NOVA SCHOOL OF SCIENCE & TECHNOLOGY

DEPARTAMENT OF
ELECTRICAL AND COMPUTER ENGINEERING

Lisa Pereira Michel

BSc in Electrical and Computer Engineering

A Methodology for Trustworthy IoT in Healthcare-Related Environments

MASTER IN ELECTRICAL AND COMPUTER ENGINEERING

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Para a minha avó, Pureza.

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Finally, I would like to thank me for accomplishing all the work I have done and for not giving up.

"The way I see it, if you want the rainbow,
you gotta put up with the rain." (Dolly Parton).

ABSTRACT

The transition to the so-called retirement years, comes with the freedom to pursue old passions and hobbies that were not possible to do in the past busy life. Unfortunately, that freedom does not come alone, as the previous young years are gone, and the body starts to feel the time that passed. The necessity to adapt elder way of living, grows as they become more prone to health problems. Often, the solution for the attention required by the elders is nursing homes, or similar, that take away their so cherished independence.

IoT has the great potential to help elder citizens stay healthier at home, since it has the possibility to connect and create non-intrusive systems capable of interpreting data and act accordingly. With that capability, comes the responsibility to ensure that the collected data is reliable and trustworthy, as human wellbeing may rely on it. Addressing this uncertainty is the motivation for the presented work.

The proposed methodology to reduce this uncertainty and increase confidence relies on a data fusion and a redundancy approach, using a sensor set. Since the scope of wellbeing environment is wide, this thesis focuses its proof of concept on the detection of falls inside home environments, through an android app using an accelerometer sensor and a micro-phone. The experimental results demonstrates that the implemented system has more than 80% of reliable performance and can provide trustworthy results. Currently the app is being tested also in the frame of the European Union projects Smart4Health and Smart Bear.

Keywords: Internet of Things, Data Fusion, Redundancy, Wearable Device, Well Being, Healthcare, Sensorial Data, Elder Population

Resumo

A transição para os chamados anos de reforma, vem com a liberdade de perseguir velhas paixões e passatempos que na passada vida ocupada não eram possíveis de realizar. Infelizmente, essa liberdade não vem sozinha, uma vez que os anos jovens anteriores terminaram, e o corpo começa a sentir o tempo que passou. A necessidade de adaptar o modo de vida dos menos jovens, cresce à medida que estes se tornam mais propensos a problemas de saúde. Muitas vezes, a solução para a atenção que os mais idosos necessitam são os lares de idosos, ou similares, que lhes tiram a tão querida independência.

IoT tem o grande potencial de ajudar os cidadãos idosos a permanecerem mais saudáveis em casa, uma vez que tem a possibilidade de se ligar e criar sistemas não intrusivos capazes de interpretar dados e agir em conformidade. Com essa capacidade, vem a responsabilidade de assegurar que os dados recolhidos são fiáveis e de confiança, uma vez que o bem-estar humano possa depender dos mesmos. Abordar esta incerteza é a motivação para o trabalho apresentado.

A metodologia proposta para reduzir esta incerteza e aumentar a confiança no sistema baseia-se numa fusão de dados e numa abordagem de redundância, utilizando um conjunto de sensores. Uma vez que o assunto de bem-estar e saúde é vasto, esta tese concentra a sua prova de conceito na deteção de quedas dentro de ambientes domésticos, através de uma aplicação android, utilizando um sensor de acelerómetro e um microfone. Os resultados experimentais demonstram que o sistema implementado tem um desempenho superior a 80% e pode fornecer dados fiáveis. Atualmente a aplicação está a ser testada também no âmbito dos projetos da União Europeia Smart4Health e Smart Bear.

Palavras chave: Internet das Coisas, Fusão de Dados, Redundância, *Wearable Device*, Bem Estar, Saúde, Sensores, População Idosa

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ACRONYMS

ADL	Activity of Daily Living
AI	Artificial Intelligence
BLE	Bluetooth Low Energy
CDS	Cloud Database Server
CKD	Chronic Kidney Disease
DNN	Deep Neural Network
EU	European Union
GATT	Generic Attribute Profile
IIoT	Industrial Internet of Things
IoMT	Internet of Medical Things
IoT	Internet of Things
IU	Irregular Uncertainty
LPAV	Lifelogging Physical Activity Validation
RU	Regular Uncertainty
RFID	Radio Frequency Identification
PSO	Particle Swarm Optimization
C-NCPS	Cloud-based Nursing Care Planning System
RBF	Radial Basis Function
BP	Backpropagation
IP	Internet Protocol
GPS	Global Positioning System

1

Introduction

The internet was firstly created by people, for people and about people. It is one of the most important and transformative technologies ever invented. Roughly 85% of citizens in the EU (European Union) used the Internet in 2019 and in some Member States 95% of the population uses the Internet at least once a week (Europäische Kommission, 2021). Nowadays, the internet is not just about connecting people, but also connecting "things", devices that can sense, register data, and communicate with each other, as well as with the internet, without the involvement of a human being.

The term Internet of Things (IoT) was firstly used as a title of a presentation at Procter & Gamble by Kevin Ashton, in 1999. Over the years, the term is mentioned several times in mainstream publications, and in 2010 the number of "things or objects" connected to the Internet, exceeded the number of people connected to the Internet. A year later, IPv6 (Internet Protocol) is launched, triggering the massive growth and interests in the IoT (Sade Kuyoro, Folasade Osisanwo, 2015). Due to the decreasing size of processors and costs of installing sensors and connectivity to objects, now is possible to connect almost everything to the internet (Liu & Lu, 2012).

IoT technology is generating huge amounts of information that can be used to create new ecosystems of business, industrial and consumer opportunities around data storage, analysis, and accessibility. Indeed, industry is marked by a series of revolutionary approaches. One was the Ford's constantly moving assembly line and coordination operations that realized huge gains in productivity (Wilson & McKinlay, 2010). Another industrial revolution is undergoing thanks to IoT, the Industrial Internet of Things (IIoT). It uses cheap, smart, and small size interconnected factory devices to improve efficiency in supply chains, prediction of the components that are likely to fail and control of the manufacturing system. In the modern days, industry becomes a combination of different techniques such as IoT, Big Data, Cyber Physical Systems, Machine Learning, and simulation. It is turning the industrial ecosystems into integrated

concepts, flowing from factory environment to production activities and business level (Saqlain et al., 2019).

Besides the mentioned applications, IoT can also have a crucial role on the steps of disaster management. Disasters, either natural or man-made, lead to large-scale destruction in terms of human lives, environment, and economy. It can improve early warnings, reduce vulnerability, and locate the victims for a possible rescue operation. An emergency system is successful if the correct information is collected at the right time, shared with the appropriate people, and presented in the right way. Hence, using IoT to implement a solution has the potential to fulfil all those necessary emergency responses (Sinha et al., 2017). For example, monitoring forest fires by placing sensors on trees that indicate when there is potential risk or when a fire has broken out. Or a system network that gathers measurements of raw vibration data from the ground and, if necessary, notifies all the nearby people of a possible earthquake. Concerning man-made disasters in the industrial sector, IoT can handle the monitoring and detection of toxic gases leaks in factories, it can also manage safeness in oil depot or coil mines, where accidents regularly happen due to power fluctuation or underground water intrusion (Ray et al., 2017).

On the consumer perspective, IoT devices are best known for their convenience, money and time saving characteristics used for fitness applications, sleep trackers and smart personal assistants. Besides this mass markets products, IoT devices can be used for medical and healthcare data collection and analysis, therefore the Internet of Medical Things (IoMT) has become a critical piece of the digital transformation of healthcare. For example, a smart home may be able to help keep elderly independent and remain longer in their homes, instead of going to nursing homes. Or an emergency detection system, can trigger necessary actions like reporting the location or categorizing the patient at an emergency medical reception based on the condition's severity (Basatneh et al., 2018).

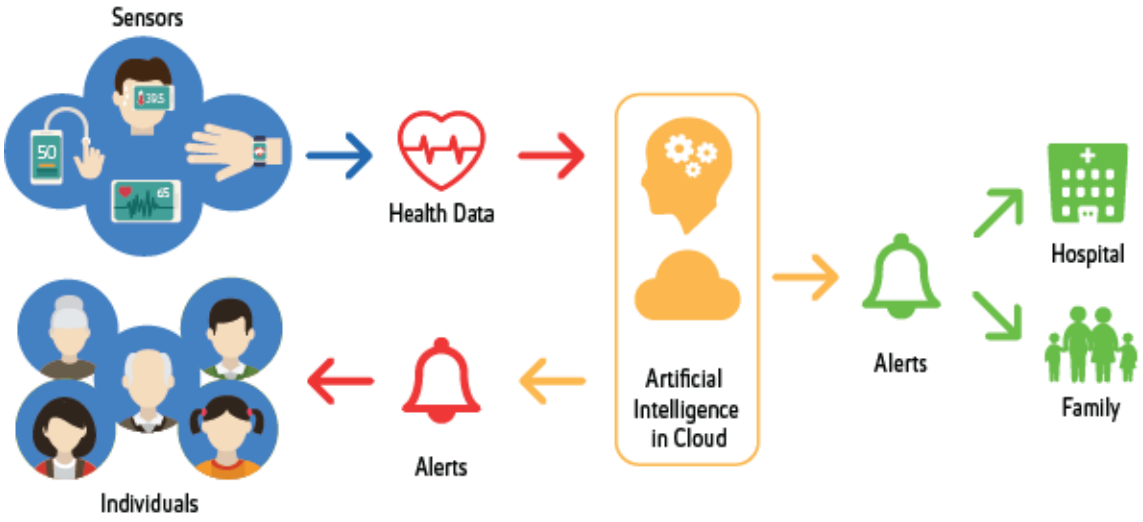


Figure 1-1: Internet of Things for healthcare (Patro et al., 2020).

