensor was stimulated twice as fast as the sleep time of the sensor which means that the sensor would be at sleep half of the times it was stimulated - hence the expected maximum accuracy would be 50 %.

Test ID	Accuracy	Sensitivity	Specificity	Stimuli[m]	Interstimuli[m]
1PLR	100%	100%	100%	2	2
2PLR	100%	100%	100%	4	4
3LPR	100%	N/a	N/a	Walk By	4
4PLR	50%	N/a	N/a	Walk By	1

Table 4.3: Accuracy, sensitivity, and specificity calculated for the PIR Living Room (PLR) based on the observations.

4.1.1.2 PIR Sensor Bathroom

The definitions of True Positives, True Negatives, False Positives, and False Negatives used in the PIR Living-Room sensor setup is showed in Table 4.4

True Positives	The PIR Bathroom triggers while in the bathroom
True Negatives	The PIR Bathroom does not trigger while not in the bathroom
False Positives	The PIR Bathroom triggers while not in the bathroom
False Negatives	The PIR Bathroom does not trigger while in the bathroom

Table 4.4: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity, and specificity of the Pir Living-Room Sensor.

The observations and results were exactly the same, since the test protocols were also the same. The only change was the positioning of the sensor, which leads to the conclusion that in this specific case, changing the location of the sensor will in no way influence its behavior.

4.1.2 Bed Sensor

Table 4.5 shows the definitions of True Positives, True Negatives, False Positives, and False Negatives used in the Bed sensor setup.

Based on the definitions in Table 4.5 the observations has been labelled as shown in Table 4.6.

True Positives	The Bed Sensor detects when a person is present in bed
True Negatives	The Bed Sensor detects when a person is absent in the bed
False Positives	The Bed Sensor detects presence of a person or fails to detect absence when the person is absent in the bed
False Negatives	The Bed Sensor detects absence of a person or fails to detect presence of a person when the person is present in the bed

Table 4.5: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity, and specificity of the Bed Sensor.

Test ID	True Positive	True Negative	False Positive	False Negative	Stimuli[s]	Interstimuli[s]
1B	10	10	0	0	30	30
2B	10	10	0	0	60=1min	30
3B	10	10	0	0	120=2min	60=1min
4B	10	10	0	0	180=3min	60=1min
5B	10	10	0	0	300=5min	60=1min
6B	5	5	0	0	600=10min	300=5min

Table 4.6: Trial data from the Bed Sensor (B) labelled as True Positives, True Negatives, False Positives, and False Negatives

Test ID	Accuracy	Sensitivity	Specificity	Stimuli[s]	Interstimuli[s]
1B	100%	100%	100%	30	30
2B	100%	100%	100%	60=1min	30
3B	100%	100%	100%	120=2min	60=1min
4B	100%	100%	100%	180=3min	60=1min
5B	100%	100%	100%	300=5min	60=1min
6B	100%	100%	100%	600=10min	300=5min

Table 4.7: Accuracy, sensitivity, and specificity calculated for the Bed sensor (B) based on the observations

The accuracy, sensitivity, and specificity were calculated and presented in Table 4.7.

All the tests performed presented excelent results regarding the metrics of evaluation (accuracy,sensitivity and specificity).Changing the time frames-stimuli and interstimuli time did not affect the sensor responsiveness and behaviour, showing its reliability and consistency.

4.1.3 Chair Sensor

The definitions of True Positives, True Negatives, False Positives, and False Negatives used in the Chair Living-Room sensor setup is showed in Table 4.8.

True Positives	The chair sensor detects when a person is seated on chair
True Negatives	The chair sensor detects when a person is absent chair
False Positives	The chair sensor detects presence of a person or fails to detect absence when the person is absent chair
False Negatives	The chair sensor detects absence of a person or fails to detect presence of a person when the person is seated on chair

Table 4.8: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity, and specificity of the Chair Sensor.

Based on the definitions in Table 4.8 the observations has been labelled as shown in Table 4.9.

Test ID	True Positive	True Negative	False Positive	False Negative	Stimuli[s]	Interstimuli[s]
1C	10	10	0	0	30	30
2C	10	10	0	0	60=1min	30
3C	10	10	0	0	120=2min	60=1min
4C	10	10	0	0	180=3min	60=1min

Table 4.9: Trial data from the Chair Sensor (C) labelled as True Positives, True Negatives, False Positives, and False Negatives

As was verified with the bed sensor, the application of the same sensor, however with a different configuration, it was possible to obtain excellent results despite the object of study being modified. The accuracy, sensitivity, and specificity were calculated as shown in Table 4.10.

Test ID	Accuracy	Sensitivity	Specificity	Stimuli[s]	Interstimuli[s]
1C	100%	100%	100%	30	30
2C	100%	100%	100%	60=1min	30
3C	100%	100%	100%	120=2min	60=1min
4C	100%	100%	100%	180=3min	60=1min

Table 4.10: Accuracy, sensitivity, and specificity calculated for the Chair sensor (C) based on the observations

4.1.4 CO_2 Sensor

The definitions of True Positives, True Negatives, False Positives, and False Negatives used in the CO_2 sensor setup is showed in Table 4.11.

True Positives	The Co2 sensor increases the Co2 concentration (ppm) when a person has entered the room
True Negatives	The Co2 sensor decreases Co2 concentration (ppm) when a person has left the room
False Positives	The Co2 sensor increases Co2 concentration (ppm) or fails to decrease when a person has left the room
False Negatives	The Co2 Sensor decreases Co2 concentration (ppm) or fails to increase when a person has entered the room

Table 4.11: Definitions used to evaluate the obtained data and to calculate accuracy, sensitivity, and specificity of the CO_2 Sensor.

Based on the definitions in Table 4.11 the observations has been labelled as shown in Table 4.12.

Test ID	True Positive	True Negative	False Positive	False Negative	Stimuli[m]	Interstimuli[m]
1CO	0	0	20	20	4	2
2CO	20	0	0	20	8	4
3CO	20	20	0	0	20	10
4CO	20	20	0	0	30	15

Table 4.12: Trial data from the CO_2 Sensor (CO) labelled as True Positives, True Negatives, False Positives, and False Negatives

The accuracy, sensitivity, and specificity has been calculated as shown in table 4.13. As it is showned, the CO_2 sensor had an accuracy of 100% both in test 3CO and 4CO. This was also the tests with the biggest stimuli and interstimuli time. It is also notable that when the stimuli and interstimuli time drop, all metrics of evaluation fall. The possible reason for this to happen is related to the delay of the sensor in acquiring the data about the environment that surrounds it.Nevertheless, the sensor has proved to be quite reliable if we take into consideration a time delay longer than the used in 2CO test. This way, it can correctly indicate an increase of CO_2 concentration when a person enters the room and a decrease when leaves.

Test ID	Accuracy	Sensitivity	Specificity	Stimuli[m]	Interstimuli[m]
1CO	0%	0%	0%	4	2
2CO	50%	50%	0%	8	4
3CO	100%	100%	100%	20	10
4CO	100%	100%	100%	30	15

Table 4.13: Trial data from the Co2 Sensor (CO) labelled as True Positives, True Negatives, False Positives, and False Negatives

4.2 Study 2 - EDL Classification

The following section presents the obtained results from Study 2 - EDL Classification. The purpose of this study is to investigate the usage of a broad range of sensors and the data acquired from those sensors to be combined in a distributed home for monitoring EDLs adressing research question (**RQ4**) and objective **O4, O5** and **O6**.

This study was conducted by using the RDA platform, presented in the methods chapter and the data collected while the participants were performing different EDLs. Moreover, it will be demonstrated of how a feature vector is generated from raw data. The sections on DT and KNN include model selection, classification and evaluation.

4.2.1 Feature Creation

Figure shows an example of how raw data was transformed into a feature vector. The feature vector present only shows the dimensions impacted by the raw from the PIR sensors. As it can be seen, the Start and End markers specify the time interval for the performed scenario.

The PIR activity dimensions in the feature vector are defined such that if the PIR sensor fires in the ninety second time interval, the dimension is set to one otherwise the dimension is set to zero. The timestamp from a PIR firing is added from the Start event timestamp and the jumps in time are the PIR firing intervals.