IoMT has the capability to avoid overloads of healthcare infrastructures (Figure 1-1) and can be part of the solution for problems that have accompanied medicine and healthcare throughout history. For instance, RFID (Radio Frequency Identification) technology can help identify issues in the workflow of hospitals and eliminate the risk of stock-outs, by enabling hospitals and other healthcare facilities to keep the right quantities of medications in stock ("Global Smart Healthcare Market Size Report, 2020-2027," 2020). Wearables can also bring several benefits as they collect health information of individuals in real time and activate alerts accordingly. One of the benefits is allowing old people to stay longer and healthier in their homes, rather than going to a nursing home when their health condition worsens.

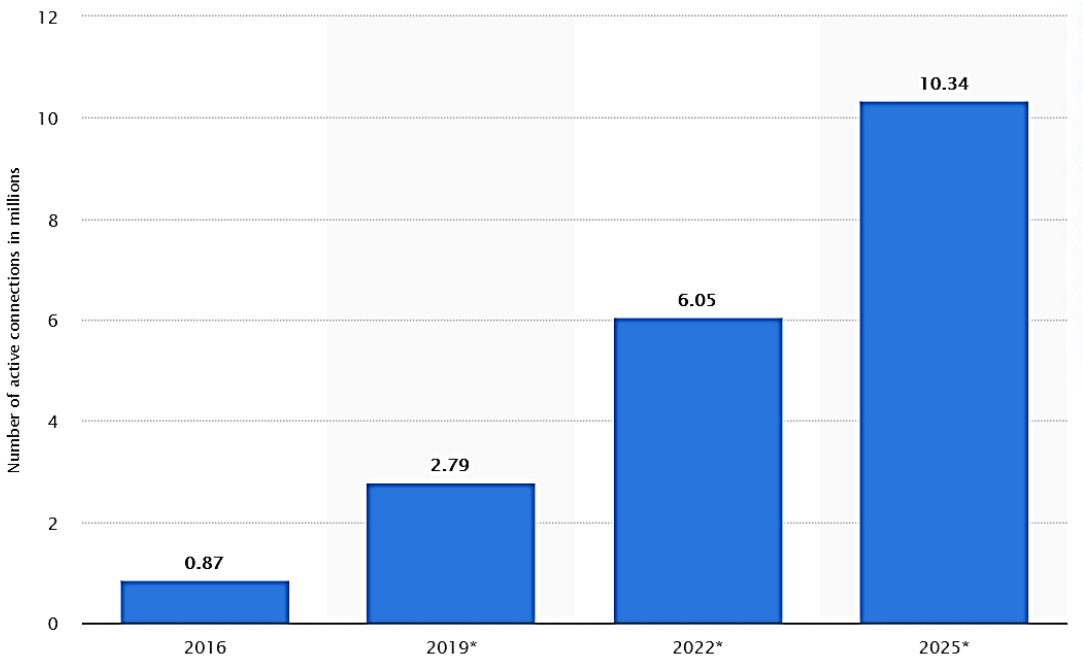


Figure 1-2: Number of IoT active connections in healthcare in the European Union (O'Dea, 2019).

According to Figure 1-2, the number of IoT healthcare active connections is expected to grow over the years. It was 0.87 million connections in 2016, and it is expected to achieve 10.34 million connections by 2025, therefore the number of IoT healthcare devices is also expected to grow.

1.1 Motivation - Trustworthy Systems

As IoT technology deals with sensitive personal data, trustworthiness is essential, especially when referring to the vision of trusting intelligent systems to make countless daily decisions that impact human lives (Melo-Almeida et al., 2016). Trustworthiness in systems is composed by five characteristics: reliability, resilience, safety, security and privacy. (Buchheit President, 2018). These characteristics refer to the data of the system itself, that greatly influence the trust that people have in the system. If the system data does not have those five characteristics, then

the system will not be defined as trustworthy, and people will create distrust and will be more averse to using it.

Trustworthiness in a human-automation relationship has a variety of definitions, as it can be seen as an intention or willingness to act, or as an attitude or expectation. J. D. Lee & See (2004) define trust as *"the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability".* Hence, performance, process, and purpose are frequently identified as the bases of human-automation trust (see Figure 1-3):

- **Performance** information describes what the system does; it is linked to the expectation of consistent, stable, and desirable behaviour of the system.
- **Process** information represents how the system works, if the algorithms are understood and can achieve the goals, the tendency to trust the system is greater.
- **Purpose** reflects if the designer's system intention matches the use of it. Describes why the system was developed.

Risk is the extent to which there is uncertainty about the consequences of a decision made in a given situation. The level of trust is different according to a high or a low risk situation (Chancey et al., 2017; J. Lee & Moray, 1992; Zhao et al., 2019).

As it is shown in Figure 1-3, false alarms (when systems signal an alarm that afterwards is proven unfounded), and misses (occur when the system fails to recognize the situation that is supposed to trigger the alarm) influence the level of trust in the automated system, particularly on compliance/reliance behaviours. Meaning that, after multiple false alarms, the tendency is to delay the response to the system alarm, or even ignore it, reducing the system compliance. Whereas the effect of misses leads to an increase of human control over the system, reducing its reliance (Chancey et al., 2017).

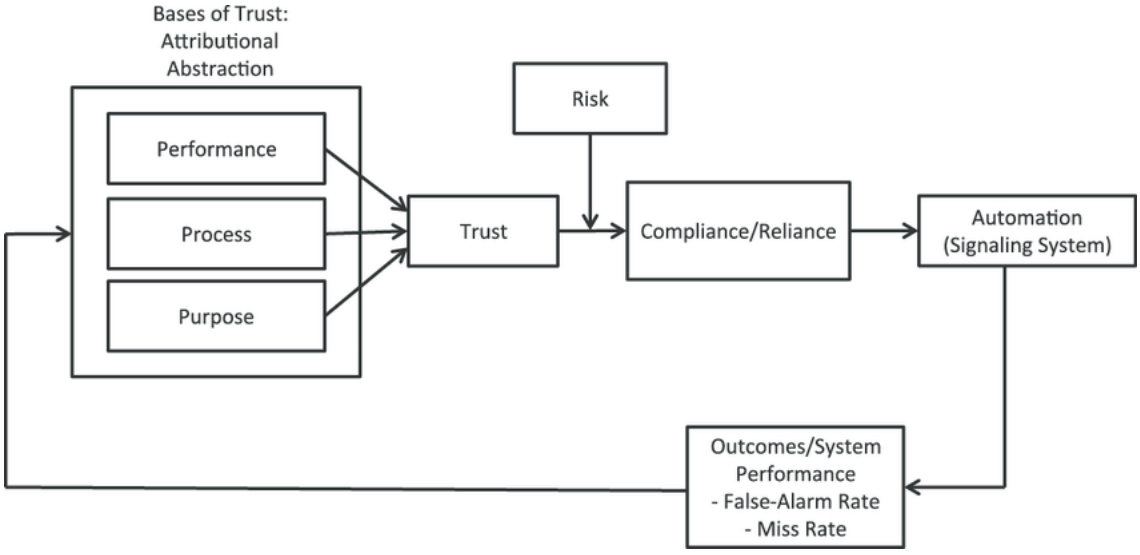


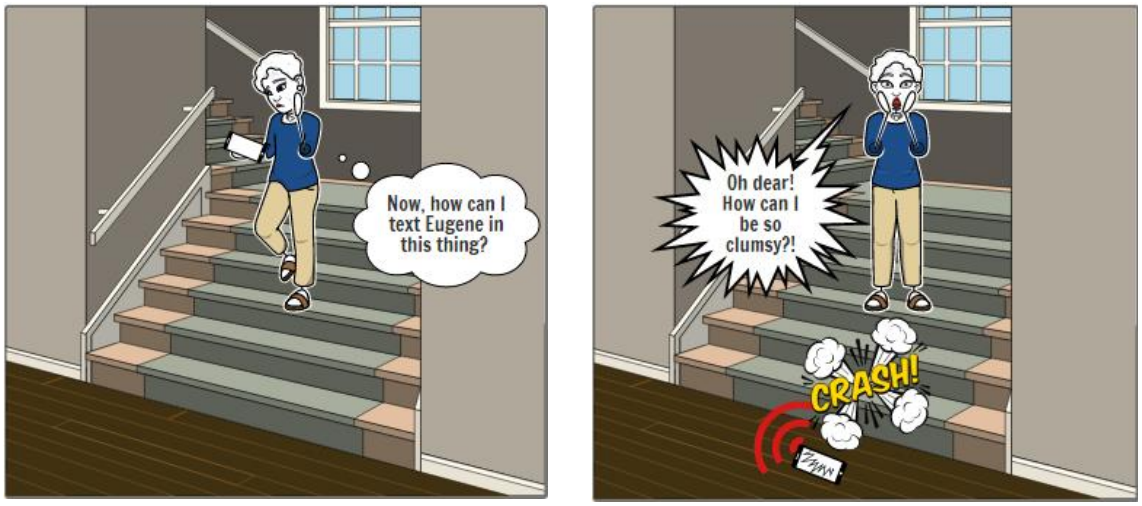
Figure 1-3: Model of human-automation trust on compliance/reliance behaviours (J. D. Lee & See, 2004).

As introduced before, IIoT and IoMT have the potential to create a tremendous impact in society and are indeed the fuel for the ongoing industrial revolution. However, lack of trust

and trustworthy systems harness that potential greatly. The scenarios illustrated in the following sections highlight the need for an increased level of trust when addressing IoT in healthcare-related environments, and how that trust can actually support an independent lifestyle of the elderly for longer periods of time during their retirement years.

1.1.1 Trust when Living at Home

Fall detection systems have the potential to save someone's life, especially elderly people, where a fall can have serious impacts. The response speed could be lifesaving in these situations, therefore this IoT based system can have a direct impact on the severity of the injuries and on the reduction in the fear of falling, since many of the fallers feel more confident using the system.



Maria, an 80-year-old woman, lives alone in her house. One night, she is coming down the stairs and, accidentally, drops the phone and breaks it. The phone's fall detection application assumes that Maria has fallen and immediately triggers actions that call for help. Within minutes, help arrives but encounters a not expected situation, as it is shown in Figure 1-4.