The raw data contais both PIR Living Room and Bathroom presence events which is why sometimes the PIRs are set to one. Finally the active time is possible to be extracted , by subtracting the last 1, indicating presence and the closest 0, indicating absence.

Sensor	TimeStamp
Start	1581933590
PIR Living Room	1581933600
PIR Bathroom	1581933600
PIR Living Room	1581933630
PIR Living Room	1581933720
PIR Bathroom	1581933750
PIR Living Room	1581933810
PIR Living Room	1581933820
PIR Bathroom	1581933840
PIR Living Room	1581933910
PIR Living Room	1581934000
End	1581934010

Feature Vector= [0 0 1 1 1 0 1 0 1 0]

PIR Bathroom and Living Room activity in 90 seconds intervals

Figure 4.1: Raw data transformed into a feature vector. Only the dimensions impacted by the sensor firings are included

4.2.2 Scenario 1 - Sleeping Activity

The Scenario 1 as explained in chapter 3 - Methods, section 3.7 - EDL Scenarios, subsection 3.7.1. The activity to be analyzed is the Sleeping Activity, which constitutes a basic acitivity of daily living.

4.2.2.1 Scenario 1A

The subscenario 1A consisted on the the test subject lying down in bed and decide to sleep for the next hour. The expected result matched the actual result obtained as can be seen in the figure 4.2, which demonstrates the behavior of the sensor throughout the experimental scenario. The pre-processing method was an active low-pass filter.

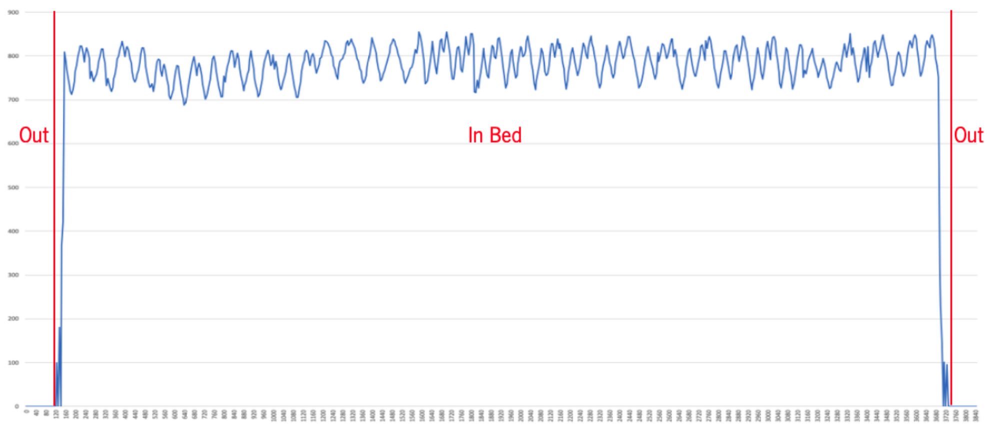


Figure 4.2: Scenario 1A graphical representation

The sensor, consisting of a capacitive sensor, could have been configured in three different ways: buttons, sliders, and proximity sensors. The scope of application, led to the programmed configuration being as proximity sensor. All software parameters were adjusted and the auto tuning algorithm was removed since the tuning process was manual.

The value on the y-axis corresponds to capacitance (Cx) of the capsense converted into a raw count value. As the sensor has two loops, the output is the result of the difference between the values obtained by both loops- differencial count.

The red lines symbolize when the test subject got into bed and left. The intermediate period symbolizes the static activity, which is the period in time where the subject is still and has no motion or movement in any dimension. The motion before and after the sleeping static activity can also be seen as an acitvity, a dynamic activity or a transition activty. In this particular case, consisted a stand-to-lay down and and lay down-to-stand.

4.2.2.2 Scenario 1B

Similar to scenario 1A, the scenario 1B consisted on the test subject lying down for little recovery. The actual result can be seen in figure 4.3. The test subject performed two short breaks, both of 10 min each and standing for time intervals of 2 min each.

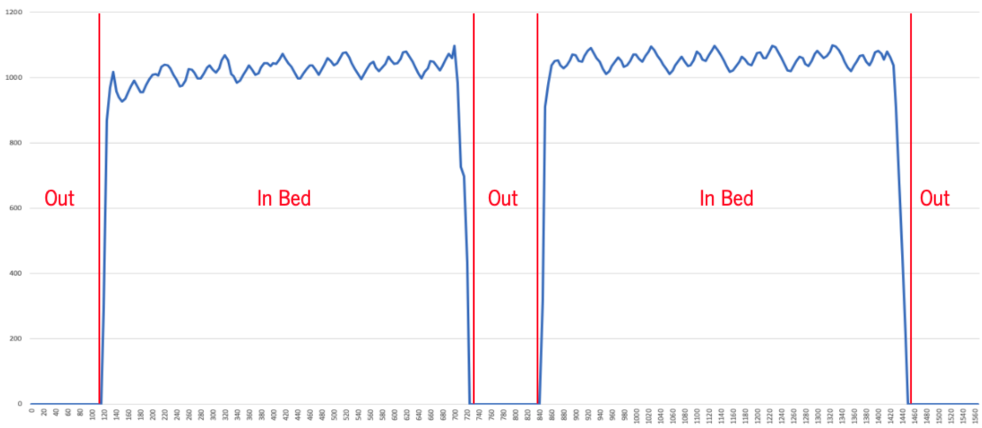


Figure 4.3: Scenario 1B graphical representation

The transitions between states are quite clear due to the quick response of the sensor in increasing its differential count value. The differencial count value was higher in relation to the first scenario, due to the part of the body positioned vertically parallel to the sensor. In the first scenario, it was the head of the test subject and in this it was the chest area, thus increasing the contact surface.

4.2.3 Scenario 2 - Seated Activity

The scenario 2 as explained in chapter 3 - Methods, section 3.7 - EDL Scenarios, subsection 3.7.2, consisted on analyzing Seated Activity. The sensor was placed on the foam of the chair vertically. The expected result matched the actual result obtained as can be seen in the figure 4.4.

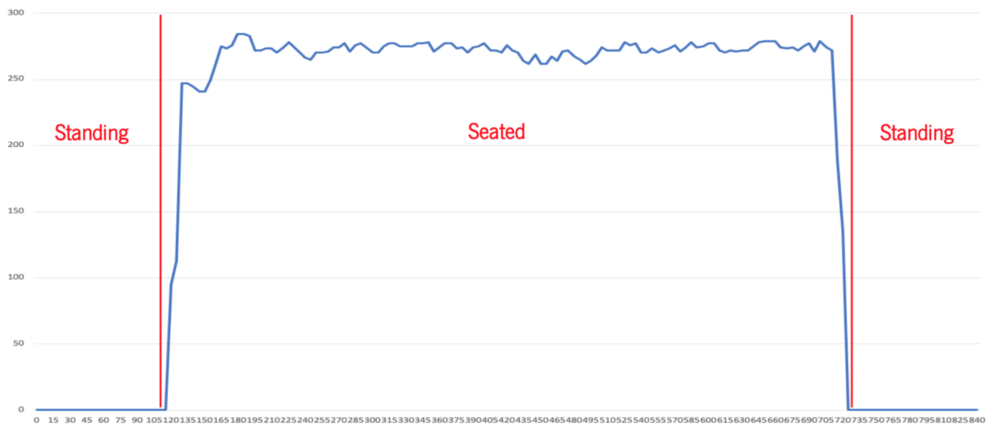


Figure 4.4: Scenario 2 graphical representation

As described in the scenario expected result, the main condition was that the test subject would remain completely upright on the chair for 10 minutes, since by being configured as a proximity sensor, the proximity of the back of the test subject to the sensor will influence the results to be obtained.

The transitions between states are also easily noticeable, as in scenario 1, a static activity - Sitting and two dynamic activities, stand-to-sit and sit-to-stand.