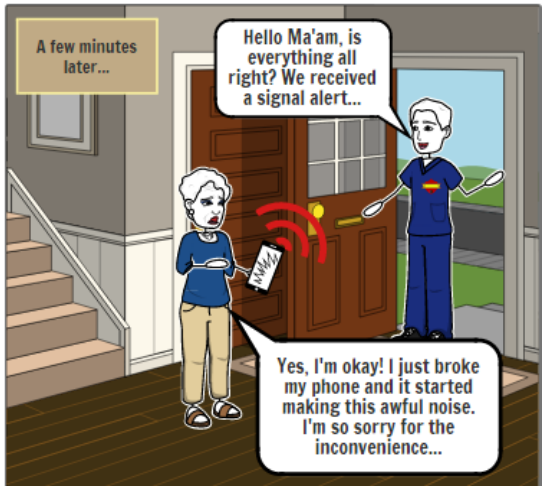


Figure 1-4: Story board of a fall detection system

This type of situation leads to a loss of trust from the users and help team, to a waste of time and limited resources and to a misappropriation of help from real emergencies. To become a trustworthy system, it should have some sort of validation method that ensures that a fall has indeed happened, or on the contrary, if it is a false alarm. For example, a button, that if it's pressed, it can cancel the

automatic fall alert trigger (Igual et al., 2013). Or contact a trusted one to validate the health status of the elderly before calling the emergency system.

1.1.2 Trust when at Someone Care

Patient alarm systems detect when a person has, either accidentally or deliberately moved to leave the bed. The system perceives the location of the body, so it actuates an alarm if the patient is in an unsafe position, indicative of leaving the bed. Typically, the alarm will remain actuated until someone turns it off.

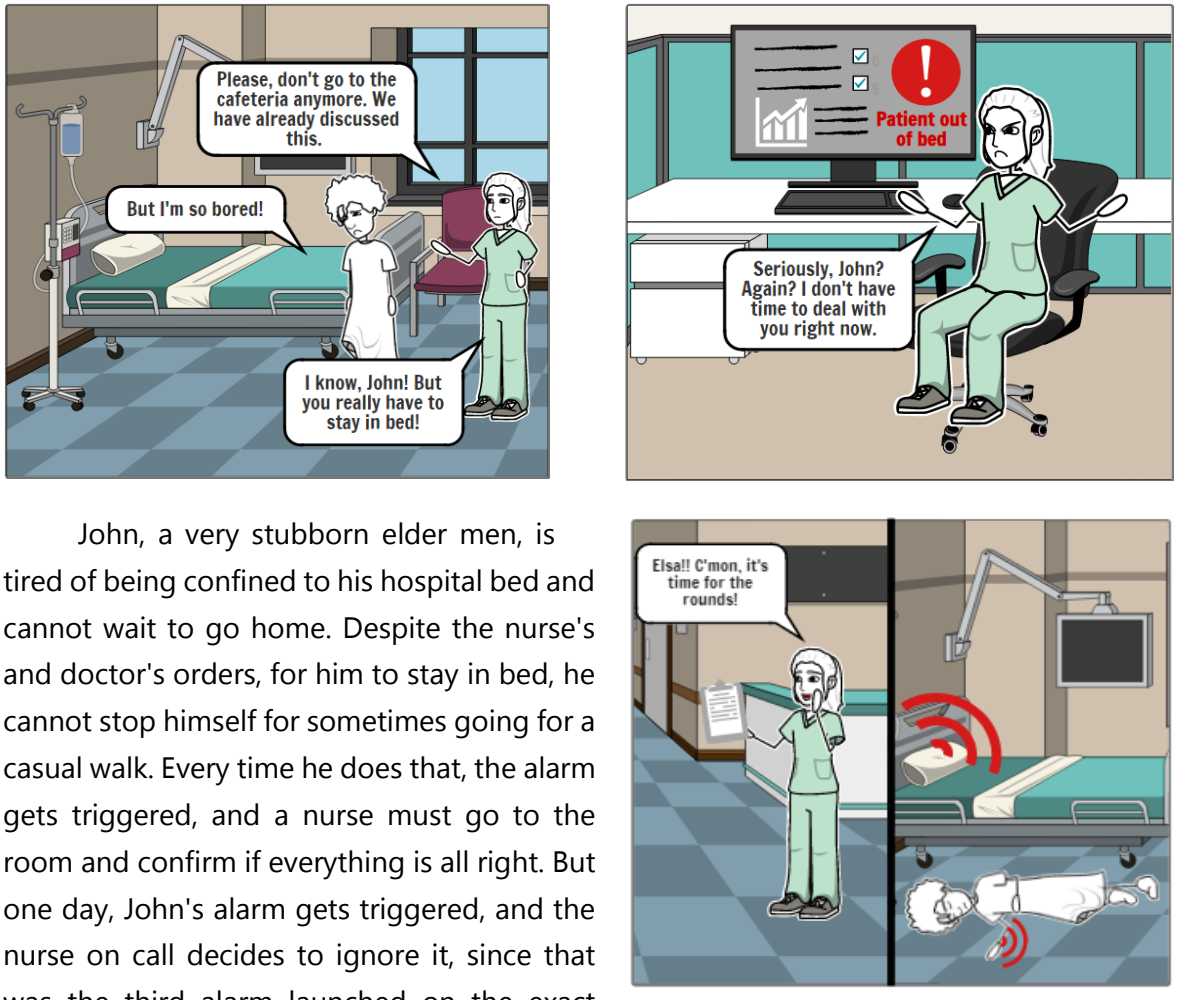


Figure 1-5: Story board of a patient bed alarm system

John, a very stubborn elder men, is tired of being confined to his hospital bed and cannot wait to go home. Despite the nurse's and doctor's orders, for him to stay in bed, he cannot stop himself for sometimes going for a casual walk. Every time he does that, the alarm gets triggered, and a nurse must go to the room and confirm if everything is all right. But one day, John's alarm gets triggered, and the nurse on call decides to ignore it, since that was the third alarm launched on the exact same day, so she innocently thought he was disrespecting the orders again. Little did she know, as it is shown in Figure 1-5, that this time was a true alarm.

Although, it can help caregivers, inaccurate or false alarms can have the opposite effect, they can originate alarm fatigue, where the nurses become numb and ignore true alarms that require intervention (Balaguera et al., 2017; Tucknott & Sorenson, 1984). Therefore, the system,

to become trustworthy, must ensure that the patient is indeed in a dangerous situation or not. For example, it can have a press button, for the patient to confirm if he is in the bed, or have multiple sensors, placed around the room. This way the system has several input data to base itself.

1.2 Research Methodology

Every scientific research has a defined methodology, to ensure the success of the search and its productivity. Such methodology may vary, according to the work and person. Therefore, the steps of the research methodology chosen for this thesis is presented in Figure 1-6.

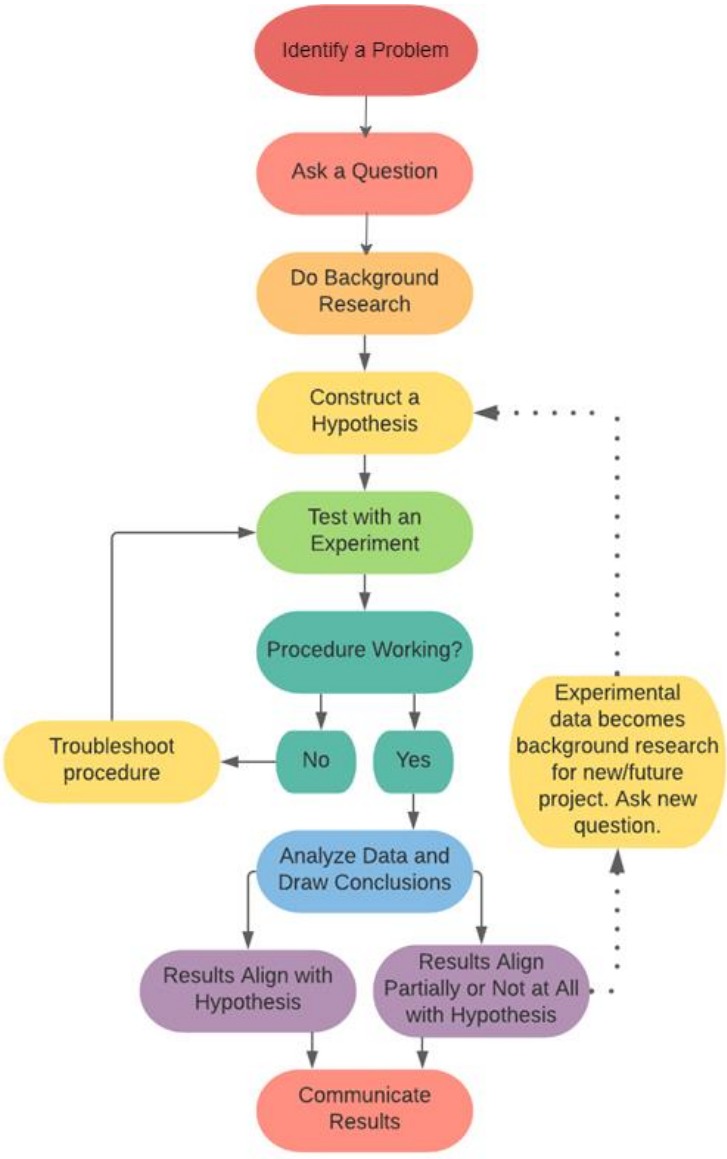


Figure 1-6: Scientific research methodology diagram adapted from (Gould, 2001)

With an eight-step configuration, the research methodology consists in the following steps:

1. **Problem identification:** the first step consists of identifying a meaningful problem which captures the attention of the author, and it is worth solving. In this thesis it is identified in the Motivation section 1.1.
2. **Research question:** in this step, the definition of a valid research question is made. It is presented in the section 1.2.1. The process of answering this question will help guide and focus the writing, research, and system development.
3. **Collect information:** important and relevant background information is collected on the topic, enabling the author to make a solution proposition. The Background Research is described in chapter 2 of this thesis.
4. **Formulate solution:** after analysing the collected background information, the author proposes an educated testable solution to the problem identified. Presented in the chapter 3 of this thesis.
5. **System development and testing:** after having made a proposed solution and the research question, it is time to start developing the solution and continuously test its validity. Shown in chapter 4 of this thesis.
6. **Validation:** in this step, the results from the testing phase are analysed and the proposed solution is evaluated if is valid or not. If not, it is necessary to go back to step three and formulate a new solution. If it is validated, results are discussed. Section 4.3 describes this step.
7. **Conclusions:** the author takes the conclusions on the success from the research and system development. This step is presented on chapter 5 of this thesis.
8. **Publishing:** in this final step, if the solution is validated and after having taken relevant conclusions it is important to start writing an article to publish the findings throughout the work.