4.2.4 Scenario 3 - Walking Activity

The Scenario 3 as explained in chapter 3 - Methods, section 3.7 - EDL Scenarios, subsection 3.7.3, consisted on analyzing is the Walking Activity, which constitutes a basic activity or depending on the context, can be considered as a transiction or ambulatory activity.

The scenario consisted on the the test subject walking around the living room area. The expected result matched the actual result obtained as can be seen in the figure 4.5, which demonstrates the firing behavior and steady state of the sensor throughout the experimental scenario.

The first red line symbolizes when the test subject entered the room. The PIR sensor fires and goes to "presence state". The intermediate period symbolizes the sensor active state, indicating presence in the area. During this period of time, the PIR signals activity in the living room, as can be seen in the red line indicating PIR fires presence. After a minute of signaling, the test subject

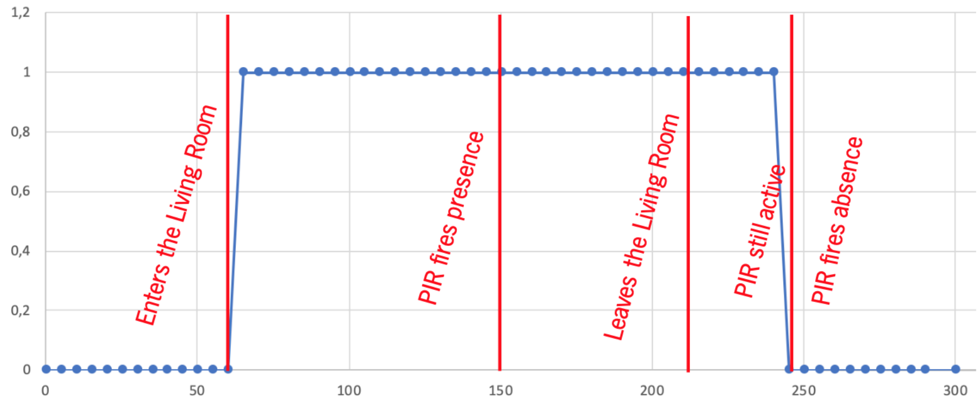


Figure 4.5: Scenario 3 graphical representation

leaves the living room. The sensor remains active until the 90 seconds seconds sleep time and then, the PIR fires absence.

4.2.5 Scenario 4 - Fall

The Scenario 4 as explained in chapter 3 - Methods, section 3.7 - EDL Scenarios, subsection 3.7.4, consisted on detecting a fall and try to simulate a fall as close as possible to a case that resembles a real case. This is the most complex scenario, due to being within the edl category, an adverse event. The test subject wakes up during the night and goes to the toilet. Leaves the toilet and falls on returning to bed, cannot get up, lying on the floor for the next hour.

The fall scenario can be seen as a combination of the previous scenarios, since in order to detect a fall without the use of a type of wearable sensor, such as an accelerometer on the patient's wrist, the strategy consisted on following a timeline of events. Based on the present event, knowing the past event and the current state of all sensors involved in the scenario, the current sequence would be analyzed in a 10 minute time window.

A Fall was categorized as a composition of activities which means that is a complex activity and thus, is composed of an ordered succession of simpler activities. The ordering of the simple activities was defined so that it was a possible scenario to happen in real life and the activities have time-related connections to each other. As states of this scenario: unknown state, which is not possible to know the patient's activity at that time, sleeping, which indicates that the patient is in bed sleeping, walking, counted as a transient state, which means that there will be a state transition, toileting state indicating that the patient is in the bathroom and fall state.

Ideally, the training set should be labelled from real-world data. However, this was not possible, and therefore both classification schemes were trained using a generated data set. As an attempt to bring the perspective of time and context into the classification models, Last Class was added to the feature vector.

The alternative method was a sliding window, where sensor data accumulates over a period. This generates and activity and heat map and therefore provided the perspective of time and context. This method is suitable because it was chosen a sensor high transmission rate.

4.2.5.1 K-Nearest Neighbour (KNN) Classifier

In KNN, k is configured to 4, which means that four of the nearest neighbours define the output. Usually, an increasing k provides more stable predictions than in cases where k = 1, as majority voting is producing the outcome instead of a single near neighbour. Increasing k above a certain point would lead to an increased number of errors.

The optimal value of k can be found by running iterative cross-validation and increment the value of k in each iteration. The value of k is then chosen based on the most accurate results. However, the results of the KNN classifier, indicate that no further optimisation for k can be achieved and the value of k is therefore not investigated.

As mentioned in chapter 3, section 3.8.0.3 - Evaluation Criteria, using accuracy alone as the only reporting metric often results in a poor reporting. Thus, alongside the classification accuracy metric , three other classification metrics were used: Recall, Precision and F1 Score, all of them described by the equation (3.5, 3.6, 3.7) in chapter 3, section 3.8.0.3.

Table 4.14 present the result of a validation set for KNN. The full set accuracy was 96%. The results obtained are dependent on the use of the training data set and the remaining data set used as a test.

KNN

State	Precision	Recall	F1 Score
Unknown	98%	100%	99%
Sleeping	100%	95%	98%
Walking	40%	100%	58%
Toileting	92%	93%	92%
Fall	96%	99%	98%

Table 4.14: Results for testing validation using KNN

In the case of the table 4.15 , the results were obtained using a particular instance of cross validation - leave-one-out cross-validation.The full set accuracy was 94%. The train data set and test data set were the same ones used to obtain the results of the table 4.14.

KNN Leave-One-Out Cross Validation

State	Precision	Recall	F1 Score
Unknown	95%	97%	96%
Sleeping	98%	94%	96%
Walking	31%	64%	42%
Toileting	89%	84%	86%
Fall	96%	99%	97%

Table 4.15: Results of leave-one-out cross-validation for KNN

4.2.5.2 Decision Tree (DT) Classifier

In Decision Tree, the algorithm used was the C4.5, which constitutes a decision tree type of classifier. The main advantage when using this algotrithm was that it inherently mitigates the model overfitting. As it happened with KNN, the results obtained are dependent on the use of a training data set and remaining data set used as a test.

Table 4.16 present the result of a validation set for DT.The full set accuracy was 87%.

Decision Tree

State	Precision	Recall	F1 Score
Unknown	63%	100%	77%
Sleeping	100%	93%	96%
Walking	45%	100%	87%
Toileting	98%	68%	81%
Fall	70%	84%	77%

Table 4.16: Results for testing validation using DT

In the case of the table 4.15, the results were obtained using leave-one-out cross-validation. The full set accuracy was 86%

Decision Tree Leave-One-Out Cross Validation

State	Precision	Recall	F1 Score
Unknown	63%	100%	77%
Sleeping	97%	92%	95%
Walking	0%	0%	N/A
Toileting	98%	66%	79%
Fall	66%	83%	74%

Table 4.17: Results of leave-one-out cross-validation for DT

4.2.6 Further Investigation

The purpose of this investigation was to estimate the number of people in a room in which a constant CO_2 concentration is being maintained for environmental comfort. In this experiment, to test the variation of the air flow and consequently the change in the concentration of CO_2 in the space, it was simulated that the test subject was in the room and that it opened a window, signaled by the label -ventilation.

The AAL Lab was not possible to fully perform this test due to several factors. One crucial aspect was the fact of having a fan that does the ventilation of the space. Having a fan that does the ventilation of the space and therefore the concentration of CO_2 is always being influenced by the variable-amount of ventilation. Secondary experiments were performed, such as the one represented in figure 4.6.

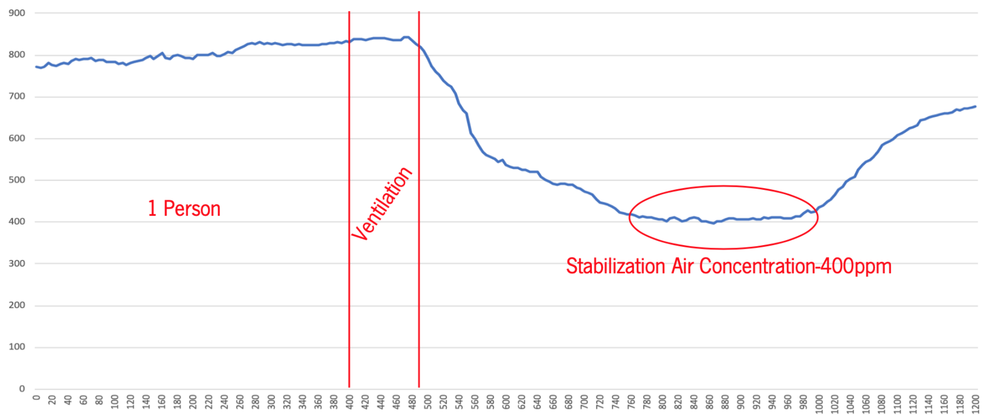


Figure 4.6: CO_2 behaviour graphical representation

The window was open for about a minute, which caused a noticeable drop in the concentration of CO_2 , which was also sufficient for the sensor to find a stabilization point, precisely at the concentration of CO_2 for which it had been calibrated - fresh air (400ppm).

As a future measure, it was suggested to use a more robust sensor and a space with a controlled CO_2 concentration before any experiment was carried out.

Chapter 5

Discussion

The following chapter discuss the obtained results and the selected methods used in this dissertation. Initially the methods for obtaining knowledge in the background study will be discussed. This is followed by a discussion of methods used and obtained results for Study 1 - Validity & Reliability and Study 2 - EDL Classification.

5.1 Preliminary conclusion RQ1

RQ1 *Which AAL technologies have been used to support the elderly and caregivers?*

As mentioned in section 2.1 of Chapter 2 - Background & Related Work, the services supporting the elderly and caregivers, include the possibility of creating an intelligent environment to reduce the use of dedicated nursing personnel care or avoid the hospitalization.

The shift in healthcare was possible due to the emergence of Ambient Assisted Living environments, which has been reflected in the use of platforms such as smart home care setups (section 2.1.1), converging the usage of embedded system devices and some of the most used pervasive sensing technologies (section 2.1.2) such as: Passive Infrared (PIR) Motion Sensors, Pressure Sensors, Video Sensors and multicomponent setups, combining more than one of these monitoring technologies.

5.2 Preliminary conclusion RQ2

RQ2 *Which methods have been used to monitor and classify EDL?*

Building the bridge between AAL environments and support the elderly and caregivers, it was important to adress which activities are perfomed inside this environments in a daily basis. As mentioned in section 2.2 of Chapter 2 - Background & Related Work, is presented the concept of Events of Daily Living (EDL), being defined as a category of events that include all events or activities a person could perform throughout a day. The three subcategories identified and defined according to the literature were: ADL, IADL and AE.

As mentioned, the present dissertation focused on the analysis of ADL defined as the common, everyday self-care skills we all need to live safely and independently on a day-to-day basis, and AE defined as unintended events like a fall that leads to negative health consequences.

From a learning perspective, the EDL classifcation tasks requires learning a decision rule or a function associating the inputs data to the classes (activities). The two main directions in machine learning techniques: supervised and unsupervised approaches. The focus was on the supervised learning models for human activity recognition applications, KNN and DT, being train-based methods applied to recognize EDL.

5.3 Study 1 - Validity & Reliabilty

This section will provide a discussion of the methods used and the obtained results from Study 1 - Validity & Reliability.

5.3.1 Discussion of methods

Study 1 - Efficacy Study investigated each sensor as a stand-alone solution to validate the performance and reliability of the sensor. The purpose of this study was to ensure that each sensor performed as expected before being combined in a multi-sensor in Study 2- EDL Classification.

The sensors have all been tested, including sensors in the same category/same features, which means that each sensor has been individually tested e.g. both PIR sensors have been tested and not only the PIR Bathroom or the PIR Living Room. The sensors were also tested in the same location in Study 1 - Validity & Reliability as they were in Study 2 - EDL Classification. Therefore, were able to reveal any potential problems with the future test location and in this way, the sensors would perform exactly the same way.

The PIR sensor had only one available dormant setting which were one and half minutes. It could not be set to anything in between 5 or 10 seconds. In the two studies of this dissertation the dormant time setting was a compromise between the temporal resolution of the other sensors data and the battery lifetime, which was not investigated in this dissertation.

5.3.2 Discussion of results

The results from analysing the validity and reliabilty of the PIR Sensor Living Room are presented in 4.3, where the accuracy in test 1PLR, 2PLR and 3PLR were 100% and 50% in test 4LPR. As explained, it was not possible to calculate the sensitivity and specificity in 3PLR and 4PLR due to the definition of the test scenario and particularly in test 4LPR the sensor was stimulated twice as fast as the dormant time, expecting a maximum accuracy of 50%.

The stimulated time that caused the low accuracy by the many false positives, is the worst case scenario since in order to make the times more reliable, the timestamp is defined by the sensor at the stimulus time and not by the server when it receives the data, thus avoiding the small delay that could be introduced by the data transmission.

The same procedure was performed for the PIR Bathroom. Being both PIR sensors equal, it was expected that the behavior of both would be the same or similar, which turned out to be the case.

The results in table 4.7, for the Bed sensor shows that it was able to detect whether a person was absent or present in bed with an accuracy, sensitivity and specificity of 100% for all the the stimuli/interstimuli time, being able to conclude that changing the time frames, it would not affect the sensor responsiveness and behaviour, turning out to be a valide and reliable sensor to be used further in the Study 2 - EDL classification in order to classify EDLs. The results in table 4.10, for the Chair sensor, show that the device was to detect whether a person is seated on the chair or standing with an accuracy, sensitivity and specificity of 100% for all the the stimuli/interstimuli time. In this test protocol, as it was verified with the bed sensor, the same sensor was applied with a different internal configuration. It was possible to conclude that a setup change would not change the sensor behaviour, safeguarding a new configuration according to its installation environment.

The results for the in table 4.13. The accuracy in test 1CO, 2CO, 3CO and 4CO were 0%, 50%, 100% and 100%. Th results on test 3CO and 4CO were the test with the biggest stimuli and interstimuli time, which consequently makes the sensor have a longer time to acquire the concentration of CO_2 gas and thus stabilize its behavior. In this case, the sensor has proved to be reliable if the sensor limitations were not put to the test, like in scenario 1CO and 2CO, where the sensor delay in acquiring the data about the environment that surrounds it, led to a fall on the value of the evalutation metrics.

5.4 Preliminary conclusion RQ3

RQ3 *To what specifity, sensitivity and accuracy does a single sensor perform classifying basic activities of daily living?*

All five sensors were able to reach a higher accuracy, sensitivity, and specificity close to or at 100%, but the results also showed that the accuracy, sensitivity, and specificity decreased drastically to 0% and 50% when the sensor's limitations were put to test.

5.5 Study 2 - EDL Classification

This section provides a discussion of the methods used and the obtained results from Study 2 - EDL Classification.

5.5.1 Discussion of methods

During Study 2 - EDL Classification several issues were experienced with the setup. One of these issues were related with the PIR sensors and with the data delivering - when a sensor were stimulated, for instance walking in front of a PIR sensor, the data from the sensor did not reach the raspberry pi, so it was not being possible to work as a gateway, converting messages from the zigbee protocol to the Message Queue Telemetry Transport (MQTT) protocol and sending them to the server.In some cases a default connection failure message was sent. A room between the lab had a lot of electrical equipment, which could generate a lot of noise and that could be a reason why the sensors had issues with delivering data. Furthermore, this issue was solved through a signal repeater to improve the PIR communication range and by changing its positioning to another bathroom. Alongside this issue, other difficulties were overcome. They will be elaborated later in the discussion on the feasibility of using this broad range of sensors in a distributed home setting for monitor EDL, RQ4.

5.5.1.1 EDL Scenarios

In this dissertation four EDLs were chosen to investigate whether it was feasible to classify EDLs with commercial off-the-shelf-sensors. These EDLs were chosen based on an investigation of the literature and what was feasible within the laboratory setting.

The scenarios were inspired from the literature but the time consumption of EDLs were adjusted to make each scenario feasible. The four EDLs give an insight in the feasibility of classifying EDLs with commercial off-the-shelf sensors.