1.2.1 Research Question

The aim of this thesis is to study trustworthiness in IoT systems, more concretely, in a healthcare and wellbeing IoT environments, in the hope to define a methodology that has the potential to increase trust in these systems.

The question that this thesis proposes to answer is:

"How can one enhance trustworthiness in IoT intelligent systems, in order to increase user adoption, supporting the monitoring and decision-making processes that impact human lives?"

1.2.2 Hypothesis

The proposed hypothesis was formulated to answer the problem stated in the research question and its validation will be pursued by the presented research work.

> By using multiple information sources and introducing redundancy to the system, trustworthiness in IoT systems will increase, rising users' adoption

1.3 Document Structure

The dissertation is structure in five chapters:

1. **Introduction:** where the topic, purpose, relevance, and motivation of the study is presented. The research question and hypothesis are also presented in this chapter.
2. **Background research:** it is presented a set of concepts related to the work topic that are considered relevant to the study of the domain and provide a body of knowledge necessary to analyse the research question.
3. **Proposed solution:** it is presented and explained the conceptual methodology, its architecture and workflow. Followed by a more detailed explanation of the methodology main topics.
4. **Implementation and validation:** it explains the developed and implemented solution that uses the conceptual methodology. Implementation details, more concretely, communication protocols, motion detection, audio detection and confidence degree and alert actions are explained. The solution experimental results and its discussion are also presented.
5. **Conclusions and future work:** the final conclusions and future work are presented in this chapter, as well as the potentialities the developed methodology has.

2

BACKGROUND RESEARCH

As before mentioned, IoT is exponentially increasing, which leads to an era of smart technology with intelligently connected devices and systems that allow machines to automatically interact and communicate with other machines, environments and infrastructures (Dudhe et al., 2018).

With the huge volumes of data collected through the connected IoT devices, Artificial Intelligence (AI) algorithms and techniques can analyse and learn from the generated data to create public services and value. AI is, as Professor John McCarthy, in 1955, said, *"the science and engineering of making intelligent machines"* (Mohamed, 2020). AI has various related areas, such as Machine Learning, Cyber Physical Systems, and Big Data. All of which rely on information from data, collected through techniques such as data fusion and data management. The combination of these techniques provides promising solutions for real-time monitoring activities among other scenarios.

In the following sections, it is presented a set of concepts related to intelligent IoT systems that are considered relevant to the study of the domain and provide a body of knowledge necessary to analyse the research question.

2.1 Data Management

Data Management plays a crucial part in developing effective and intelligent IoT applications, in various fields. From basic sensor nodes, that collect and report the data, to the ones capable of processing the incoming information and taking an action accordingly. A layered architecture of IoT, as it is presented in Figure 2-1, can involve processes of data collection, pre-processing, analytics, and visualization (Ma, Wang, & Chu, 2013).

The following sections develop the mentioned processes of data management.

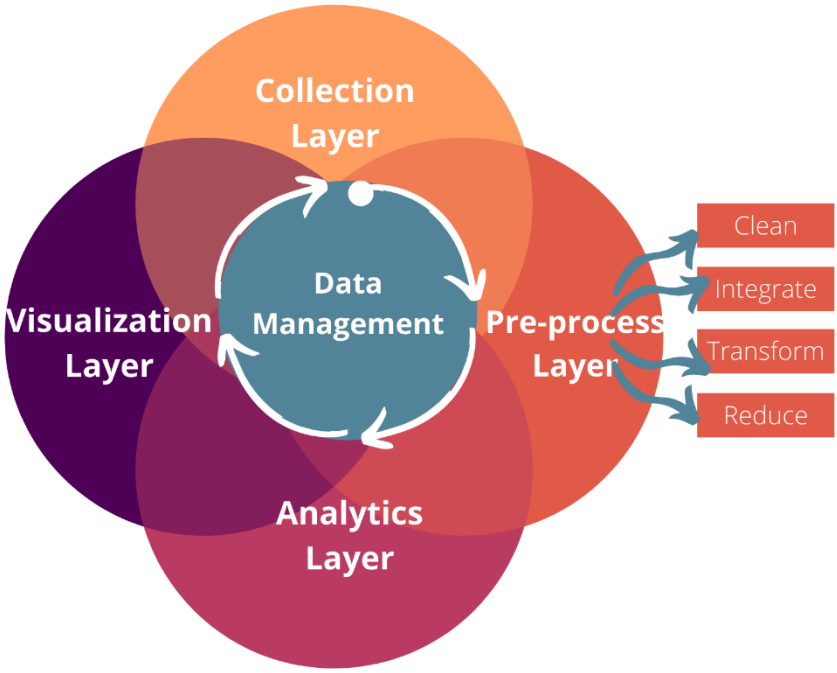


Figure 2-1: Data management diagram.

2.1.1 Data Collection

Data collection can be the link between physical and cyber worlds. It can connect one or numerous IoT devices, such as RFID readers, wireless sensors, GPS systems, with cloud-based systems that have the power to reason and make informed decisions over the collected data (Agostinho et al., 2019). The purpose of this layer, is to gather relevant information, from diverse sources, to monitor and measure data (Ma et al., 2013). Due to this tracking, IoT systems can detect real-time events or faults occurring in a process, without human centric and manual operations.

2.1.2 Data Pre-processing

Incoming data, frequently, is incomplete and inconsistent, and affects the data output. To avoid this negative influence, data pre-processing is used to facilitate the data analytics stage. Typically, it consists in:

- **Data cleaning** processes, to complete missing values (Bayesian formula or Decision Tree) or clean out noisy data (Binning, Regression, Clustering) (Cox, 2004).

- **Data integration** processes, to combine data from various sources. The main issue is schema integration, which is avoided by using metadata that can be correlated between different datasets.
- **Data transformation** processes, to consolidate the data into standard formats. It involves data normalisation, smoothing, aggregation, generalisation, and attribute/feature construction (Agarwal, 2014).
- **Data reduction** is adopted to minimize the data size and increase data storage efficiency to produce the same analytical results as the original data. It may include data compression, numerosity reduction (linear regression model, histograms, sampling), and dimension reduction (feature selection, statistical and heuristic methods) (Agarwal, 2014).

With the above techniques, data is into a suitable form for the upcoming procedure.

2.1.3 Data Analytics

Data analytics processes and analysis of the gathered data, with the purpose of extracting meaningful information from the data, produced by sensor devices. It can be an intelligent learning mechanism for prediction (i.e., regression, classification, and clustering), data mining and pattern recognition. IoT data calls for a new class of analytics, Big Data, born from the enormous amount of sensing devices, that collect and/or generate various sensory data over time (Mohammadi et al., 2018).

2.1.4 Data Visualization

Data visualization concerns on representing the now processed and analysed data, containing the information extracted by the data analytics stage. The displayed data enables decision makers to see quick and relevant information in an easy-to-understand form. It helps them discover patterns, comprehend information, form an opinion and make an accurate decision (Sadiku et al., 2016).

As mentioned before, intelligent systems deal with super sensitive data, therefore it is mandatory to ensure some level of trustworthiness in the data's system. Certain methods, that reinforce trustworthiness, introduce redundancy in the systems, which is not resource efficient, others identify and process sensitive neurons/layers in which errors can significantly affect the accuracy of the system (Shafique et al., 2018).

2.2 Data Fusion

To improve accuracy and avoid misclassifications, multisensory techniques can be employed in a way that it is hardly performed by the same set of sensors working separately. Data fusion

is a multi-disciplinary research area that uses knowledge from many diverse fields such as signal processing, information theory, statistical estimation and inference, and artificial intelligence (Khaleghi et al., 2013). The concept is present everywhere, for example, to evaluate a wine, a sommelier, does not only use his taste, but also his vision and sense of smell.

The process, for example, to recognize daily living activities (e.g. sitting, walking, running) in mobile systems, has several stages and include a number of different sensors, as it can be seen in Figure 2-2 (Pires et al., 2016).

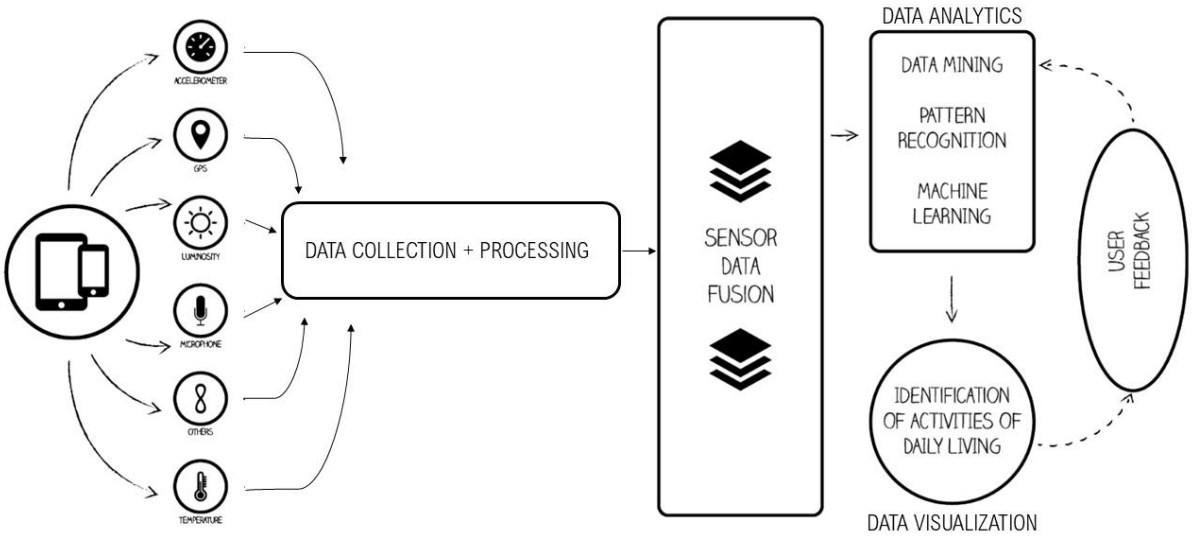


Figure 2-2: Schema of a multi-sensor mobile system to recognize activities of daily living based on (Pires et al., 2016).