To gain a more comprehensive understanding, more EDLs need to be included to be adjusted to the several range of activities performed in a day time and the time consumption of EDLs needs to be adjusted to a more realistic one.

Several studies investigated the feasibility of using sensors to identify EDL, such as those taken from the literature present in chapter 2 - Background & Related work, applied to the area of smart home care, in which different pervasive sensing technologies are used.

A common issue with the literature is that it is rarely described how they define EDL, thus making it impossible to reproduce the experiments, and if they do, the installation environment of the sensors differs as well as the participants' own behavior, so it is not possible to make a linear comparison between both works.

5.5.1.2 Data processing & Evaluation

The feature vector allows for an interpretation of the raw sensor data. In the current format the EDLs time span limits the feature vector because the feature vector always span one and half minutes. This time span was ideal for this dissertation since it covered the longest EDL, but in real life EDLs does not have the same time span. An advantage of using the feature vector is that it allows the current solution to be extended with more sensors because more dimensions could be added to describe new sensors or new sensor types.

As in many classification problems, extracting large numbers of features normally provide high classification accuracy but require considerable computational resources. Extracting low number of features requires small computation resources but provide low classification accuracy because the features contain a small number of values for certain classes. The ideal process is a low number of very representative features from raw sensor data.

When evaluating an ML model, a division is made between the training set and the validation set. By separating the data it would be possible to estimate the true validation error of the chosen classifier, in this case either KNN or DT, by using the training set to train the model and the validation set to validate the model. As mentioned in chapter 3 - Methods, this study used a particular instance of cross validation, the leave-p-out method. The value of p = 1. This is known as Leave-one-out cross validation. Other works have used an alternative to k-fold cross-validation which is called Leave-One-Out-Cross-Validation.

The Leave-one-out method is generally preferred over the K-fold because it does not suffer from the intensive computation, as number of possible combinations is equal to number of data points in original sample or n.

5.5.2 Discussion of results

The raw data for Study 2 - EDL Classification was obtained from the EDL scenarios, where the commercial-of-the-shelf sensors were used to monitor the test subject behaviour.After the data being collected the raw sensor data was transformed into a comprehensible format - a feature vector. Hereafter the two statistical models - KNN and DT - were applied to the feature vector in combination with Tleave one-out crossvalidation. The following section discuss the obtained result for KNN and DT.

5.5.2.1 K-Nearest Neighbout (KNN)

Table 4.14, shows the Precision, Recall and F1 Score obtained by KNN using the validation set or test set. The full accuracy was 96%, the precision range in majority between 92% to 100%. The lowest precision was the walking activity, but since it is an ambulatory or transisition activity, the PIR sensors would fire sometimes, even if it is not intended to happen, leading to the presence of several false positives.The recall was between 93% and 100%.The F1-Score was between 92% and 100%, except the walking activity, since f1-score depends on both Precision and Recall, and the Precision metrics being low will influence the F1-Score metric.

Table 4.15, page 80, shows the Precision, Recall and F1 Score obtained by KNN using the particular instance of cross validation: leave-one-out cross-validation. The full accuracy was 94%, the precision range between 89% and 98%, except for the walking activity as it did happen in KNN model. The recall was between 84% and 99% and the f1-score between 86% and 97%.

5.5.2.2 Decision Tree (DT)

Table 4.16, show the Precision, Recall and F1 Score obtained by DT using the validation set or test set. The full accuracy was 87% , the precision range in majority between 63% and 100% .The recall was between 68% and 100%.The F1-Score was between 77% and 96%.

Table 4.17, shows the Precision, Recall and F1 Score obtained by DT using leave-one-out cross-validation. The full accuracy was 86%, the precision range between 63% and 98%, except for the walking activity as it did happen in KNN model. The recall was between 66% and 100% and the f1-score between 74% and 99%.

5.5.2.3 Model Comparisson KNN vs DT

In all the 5 KNN classes had a significant higher Precision, Recall and F1-Score, compared to the corresponding DT model. A reason why KNN performs better than DT could be that KNN does not make any assumptions towards the decision boundaries and it has the ability to handle complex arbitrary boundaries and unlike decisions trees, it can handle multiple attributes and complex interactions.Another reason why KNN performs better than DT could be that not all the assumptions are about spatial distribution or the classifier's structure.

In general both KNN and DT models had a high accuracy. This high accuracy is caused by the definition of true negatives in multi-class classification problems. Every time a scenario was labelled true positive the other scenarios were labelled true negative. Even if the scenario was labelled as false positive, the other scenarios will be labelled as true negative and one will be labelled as false negative. From this, it is obvious that there will be a skewing between the proportion of true positive and true negative and that the accuracy will tend to be high. The equation for accuracy 3.1, contain true negatives on both sides of the fraction line. When the number of true negatives is much higher as big as the other values, it will more or less nullify these measures and the accuracy will artificially be close to 100%.

5.5.2.4 Transferability

If the RDA platform was to be implemented in a real world setting, several considerations needs to be taken into account. Study 2 - EDL Classification relied on time compressed EDLs which differ from real world EDLs. If the EDLs had not been time compressed, they would still differ from real world EDLs since there are many different ways to perform a specific EDL in the real world. In this study, only one of these ways were investigated, e.g. only one way of going to the toilet and one way of laying down in bed.

The feature vector was designed specifically to contain information of one and half minutes or below which is not applicable in a real world setting, since EDLs can have a duration of more than one and half minutes. Therefore, a new interpretation of the raw data is necessary. This could either be done by making the feature vector independent of time, or represent the time in another way, or even make several feature vectors that specifically looks for EDLs with a certain duration.

5.6 Preliminary conclusion RQ4

RQ4 *Is it feasible to use a broad range of sensors and the data acquired from those sensors be combined in a distributed home for monitoring EDL?*

Based on the studies with the research data acquisition platform, it was found feasible to combine a broad range of sensors in a distributed home created in an AAL laboratory setting. In this particular case, the broad range of sensors are represented by two PIR sensors, bathroom and living room, a CO_2 sensor, a bed and a chair sensor.

This dissertation experienced complications when implementing the platform in the AAL laboratory. Among the complications, it is worth mentioning the case of the bed sensor, which suffered from noise interference, due to being placed in proper hospital beds and the bed support being made of metal. The multiplexer used to multiplex the signal from the bed sensor and the chair sensor also suffered some fitting problems with the board, having been changed later.

The CO_2 sensor also suffered some calibration problems since it was not possible to calibrate it involved in a gas with a certain concentration of CO_2. It had to be calibrated outdoors, which brought the problem wind "entering" the filter, inducing error in the calibration algorithm. This process was all carried out manually using the commands sent via the serial port terminal.

The PIR sensors, the installation process was relatively simple. One of the sensors was placed in the bathroom and another in the living room. Communication with the board was established through a zigbee usb stick. Due to the scope of the zigbee protocol and so that the signal from the bathroom was received, a signal repeater was placed on the wall.

Regarding all of this issues and respective adjustements, it was found feasible to combine data from this broad range of sensors to classify EDLs. The data collected was normalized in the form of a feature vector, from which the classification was performed using the ML models, KNN and DT.

Chapter 6

Conclusion

This dissertation investigated the concept of events of daily living and the feasibility of classifying them based on basic sensor inputs from commercial off-the-shelf sensors. More specifically, based on the problem definition, the aim was to devellop and evaluate a multisensorial pervasive research platform with built-in embebbed inteligence capable of monitoring senior citizens and patients under non-critical continuous care on a nursing home and classify their EDL.

The **hypothesis H1** - ”It is feasiable to model and classify EDL based on the input of commercial off-the-shelf sensors”. By analysing this hypothesis, two research questions (**RQ1** & **RQ2**) were specified of which two surveys on the literature, Chapter 2 - Background & Related Work, were realized, one to obtain the big picture of the type of pervasive sensing technologies used in one of the branches of AAL - smart home care. The COTS used: bed sensor, chair sensor, PIR sensors and CO_2 sensor, were chosen based on the different projects presented in this surveys on the literature. The other research question reviewed the methods used in EDL classification and based on the review of the literature, was chosen to use KNN and DT. With that being said and based on the two literature surveys, it can be concluded that it was preveously feasible to model and classify EDL based on the input of COTS.

The **hypothesis H2** - ”It is feasible to classify basic activities of daily living based on a basic sensor input from a single sensor”. By analysing this hypothesis, one research question was specified (**RQ3**) of which a study was realized to test and validate each sensor chosen based on the knowledge taken from the hypothesis 1 validation , Study 1 - Validity & Reliability. The study was performed to ensure that each sensor performed as expected before being combined for further investigation. Each sensor was evaluated according to accuracy, sensitivity and specificity. To ensure that the tests are reliable,consistent and reproducible, a series of protocols were designed, chapter 3 - Methods, section Experimental methods. The results showed that all five sensors were able to reach a higher accuracy, sensitivity and specificity, keeping in mind that this evaluation metrics would fall if the sensor´s limitations were put to the test. With that being said and based on the test protocols defined and results obtained, it can be concluded that it would be feasible classify basic activities of daily living based on the input of a single sensor.

The **hypothesis H3** - "It is feasible to combining a broad range of ambient sensors (PIR, Bed, Chair and CO_2) in a distributed home environment for monitoring EDL". By analysing this hypothesis, one research question was specified (**RQ4**) of which a study was realized to investigate the combination and integration of a broad range of sensors(sensors from H1 and tested/validated in H2) to classify EDL. The study used the RDA platform to collect the data from the EDL scenarios, chapter 3 - Methods, section EDL Scenarios. The data collected was analyzed by the ML models chosen in H1 - KNN and DT. Despite some complications for the platform to be stable and ready, the results in chapter - Results showed in general that KNN performed better than DT in classifying the classes: Unknown, Sleeping, Walking, Toileting and Fall. Nevertheless, both ML models had a high accuracy, precision, recall and f1-score. With that being said and based on these results, it can be partially concluded that is feasible to combine these broad range of sensors places in a distributed environment for monitoring EDL. As stated in chapter 5 - Discussion, section Transferability, if the EDLs had not been time compressed, they would still differ from real world EDls, since there are enumorous ways to perform edls and this dissertation cannot guarantee that you metrics results will be high for others cases.Moreover, the lack of participants matching the target group (elderly), can also influence the results.

6.1 Future Work

This section highlights the suggestions for the future work of this dissertation reseach topics. One area that should be improved is the testing methodology. A general problem of the studies is the absence of test participants matching the target group, mainly due to time limitations during my internship at the AAL laboratory and other conditions namely restrictions associated with covid 19.It should be prioritised to conduct the studies, which include ADL, with actual elderly people as test participants, as originally intended.

The fall scenario could be improved regarding the lack of a more extensive dataset. Due to the fact that real falls are not a part of the experimental protocol, elderly people can unproblematically perform the experiments, as the original plan proposed. It is suggested to perform a clinical trial at a nursery home care.

The RDA platform architecture is completely malleable, in the sense that it was designed to support the addition of other sensors to the platform. It could be relevant to work around it, namely through the addition of wearable technology, since this dissertation only focused on ambient sensors and wearable sensor have not been investigated regarding their ability to monitor EDL. It is possible that including the wearable technologies into a platform like the one develloped in this dissertation, would expand the possibilities of monitoring EDL and maybe yield better results at the classification metrics used and the same applies to other classification methods, to investigate whehter they have performed better than KNN and DT.

The addition of wearable technologies will be carried out by other master students of the ambient assisted living course at Aarhus University. In one case, it will consist of using the built-in accelerometer in the smartphone and the platform developed in this dissertation. This way, they can collect information from the platform and complementary information from the smartphone, namely the number of steps and the regularity of time to tackle a sedentary lifestyle. In another case,the master students will devellop a graphical platform, in which it will be possible to see the data collected by the RDA platform in real time and thus assist in a more intuitive and graphical way the caregivers.

Another interesting perspective is that the RDA platform could be extended to receive and persist other health-related information such as heart rate, blood oxygen saturation. In these situations, a health care professional may be able to determine correlations between the activity level and health related information, potentially discovering precursors of diseases or the existence of a chronic disease that had not yet been diagnosed. These considerations are, however, long-term future work and inspired on long-term monitoring scenarios.

References

[1] M. Kroezen, G. Dussault, I. Craveiro, M. Dieleman, C. Jansen, J. Buchan, L. Barriball, A. M. Rafferty, J. Bremner, and W. Sermeus, "Recruitment and retention of health professionals across Europe: A literature review and multiple case study research," *Health Policy*, vol. 119, no. 12, pp. 1517–1528, 2015.

[2] European Commission Economy Series, *The Ageing Report*, 2015.

[3] World Health Organization, "Ageing and health," 2018.

[4] European Commision, "Europe's population is getting older.how will this affect us and what should we do about it?" *European Commission Press Release Database*, March 2005.

[5] J. R. Knickman and E. K. Snell, "The 2030 problem: caring for aging baby boomers." *Health services research*, vol. 37, no. 4, pp. 849–84, August 2002.

[6] E. Debén, T. Gallego, M. Perez, M. Gomez, J. Serra, E. Ramirez, A. Ibañez, C. Martinez, E. Alañon, and A. Morell, "DI-024 Cetuximab in the treatment of advanced metastatic colorectal cancer," *European Journal of Hospital Pharmacy*, vol. 21, pp. A79.2–A80, 2014.

[7] AAL, "AAL Forum 2014," 2014.

[8] S. J. Bartels and J. A. Naslund, "The Underside of the Silver Tsunami — Older Adults and Mental Health Care," *New England Journal of Medicine*, vol. 368, no. 6, pp. 493–496, feb 2013.

[9] G. Mancioppi, E. Castro, L. Fiorini, M. Maselli, C. Laschi, F. Cecchi, and F. Cavallo, *The use of smart tools for combined training of people with MCI: A case report*. Springer International Publishing, March 2018, vol. 544.

[10] A. M. Sisko, S. P. Keehan, J. A. Poisal, G. A. Cuckler, S. D. Smith, A. J. Madison, K. E. Rennie, and J. C. Hardesty, "National Health Expenditure Projections, 2018–27: Economic And Demographic Trends Drive Spending And Enrollment Growth," *Health Affairs*, vol. 38, pp. 491–501, 2019.

[11] Bailey Bryant, “Caregiver Shortage Could Mean 7.8 Million Unfilled Jobs By 2026 - Home Health Care News,” 2019.

[12] I. A. de Carvalho, J. Epping-Jordan, A. M. Pot, E. Kelley, N. Toro, J. A. Thiyagarajana, and J. R. Beard, “Organizing integrated health-care services to meet older people’s needs,” *Bull World Health Organization*, 2017.

[13] X. Scheil-Adlung, “Long-term care protection for older persons: A review of coverage deficits in 46 countries,” *International La*, no. 50, p. 115, 2015.

[14] A. Mastropietro, C. Roecke, S. Porcelli, J. del Bas, N. Boquè, L. F. Maldonado, and G. Rizzo, “Multi-domain Model of Healthy Ageing: The Experience of the H2020 NESTORE Project-Italian AAL Forum 2018,” 2019, pp. 13–21.

[15] M. Rebhan, “Towards a systems approach for chronic diseases, based on health state modeling,” 2017.

[16] World Health Organization, “Targets and beyond – reaching new frontiers in evidence,” 2015.

[17] S. Spinsante, M. Fagiani, M. Severini, S. Squartini, F. Ellmenreich, and G. Martelli, “Depth-Based Fall Detection: Outcomes from a Real Life Pilot.” Springer, Cham, July 2019, pp. 287–299.

[18] J. Miranda, J. Cabral, S. R. Wagner, C. F. Pedersen, B. Ravelo, M. Memon, and M. Mathiesen, “An open platform for seamless sensor support in healthcare for the internet of things,” *Sensors (Switzerland)*, vol. 16, no. 12, pp. 1–22, 2016.

[19] J. E. Bardram, “Pervasive healthcare as a scientific discipline,” *Methods of Information in Medicine*, vol. 47, no. 3, pp. 178–185, 2008.