It can be seen as an additional stop in the data management flow, enriching and combining numerous data sources, and providing the analysis layer with more complete datasets for a better AI with probabilistic, statistic, knowledge base theory and evidence reasoning methods.

According to Kalamkar & Mary (2020) there are three types of data fusion classes based on the basic functionality of fusion. In this thesis, the interest relies in the Data Association level, where some sensors may not provide all the information, or some sensors may provide noisy or incorrect information.

The challenge of activity detection systems is the difficulty to obtain good results in both sensitivity (the ability to properly recognize falls that in reality occurred) and specificity (the capability to correctly identify a movement as a non-fall). At the same time, it's important to design a system that is not extremely expensive and the least intrusive possible (Kwolek & Kepski, 2015). These mentioned challenges are relevant while developing the proposed solution, later presented.

In Ando, Baglio, Lombardo, & Marletta (2016) paper, there is a combination of different technologies to increase the performance and reliability of the system, and therefore the increase of trust in the system. The information provided by an accelerometer and a gyroscope is used to improve the classification performance, by reducing misclassifications, specifically false positives (specificity) and consequently false alarms.

The accelerometer and gyroscope are integrated on a smartphone, which is used around the user hip, and this constitutes the user node. The information collected by the sensors, about the user posture, is periodically transmitted to a centralized monitoring system. When a critical event is detected, the system immediately alerts the caregiver, by an event triggered transmission protocol.

In the methodology used, fall events and Activities of Daily Living (ADL) are characterized by the typical signatures in the time evolution of inertial quantities (acceleration and angular velocities). To classify an unknown event, a cross correlation between the inertial quantities, from the event, and the set of signatures representative of the candidate ADLs is computed. If the correlation exceeds the predefined threshold, the event is classified as potentially belonging to a specific class.

The results of the threshold algorithms are then processed by a data-fusion paradigm, which improves the reliability of the classification task by filtering out misclassifications. Acceleration data is used to implement a first classification, while data provided by the gyroscope is used to refine the classification task. The flow diagram of a classification approach is shown in Figure 2-3.

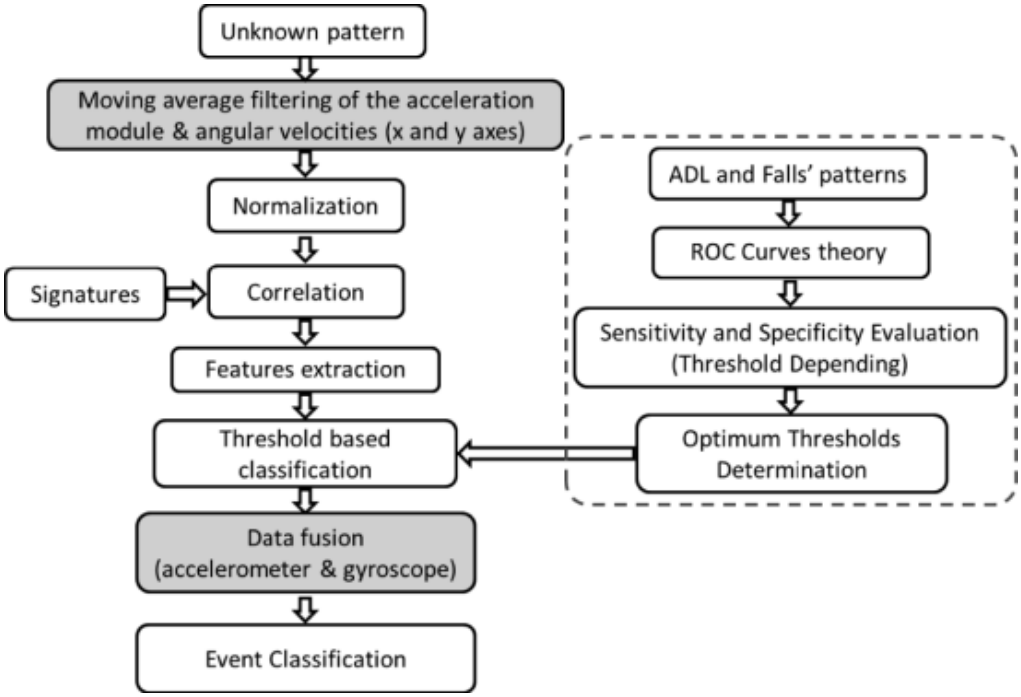


Figure 2-3: Classification approach (Ando et al., 2016).

The methodology is interesting because it provides improvement in performing the classification task between different classes of fall, which is important to avoid false alarms and therefore increase the trust on the system.

2.3 Decision Support

As the complexity of information systems evolves, so does the need to use technology to help make important decisions. In a scenario where semi-automated decisions are expected, and data is collected via several IoT sensors and devices, it is important to have techniques to rapidly fuse the incoming collected data and produce efficient, planned and informed decision-making processes (Power, 2009).

With analysis tools, it is possible to provide multidimensional data query and analysis operations to achieve quick and flexible visualisation of the results. It enables decision makers to discover hidden data in multidimensional data and internal useful information (Huang et al., 2017).

Decision Support Systems can make the difference in the healthcare and medicine area. They provide customized information, support clinical diagnosis and treatment plan processes, to enhance health and healthcare (Delir Haghighi et al., 2014).

In Lakshmanaprabu et al. (2019) paper, an online clinical decision support system using Deep Neural Networks (DNN) is developed. The IoT cloud based clinical decision support is deployed for the prediction and observance of chronic kidney disease (CKD) with its level of severity.

The proposed framework gathers data from various sources, saves it in the Cloud Data-based Server (CDS), and predicts the presence of CKD with the level of severity.

As shown in Figure 2-4, the model operates in three levels: data gathering, security mechanism on CDS and prediction system. The security mechanism will not be further detailed since it is not the area of interest of this thesis.

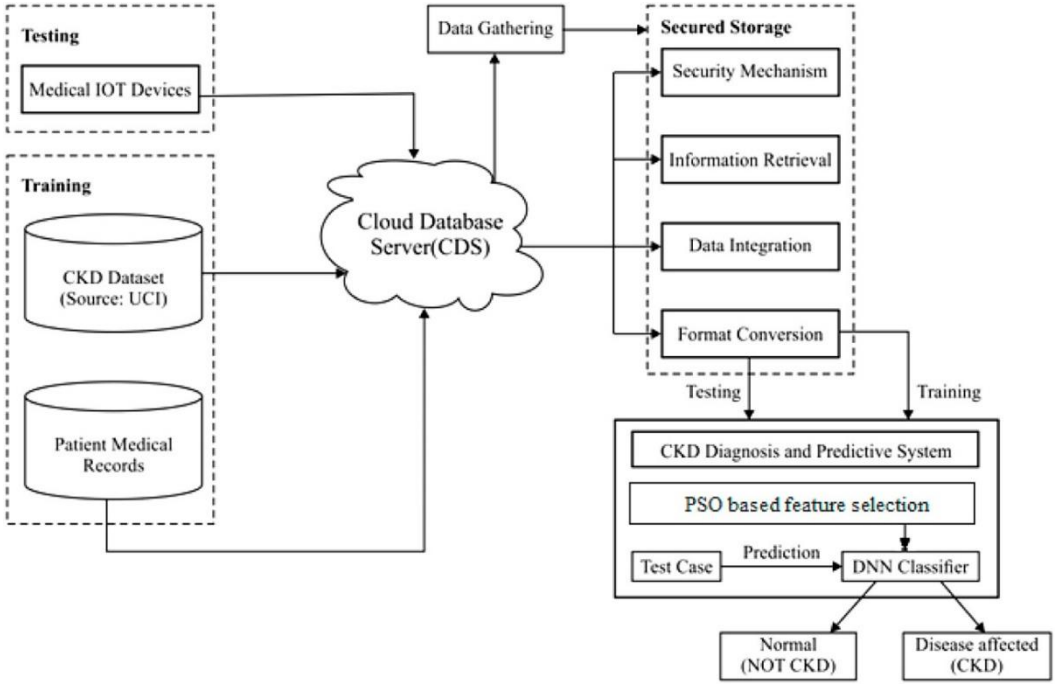


Figure 2-4: Overall system architecture (Lakshmanaprabu et al., 2019).

The data gathering module is worthwhile analysing since it has the role of gathering essential data from the CDS and IoT. Three variant kinds of data can be considered in the work of Lakshmanaprabu et al. (2019):

- **Healthcare data** of the patient, that is gathered using wearable IoT gadgets, which are operated by sensors. Successive measures are employed regularly in a particular time duration, to collect specific patient healthcare data and to be transmitted to the CDS. If the healthcare data crosses the normal values, an alert is sent to the doctors and to the data gathering for further processing, similar to the case of the patient bed alarm system presented in section 1.1.2.
- **Benchmark CKD dataset**, from the UCI Repository, which is employed to map with the real data generated by the IoT devices, and can be used to calculate a certain degree of confidence in the sensor readings (i.e. comparing with historical data).
- **Patient medical records** contain the past details of the patient's data, which is gathered from the hospitals. It is employed to map the actual data generated by the individual patient's data. This type of data can be of particular interest in cases where decisions need to be taken considering past medical history.

To improve the classification performance, a Particle Swarm Optimization (PSO) method is used to reduce the feature subset, by identifying the noisy and unwanted features.