[20] P. Rashidi and A. Mihailidis, “A survey on ambient-assisted living tools for older adults,” *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 3, pp. 579–590, 2013.

[21] A. N. Belbachir, M. Drobics, and W. Marschitz, “Ambient assisted living for ageing well - An overview,” *Elektrotechnik und Informationstechnik*, vol. 127, no. 7-8, pp. 200–205, 2010.

[22] M. Memon, S. R. Wagner, C. F. Pedersen, F. H. A. Beevi, and F. O. Hansen, “Ambient Assisted Living healthcare frameworks, platforms, standards, and quality attributes,” 2014.

[23] F. C. Delicato, L. Fuentes, N. Gámez, and P. F. Pires, "Variabilities of Wireless and Actuators Sensor Network Middleware for Ambient Assisted Living."

[24] A. Mihailidis, J. Boger, J. Hoey, and T. Jiancaro, "Zero-effort technologies considerations,chalenges and use in health, welness, and rehabilitation," *Synthesis Lectures on Assistive, Rehabilitative and Health-Preserving Technologies*, 2011.

[25] S. Blackmana, C. Matlo, C. Bobrovitskiy, A. Waldoch, M. Fang, P. Jackson, A. Mihailidis, L. Nygard, A. Astell, and A. Sixsmith, "Ambient Assisted Living Technologies for Aging Well: A Scoping Review," *Journal of Intelligent Systems*, January 2016.

[26] N. M. Garcia and J. J. P. Rodrigues, "Ambient assisted living," *Ambient Assisted Living*, pp. 1–691, 2015.

[27] P.Rashidi and D. J. Cook, "The resident in the loop: Adapting the smart home to the user," *IEEE Trans. Syst., Man, Cybern. A, Syst., Human*, pp. 949–959, 2009.

[28] B. W. Pickering, J. M. Litell, V. Herasevic, and O. Gajic, "Clinical review: The hospital of the future - building intelligent environments to facilitate safe and effective acute care delivery," 2012.

[29] G. Appelboom, E. Camacho, M. E. Abraham, S. S. Bruce, E. L. Dumont, B. E. Zacharia, R. D'Amico, J. Slomian, J. Y. Reginster, O. Bruyère, and E. S. C. Jr, "Smart wearable body sensors for patient self-assessment and monitoring," *Archives of Public Health*, 2014.

[30] R. Kavith, G. M. Nasira, and N. Nachama, "Smart home systems using wireless sensor network – a comparative analysis," 2012.

[31] P. Rashidi and D. J. Cook, "Keeping the resident in the loop: Adapting the smart home to the user," *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, vol. 39, no. 5, pp. 949–959, 2009.

[32] M. J. Rantz, M. Skubic, R. J. Koopman, L. Phillips, G. L. Alexander, S. J. Miller, and R. D. Guevara, "Using sensor networks to detect urinary tract infections in older adults," *IEEE 13th International Conference on e-Health Networking, Applications and Services*, pp. 142–149, 2011.

[33] A. M. Adami, M. Pavel, T. L. Hayes, and C. M. Singer, "Detection of Movement in Bed Using Unobtrusive Load Cell Sensors," 2009.

[34] G. Abowd and E. Mynatt, “Designing for the human experience in smart environments,” pp. 151 – 174, January 2004.

[35] B. Bouchard, S. Giroux, and A. Bouzouane, “A keyhole plan recognition model for alzheimer’s patients: First results.” *Applied Artificial Intelligence*, pp. 623–658, August 2007.

[36] E. Tapia, S. Intille, and K. Larson, “Activity recognition in the home using simple and ubiquitous sensors,” March 2004, pp. 158–175.

[37] Vic Callaghan, Jeannette Chin, Victor Zamudio,Graham Clarke, Anuroop Shahi and Michael Gardne, “Evaluation of pir detector characteristics for monitoring occupancy patterns of elderly people living alone at home,” *Journal of Management Information Systems*, vol. 2007, 2007.

[38] G. LeBellego, N. Noury, G. Virone, M. Mousseau, and J. Demongeot, “A model for the measurement of patient activity in a hospital suite,” *IEEE Transactions on Information Technology in Biomedicine*, pp. 92–99, 2006.

[39] M. Bhuiya, “Ambient assisted living using sensor and mobile technologies for elderly people,” *IJARCCE*, vol. 4, pp. 659–667, December 2015.

[40] M. Chan, E. Campo, and D. Estève, “Assessment of activity of elderly people using a home monitoring system,” *International Journal of Rehabilitation Research*, no. 1, pp. 69–76, 2005.

[41] T. Adlam, R. Faulkner, R. Orpwood, K. Jones, J. Macijauskiene, and A. Budraitiene, “The installation and support of internationally distributed equipment for people with dementia,” *IEEE transactions on information technology in biomedicine : a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 8, pp. 253–7, 10 2004.

[42] M. Nick and M. Becker, “A hybrid approach to intelligent living assistance,” October 2007, pp. 283–289.

[43] B. V. Grootven and T. van Achterberg, “The european union’s ambient and assisted living joint programme: An evaluation of its impact on population health and well-being,” *Health Informatics Journal*, 2014.

[44] G. M. Youngblood, L. B. Holder, and D. J. Cook, "Managing adaptive versatile environments," *Proceedings - Third IEEE International Conference on Pervasive Computing and Communications*, pp. 351–360, 2005.

[45] M. Perry, A. Dowdall, L. Lines, and K. Hone.

[46] T. Tamura, A. Kawarada, M. Nambu, A. Tsukada, K. Sasaki, Yamakoshi, and Ken-ichi, "E-healthcare at an experimental welfare techno house in japan," *The open medical informatics journal*, pp. 1–7, February 2007.

[47] T. Yamazaki, "The ubiquitous home," *International Journal of Smart Home*, February 2007.

[48] Q. Zhang, Y. Su, and P. Yu, "Assisting an elderly with early dementia using wireless sensors data in smarter safer home," *International Conference on Informatics and Semiotics in Organisations*, 2015.

[49] Y. Nishida, T. Hori, T. Suehiro, and S. Hirai, "Sensorized environment for self-communication based on observation of daily human behavior," February 2000, pp. 1364 – 1372.

[50] R. Al-Shaqi, M. Mourshed, and Y. Rezgui, "Progress in ambient assisted systems for independent living by the elderly," 2016.

[51] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *Communications Surveys and Tutorials, IEEE*, vol. 15, no. 3, pp. 1192–1209, 2013.

[52] T. U, Verhagen, B. Zeinstra, Hofman, Odding, P. HA, and K. BW, "Incidence and risk factors of disability in the elderly: the rotterdam study," *Preventive Medicine*, pp. 272–278, 2007.

[53] L. Chen and C. Nugent, "Ontology-based activity recognition in intelligent pervasive environments," *International Journal of Web Information Systems*, pp. 410–430, 2009.

[54] L. Chen and I. Khalil, "Activity recognition: Approaches, practices and trends," *Springer*, pp. 1–31, 2011.

[55] R. J. Gobbens, "Associations of adl and iadl disability with physical and mental dimensions of quality of life in people aged 75 years and older," *PeerJ*, 2018.

[56] U. Taş, A. Verhagen, S. Bierma-Zeinstra, E. Odding, and B. Koes, "Prognostic factors of disability in older people: a systematic review," *British Journal of General Practice*, pp. 319–323, 2007.

[57] C. J. Erickson M., Wolcott J and A. P, "Patient safety: achieving a new standard for care," *National Academies Press.*, 2003.

[58] K. G. I. Schildmeijer, M. Unbeck, M. Ekstedt, and M. L. Nilsson, "Adverse events in patients in home healthcare: a retrospective record review using trigger tool methodology," *BMJ Open*, 2018.

[59] D. McCabe, "Katz index of independence in activities of daily living (adl)," *The Hartford Institute for Geriatric Nursing, New York University, College of Nursing*, vol. 185, 2019.

[60] T. Pincus, J. A. Summey, S. A. Soraci, K. A. Wallston, and N. P. Hummon, "Assessment of patient satisfaction in activities of daily living using a modified stanford health assessment questionnaire," *Arthritis & Rheumatism*, vol. 26, no. 11, pp. 1346–1353, 1983.

[61] D. Wade and C. Collin, "The Barthel ADL Index: a standard measure of physical disability." January 2012.

[62] C. Graf and Hartford Institute for Geriatric Nursing, "The Lawton instrumental activities of daily living (IADL) scale." *Medsurg nursing : official journal of the Academy of Medical-Surgical Nurses*, vol. 17, no. 5, pp. 343–4, 2008.

[63] C. Ozge, A. Ozge, and O. Unal, "Cognitive and functional deterioration in patients with severe COPD," *Behavioural Neurology*, vol. 17, no. 2, pp. 121–130, 2006.

[64] R. W. Brown, "Detection of diabetes," *Journal of the American Medical Association*, vol. 139, no. 7, p. 474, 1949.

[65] N. Rafter, A. Hickey, S. Condell, R. Conroy, P. O'Connor, D. Vaughan, and D. Williams, "Adverse events in healthcare: Learning from mistakes," *QJM: An International Journal of Medicine*, pp. 273–277, 2014.

[66] F. Magdelijns, R. E. M. van Avesaath, E. Pijpers, C. Stehouwer, and P. Stassen, "Health-care-related adverse events leading to admission in older individuals: Incidence, predictive factors and consequences," *European Journal of Public Health*, vol. 26, pp. 743–748, 2016.

[67] R. Datta, M. Trentalange, P. V. V. Ness, J. McGloin, J. Guralnik, M. Miller, M. Walkup, N. K. Nadkarni, M. Pahor, T. Gill, V. Quagliarello, and M. Juthani-mehta, "Serious adverse events of older adults in nursing home and community intervention trials," *Contemporary Clinical Trials Communications*, vol. 9, pp. 77 – 80, 2018.

[68] B. N. Schilit and M. M. Theimer, "Disseminating active map information to mobile hosts," vol. 8, no. 5, pp. 22–32, 1994.

[69] A. K. Dey, "Context-aware computing: The cyberdesk project," *Proceedings of the AAAI 1998 Spring Symposium on Intelligent Environments*, pp. 51–54, 1998.

[70] P. J. Brown, "The stick-e document: a framework for creating contextaware application," vol. 8, pp. 259–272, 1995.

[71] A. Gregory and A. Brown, "Towards a better understanding of context and context-awareness," pp. 304–307, 1999.

[72] G. Abowd, J. Hong, S. Long, R. Kooper, M. D. Pinkerton, and C. Atkeson, "Cyberguide: A mobile context-aware tour guide," 1997.

[73] K. Cheverst, N. Davies, K. Mitchell, A. Friday, and C. Efstratiou, "Developing a context-aware electronic tourist guide: some issues and experiences," *Proceedings of the SIGCHI conference on Human factors in computing systems*, vol. 3, pp. 17–24, 2000.

[74] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, "Systems, man, and cybernetics, part c: Applications and reviews," *IEEE Transactions*, vol. 42, no. 6, pp. 790–808, 2012.

[75] J. K. Aggarwal and M. S. Ryoo, "Human activity analysis: A review," *ACM Computing Surveys (CSUR)*, vol. 43, no. 3, p. 16, 2011.

[76] T. V. Kasteren, A. Noulas, G. Englebienne, and B. Krose, "Accurate activity recognition in a home setting,," *Proceedings of the 10th international conference on Ubiquitous computing,*, pp. 1–9, 2018.

[77] K. V. Laerhoven, A. Schmidt, and W. Gellersen, "Multi-sensor context aware clothing," *Proceedings. Sixth International Symposium*, pp. 49–56, 2002.

[78] L. Liao, D. Fox, and H. Kautz, "Location-based activity recognition using relational markov networks," *19th International Joint Conference on Artificial Intelligence*, pp. 773–778, 2005.

[79] D. H. Wilson and C. Atkeson, "Simultaneous tracking and activity recognition (star) using many anonymous, binary sensors," *Pervasive computing,*, pp. 62–79, 2005.

[80] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *Biomedical and Health Informatics*, vol. 17, no. 3, pp. 579–590, 2013.

[81] R. Duda, P. Hart, and D. Stork, "Pattern classification," January 2001.

[82] A. Krause, D. Siewiorek, A. Smailagic, and J. Farringdon, "Unsupervised, dynamic identification of physiological and activity context in wearable computing," 2012.

[83] L. Rabiner and B. Juang, "An introduction to hidden markov models," *ASSP Magazine,IEEE*, vol. 3, no. 1, pp. 4–16, 1986.

[84] X. Long, B. Yin, and R. M. Aarts, "Single-accelerometer-based daily physical activity classification," *Annual International Conference of the IEEE*, 2009.

[85] L.Wang, T. Gu, X. Tao, H. Chen, and J. Lu, "Recognizing multi-user activities using wearable sensors in a smart home,," *Pervasive and Mobile Computing*, pp. 287–298, 2011.

[86] C. Zhu and W. Sheng, "Human daily activity recognition in robot-assisted living using multi-sensor fusion," *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2154–2159, 2009.

[87] P. Urwyler, L. Rampa, R. Stucki, M. Buchler, R. Muri, U. P. Mosimann, and T. Nef, "Recognition of activities of daily living in healthy subjects using two adhoc classifiers," *BioMedical Engineering OnLine*, 2015.

[88] G. Chauhan, "All about naive baye," 2018. [Online]. Available: https://towardsdatascience.com/all-about-naive-bayes-8e13cef044cf

[89] I. I. B. Kononenko and M. Kukar, "Application of machine learning to medical diagnosis. in: Machine learning and data mining: Methods and applications," 1998.

[90] I. Kononenko, "Machine learning for medical diagnosis: History, state of the art and perspective," *Artif. Intell. Med.*, pp. 89–109, 1998.

[91] J. Demsar, B. Zupan, N. Aoki, M. Wall, T. Granchi, and J. Beck, "Feature mining and predictive model construction from severe trauma patient's data," *Int. J. Med. Inform.*, pp. 41–50, 2001.

[92] R. Abraham, J. Simha, and S. Iyengar, "A comparative analysis of discretization methods for medical data mining with naive bayesian classifier," *Proceeding of the 9th International Conference on Information Technology*, pp. 235–236, 2006.

[93] A. Chakure, "K-nearest neighbors (knn) algorithm," 2019. [Online]. Available: https://towardsdatascience.com/k-nearest-neighbors-knn-algorithm-bd375d14eec7

[94] A. Cufoglu and A. Coskun, "Testing and analysis of activities of daily living data with machine learning algorithms," *International Journal of Advanced Computer Science and Applications*, vol. 7, no. 3, 2016.

[95] F. Attal, S. Mohammed, M. Dedabrishvili, and F. Chamroukhi, "Physical human activity recognition using wearable sensors," 2015.

[96] H. S. Khamis, K. W. Cheruiyot, and S. Kiman, "Application of k- nearest neighbour classification in medical data mining," *International Journal of Advanced Computer Science and Applications*, vol. 4, no. 4, 2014.

[97] G. L. Agrawal and H. Gupta, "Optimization of c4.5 decision tree algorithm for data mining application," 2013.

[98] P. Urwyler, L. Rampa, R. Stucki, M. Büchler, R. Müri, U. Mosimann, and T. Nef, "Recognition of activities of daily living in healthy subjects using two ad-hoc classifiers," *BioMedical Engineering OnLine*, vol. 14, 06 2015.

[99] Eclipse, "Eclipse mosquitto an open source mqtt broker," 2020. [Online]. Available: https://mosquitto.org

[100] G. James, D. Witten, T. Hastie, and R. Tibshirani, "An introduction to statistical learning," *Springer*, vol. 112, 2013.

[101] P. Gupta, "Cross-validation in machine learning," 2017. [Online]. Available: https://towardsdatascience.com/cross-validation-in-machine-learning-72924a69872f

[102] K. Stapor, "Evaluating and comparing classifiers: Review, some recommendations and limitations," *International Conference on Computer Recognition Systems*, pp. 12–21, 2017.