During the training phase, the authors used the healthcare data from the patient medical records, as well as the CKD dataset, to train the DNN classifier and calculate the accuracy estimation. During the testing phase, the DNN classifier classifies the patient data into normal (non-CKD) or disease affected (CKD) with its severity level, that supports decision making by

doctors, providing them a degree of confidence regarding the observed values. This notion of confidence is particularly interesting for the scenarios analysed (section 1.1.1 and 1.1.2), in particular for the one where the emergency services are contacted. If there was a degree of confidence associated with that alarm, maybe a better decision might have been taken and the services not called.

Another interesting work is the one of Amigoni, Gatti, Pinciroli, & Roveri (2005), addressing the wellbeing area, in particular using hierarchical task network for ambient intelligence applications. An ambient intelligence system creates adaptive environment that serves the user needs, in an unobtrusive manner. Their work focuses on the planning ability to find a course of actions that depend on the current state of the environment and the repertoire of actions the devices, in the system, can execute.

In Tang et al. (2019) paper, the focus is to assist decision making, of the nursing home admission staff, in providing daily healthcare services to the patients, by the use of a cloud-based nursing care planning system (C-NCPS).

The C-NCPS system is specific to the elderly and its architecture consists in a:

- **Front-end module**, collects the personal information and medical records, inputted by the patients and/or their families. These data are then sent and uploaded to the cloud. Apart from these imputed data, the information related to handle and treat various illnesses are also inputted in the cloud-based data warehouse, to facilitate the elaboration of the care plan.
- **Back-end module**, transfers relevant data, stored in the cloud, from the front-end module. It consists in a case retrieval engine, where inductive indexing and nearest neighbour method are applied for retrieving and ranking past nursing care records based on their similarity value. To improve the quality of the nursing care plan, the text mining technique is employed, in the case adaption engine, to enable searching for up-to-date health information.

With the paper's methodology, new admission applications are captured in real time and nursing care plans are planned more efficiently and of higher quality, providing the admission staff with carefully designed treatment decisions.

2.3.1 Fault Handling

IoT systems are employed in diverse environments which lead to faults caused by issues such as user error, flaws in the device hardware and software, weather, power outages, network disruption, etc (Norris et al., 2020). Either in the form of managing anomalies or eliminating uncertainties, it is interesting to analyse how one can overcome such situation to build a more trustworthy system.

Wu, Shi, Wang, Wang, & Fang (2019) propose a new feature-based learning system to classify data and detect anomaly events effectively. They use a neural network composed of Radial Basis Function (RBF) and Backpropagation (BP) networks as shown in Figure 2-5.

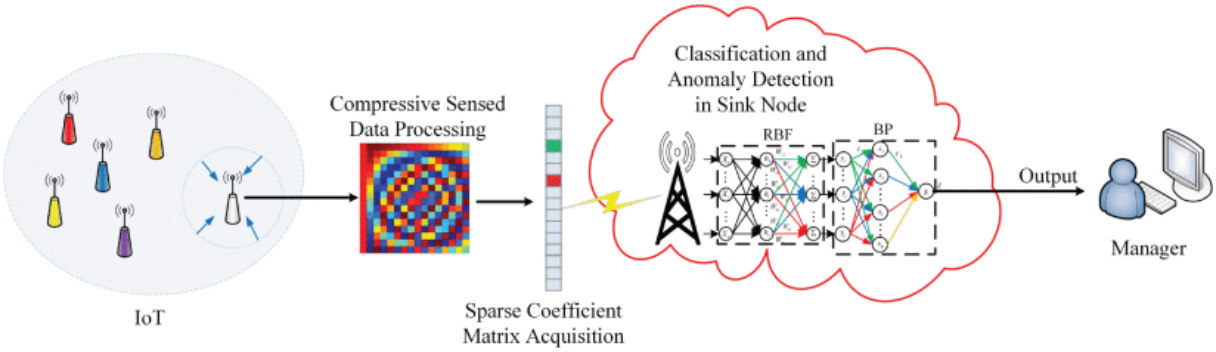


Figure 2-5: Data classification and anomaly detection (Wu et al., 2019).

As illustrated, the process to classify sensor data occurs in the sink mode, which acquires the common sparse coefficient matrix and unique sparse coefficient and then identifies data classes according to the historical data. The trained RBF-BP hybrid neural network detects anomalies in the sensor data and obtains the state anomaly probabilities. By analysing the correlation between the sensor data with the RBF, the state anomaly probability of things can be acquired for the user to make timely decisions. By providing this anomaly probability, the system gives a sense of confidence, because then the user is properly informed about the state of the system data. It is a visualization approach so that the user can better informed decisions.

Beside anomalies, uncertainty can also affect the desired system operation. Yang et al. (2018) proposes a rule-based adaptive Lifelogging Physical Activity validation (LPAV) model, to eliminate irregular uncertainties and estimate physical activity data reliability. The method of LPAV-IoT model is to first identify the key influencing factors that lead to uncertainty of LPA and then create a series of methods for qualitatively evaluating these influencing factors.

Uncertainties of LPA are categorized in irregular (IU) and regular (RU). The firsts occur accidently, frequently low and are hardly quantified by impacting factors. The causes include device malfunctions or faults, breakdown of third-party server, misuse of mobile apps and sudden change of personal circumstance. Two threshold parameters are defined, by a statistical analysis in historical data, that can filter the IUs, regarding a probabilistic distribution. RUs are inevitable to occur and impossible to eliminate. The causes that generate these uncertainties are mainly from regular influencing issues, like change of environment and intrinsic sensor's errors.

To eliminate IUs and to reduce impacts of RUs on LPA data, a set of validation rules was conducted, and a four-layer structure data validation strategy was designed as presented in Figure 2-6.

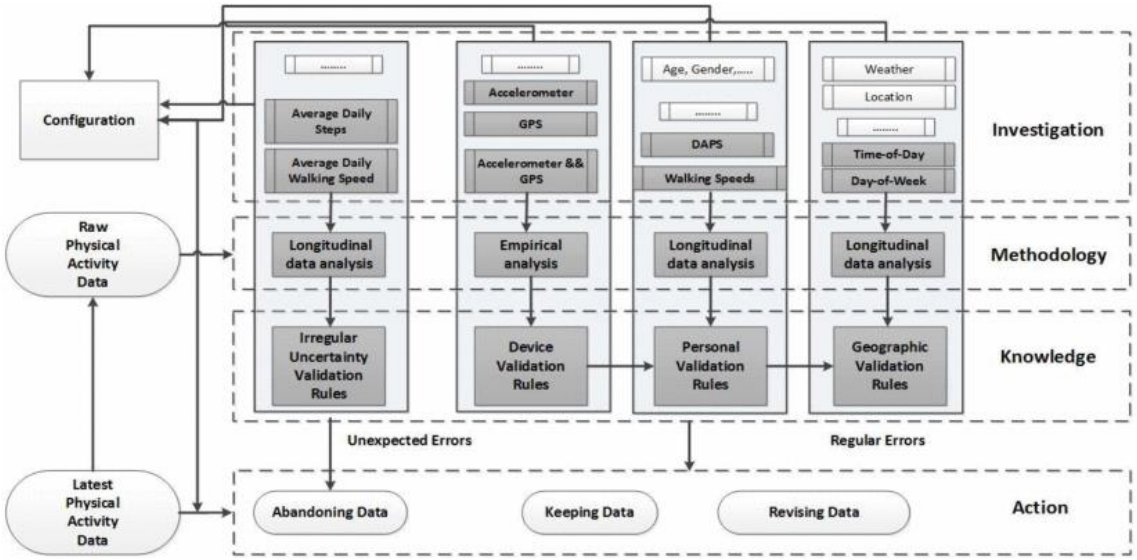


Figure 2-6: Diagram of LPAV-IoT model (Yang et al., 2018).

The structure includes:

- **Investigation level:** provides analysis and classification of detailed influencing items in each impacting factor module and establishes corresponding uncertainty measurement matrix.
- **Methodology level:** include longitudinal and empirical data analysis methods.
- **Knowledge level:** conducts validation rules and principles, to remove IUs and to explore the relationship between impacting factors and RU.
- **Action level:** contain options of executed actions on physical activity data regarding validation rules.

Just as the anomaly detection approach previous presented, this uncertainty elimination method allows for a more reliable system results and, therefore, better decisions are made based on the system outcomes.

2.4 Event Classification

AI can observe and analyse several features in order to detect events that are interesting for the system application. When the event is detected, it is categorized and can be used to trigger further actions. For example, a smart coffee machine that is turned on when it detects that its user has woken up, or a house that is unlocked by detecting its owner voice.

AI platforms that provide event classification techniques are heavily searched in the IoT world. One example is the Tensor Flow[1] open-source platform, where its users can develop and train machine learning models. With these models it is possible to classify images, sounds

[1] More information here: https://www.tensorflow.org

events, speech recognition, text classification, etc. Numerous applications, especially healthcare ones, can be developed by these techniques.

2.5 Summary and Discussion

With this chapter an introductory overview of the most important concepts supporting this thesis work is presented. The core objective of this background research is to form a consisting base support necessary for the implementation and accomplishment of the proposed solution for the problem identified.

All the analysed papers propose or describe strategies that seek to improve the system trust, by reducing misses or/and false alarms rate, or by improving the accuracy of data. Overall, they turn the systems more stable and consistent (Performance), more likely to achieve its goal (Process), therefore they strengthen the intention of why the systems were built (Purpose).

Using all the presented concepts as an inspiration, the proposed solution will be a methodology that seeks to increase trust by adding and correlating data from multiple sources, i.e., applying data fusion techniques as in Ando et al., 2016. Events can be detected and classified using AI approaches such as the one used by TensorFlow, and a fault handling routine can allow the system to learn and improve its event detection, such as the one used in Wu et al., 2019. Finally, and considering the work of Lakshmanaprabu et al., 2019, the information presented to the end user can also provide an additional sense of confidence, hence visualization and a good decision support should also be taken in consideration. It is important to mention that none of the analysed articles in the background research contain a solution that encompasses all these concepts, further presented in the next chapter. Moreover, many of them are integrated in industrial environments and not in wellbeing and health-focused environments like the application developed and presented in Chapter 4.

3

PROPOSED SOLUTION

As discussed in the introduction chapter, it is very important to have a reliable and trustworthy system when dealing with sensitive data. Especially when human wellbeing relies on decisions taken based on such data. This dissertation tries to precisely improve the data reliability and increase confidence in an IoT system for older citizens, so that they can live a more independent and happier life.

3.1 Methodology for Trustworthy IoT

Recalling that performance, process and purpose form the bases of trust (J. D. Lee & See, 2004). Regarding how the system is described, how it works and why the system was developed, the proposed solution is to design and implement a methodology for trustworthy IoT based in redundancy operations. Introducing redundancy in the system without compromising its performance, allows to enhance the quality of results by a more reliable IoT process that ultimately leads to more accurate results. Therefore, the goal of the system can be achieved with a higher degree of confidence, which is a concept inspired by background research in which each detected event is associated with it.

The confidence degree is the main point of the proposed methodology and was created to have a quantitative element that represents the confidence that the system has in each classified event. The confidence degree was also created to serve as a trigger for next actions and to be presented to the user as a decision support parameter. In Figure 3-1 it is possible to observe the methodology adopted in this work.

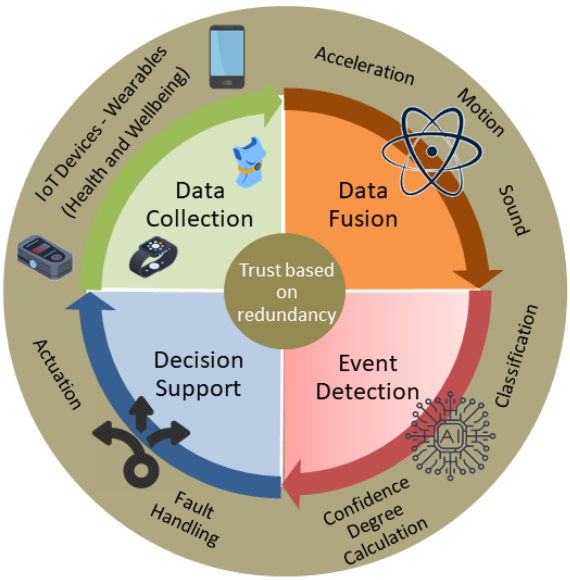


Figure 3-1: Conceptual solution methodology

Redundancy is present in each phase of the methodology which is described as follows:

- **Data collection:** redundancy is ensured by having different types of sensors as data sources. In a health and wellbeing environment IoT devices are used to achieve this goal, such as smart watches, smart shoes, smart glasses, etc.
- **Data fusion:** since there are different types of sensors as data sources, there are different types of data to be processed and analysed. Motion, steps, or audio data can be combined to create redundancy because they describe the same event in different ways.
- **Event detection:** in the methodology designed, as mentioned, the event classification involves the calculation of a degree of confidence) that depends on the combination of the different data sources. Actions will be triggered depending on the degree of confidence value.
- **Decision support:** the presented methodology has a fault handling technique, which confirms if the event detected is correctly classified, with this being another form of redundancy. Depending on the fault handling outcome, further actions (actuation) are taken as a form of decision support.

In conclusion, to ensure the maximum trust on a IoT system, there should be a number of redundant data sources for a meaningful data fusion and a proper event classification with a significant degree of confidence calculated.

3.2 Workflow in Fall Detections Scenarios

The methodology presented earlier is generic enough for any IoT-based scenario. As healthcare is a large domain with many applications of interest, this dissertation selected a fall

detection scenario to instantiate the methodology. Diagram of Figure 3-2 represents the behaviour of a IoT system, with multiple data sources.

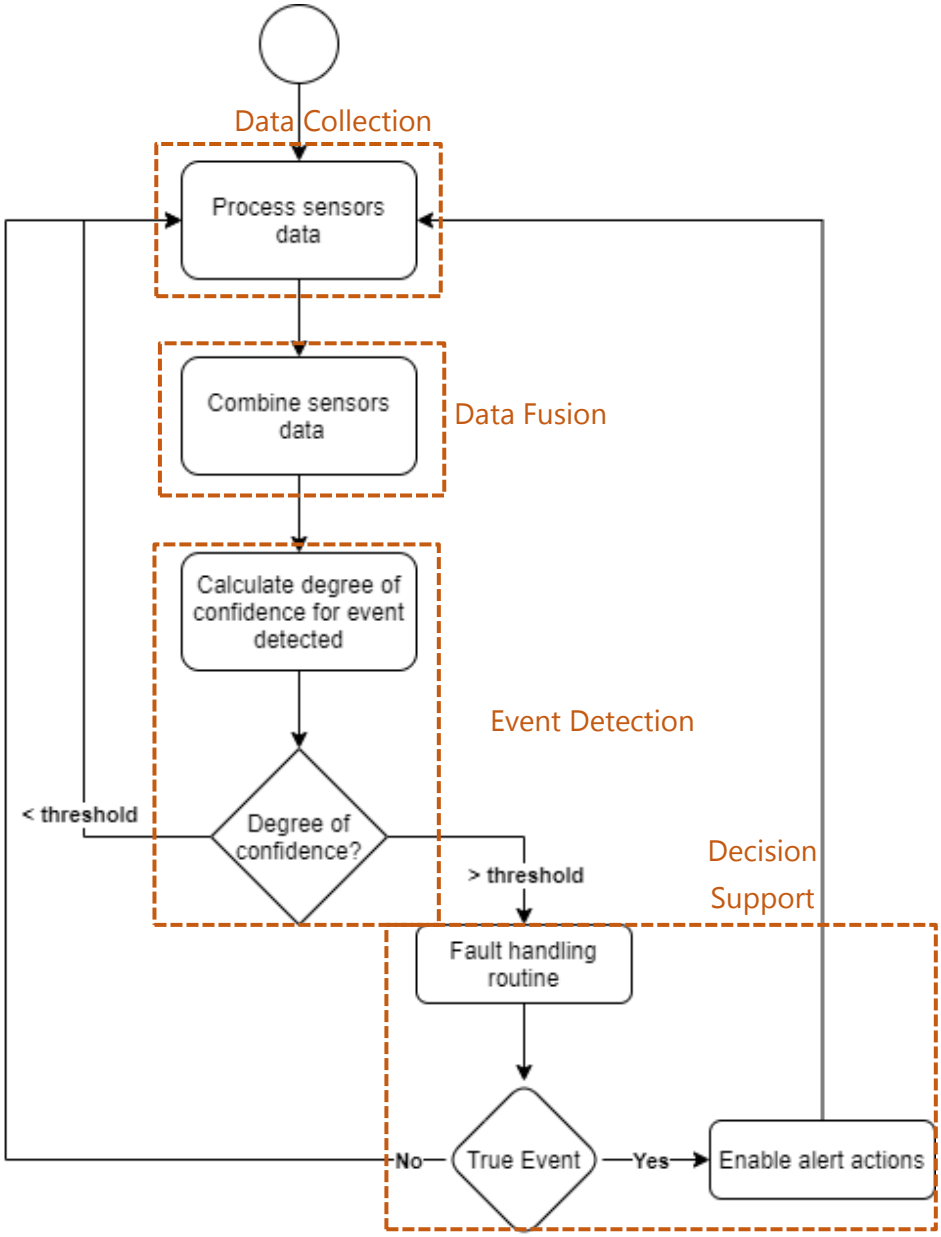


Figure 3-2: Methodology workflow

To start, the system must be operational, therefore the sensors need to be enabled and connected. The selected sensors might need a Bluetooth connection to send its data, or another protocol activated, so the processing unit needs to apply the Bluetooth Low Energy (BLE) protocol, as well as any other common protocols needed.

After that, the system is ready to receive, process and combine the sensors data. The outcome of that fusion allows the calculation of a degree of confidence that, depending on its value, enables a fault handling technique. If the fault handling routine concludes that a relevant

event has indeed happened (true event), it activates alert actions and afterwards continues processing sensor data. If the fault routine declares that a relevant event did not happen (false event), then the system does not bother the user and continues processing sensor data.

Using the scenario in Figure 1-5 as an example, the data sources would be the pillow and the motion sensors. When one of these sensors started sending information that the patient was no longer in bed, the system would calculate a degree of confidence from data sent by both sensors. If the degree of confidence was higher than a certain value, the system would activate, for example, an alert button (fault handling routine) that, if not pressed, the system would assume that a fall had happened and notify (alert action) the nurses of the situation. This way, the true alarm would be detected contrary to what is seen on the scenario.

In the Figure 1-4 scenario, the proposed methodology would avoid the unnecessary help sent, because it would have more than one sensor, as a data source, and therefore the added sensor could verify that a fall did not happen. Additionally, there would be an alert button that if pressed, could confirm that the user was fine. In conclusion, a false alarm would be avoided.

3.3 Data Management Architecture

The layered architecture designed and represented in Figure 3-3, is similar to the data management architecture from chapter 2. For easier understanding, a fall detection mobile application, using the trustworthy methodology, will be used as an example.

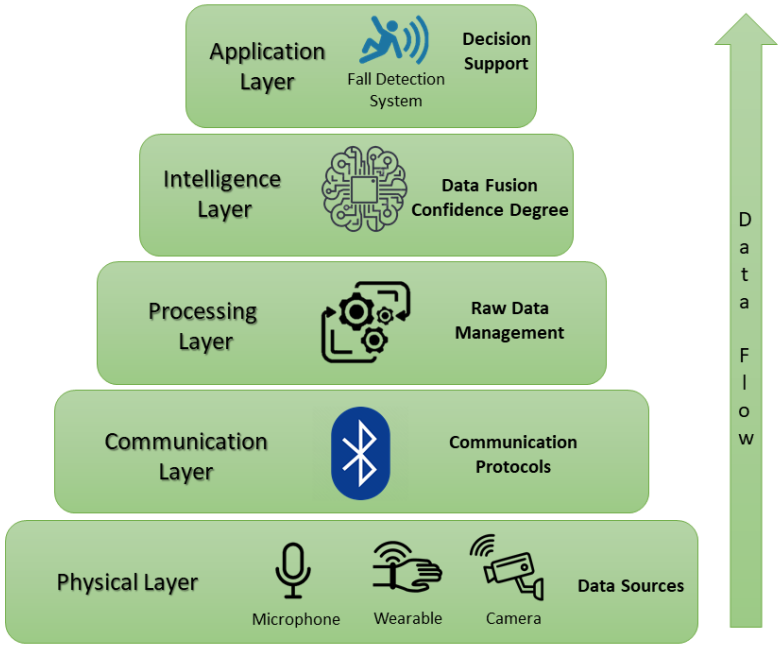


Figure 3-3: Methodology layered architecture

In general, it can be categorized into 5 layers: physical, communication, processing, intelligence, and application:

- **Physical layer** makes the connection between the physical parameter (e.g. temperature, speed, pressure) to be measured and the digital processing system. In the example, the microphone, the motion wearable, and the camera define the boundaries of the physical layer.
- **Communication layer**, or transport layer, is the link between the physical devices and the processing unit. It has been changing throughout the years, from the first cable phones to the high speed 5G network. In the example, the communication link is needed between the smartphone sensors, which probably will be done by Bluetooth. The communication between the microphone and the system also needs communication protocols and, eventually, permissions to use audio data.
- **Processing layer** is necessary because the sensors data received from the communication layer comes in its raw data form. Therefore, the system needs a processing layer, where data is cleaned and transformed to be appropriate for the next stage.
- **Intelligence layer** purpose is to draw conclusions from the data, received from the previous layer, to trigger the necessary actions. In this case, it is in this step that the data fusion and the confidence degree calculation is done to conclude if a fall has occurred.
- **Application layer** delivers specific services to the user, according to the intelligence layer. It is the level with most user interaction that is why simplicity and smoothness are required. In this case, the system is a fall detection mobile application, where the conclusions from the intelligence layer are presented in the app interface. This information enables the user to make more informed and supported decisions about next steps.

3.4 Event Detection and Decision Support

As seen in the fall scenarios of chapter 1, the system's failure was in correctly classifying the detected event and not having a confirmation technique for that classification, which lead to a false and a missed alarm. This failure was the focus of the presented work when developing the methodology, which concluded that a system needs a data fusion, from more than one redundant or complementary data source, to properly classify a detected event and have a validation technique to confirm that event.

To bring the different types of data together and classify an event detected it is necessary to have a common "language" that translates the information received. For that, a confidence degree was developed.

3.4.1 Confidence Degree

The confidence degree, as previously mentioned, is a value that represents the confidence that the system has in the classification of the detected event and is calculated from the fusion of

data obtained from the system's data sources. It is the innovative element of this work, since it serves not only as a trigger for next actions but also as a way to indicate to the user how sure the system is of the detected event. This display also serves as a decision support for the user to make a more informed decision.

The principle is, the higher events number detected, from the different data sources, the higher is the degree of confidence and, therefore, higher is the trust on the system. Using Figure 1-5 scenario as an example, the pillow and motion sensors are continuously sending information for the fall system to process. When the values received from one sensor would indicate an event has happened (a possible fall), the system combines the values received from both sensors and calculates the confidence degree. If both sensors' values indicated that a fall had occurred, the confidence degree would be higher than if only one sensor indicated that a fall had occurred. This way the system uses redundancy by confirming an event detected by one sensor with values from other(s) sensor(s).

To have a more complete and reliable confidence degree method, the system should also have a timeframe that allows all relevant events detected to contribute to the confidence degree within that timeframe. This means that a relevant event detected affects the confidence degree for a certain period of time. Using the Figure 1-5 scenario again as an example and defining that the time frame chosen is 10 seconds. If the pillow sensor detected a possible fall and 5 seconds later it detected another, the system would consider both pillow events for the confidence degree calculation.

The confidence degree calculation also serves as a condition to trigger the fault handling routine.

3.4.2 Fault Handling Routine and Next Actions

The fault handling routine can take many forms, it can be a button that if pressed it confirms the detected event, it can be a voice recognition technique that asks for the user to talk to confirm that nothing happened. Either way, this redundancy approach is necessary to increase even more the reliability system and therefore the trust on the system.

The fault handling routine is also a condition to trigger the next actions, that notify the user for the event detected. In addition to notifying the user of what has happened and indicating the recommended next steps, just as the anomaly probability visualization from Wu et al. (2019) paper, it is also interesting to show the degree of confidence so that the user can make the most informed decision possible.

4

Implementation and Validation

The methodology presented in Chapter 3 has been idealized to respond to the fall detection scenarios illustrated in Sections 1.1.1 and 1.1.2, but is generic enough to be extrapolated to any IoT system with multiple data sources. This chapter presents the implementation details of a fall detection android app developed instantiating the methodology. The name of the app is Fall Fusion, and it was developed in the Android Studio tool.

4.1 Devices Used

In the designed solution, there are two different types of input data: motion and audio. This choice of data was made because a fall is characterised by a rapid and uncontrolled movement often accompanied by a sound coming from the fallen person or/and an object hitting a surface. Therefore, the combination of these two types of data has the potential to successfully detect a fall.

For the motion data, the system uses a 3-axis accelerometer integrated in a wearable sensor. The plan was to use the Upright[2] device for that purpose because it is a commercial device and has the proper type of accelerometer for the proposed solution. However, after successfully connecting with it, the movement data received was not raw, this means that the values were converted before they were sent to the smartphone by Bluetooth. Therefore, they couldn't be properly interpreted and because of this the Upright device was considered inadequate.

Ultimately it was decided to use a wearable sensor used in some European Union research projects, where the development of this thesis is being incorporated (e.g. Smart4Health[3]). The wearable isn't a commercial sensor but includes all the functionality

[2] More information here: https://www.uprightpose.com
[3] More information here: https://smart4health.eu/en/

needed for the fall detection system. More information about the validation in the research projects is included in Section 4.4.

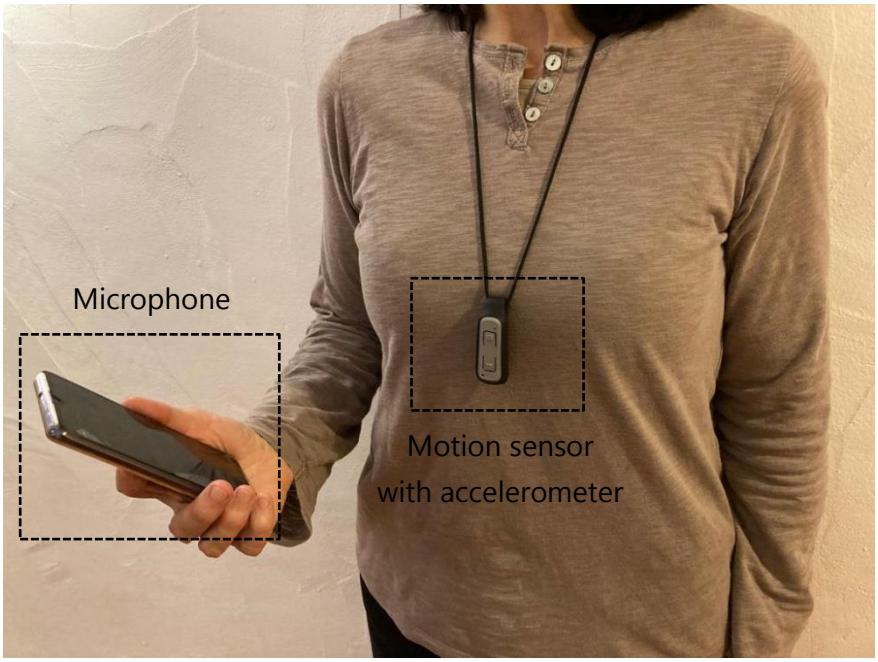


Figure 4-1: Devices used

Regarding the audio data, a smartphone microphone serves the purpose because it is going to be used both as a sensor and as a processing unit. The smartphone used is the Samsung Galaxy A41 smartphone. Both devices are shown in Figure 4-1.

4.2 Implementation Details

The solution architecture, which is adapted from the methodology architecture, is presented in Figure 4-2.

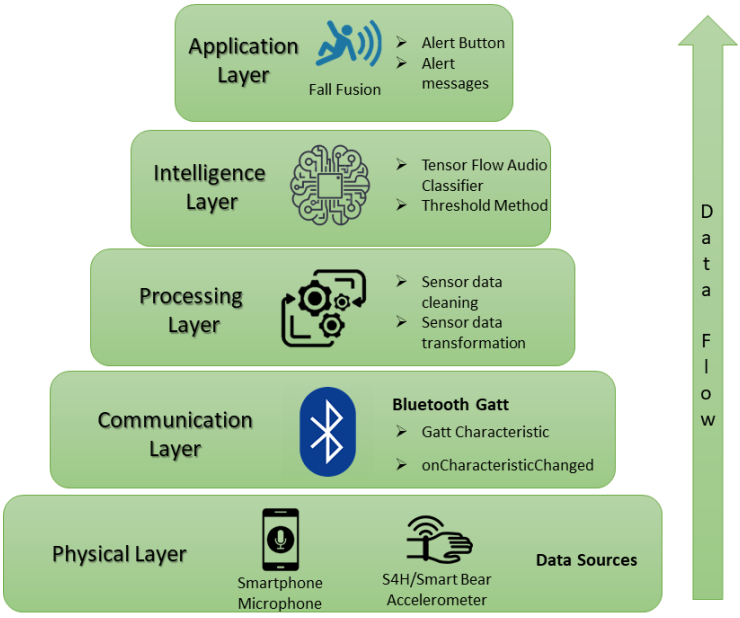


Figure 4-2: Implemented solution architecture

In the implemented solution the physical layers contain a smartphone microphone and a wearable accelerometer. The communication link between the smartphone and the wearable sensor will be done by Bluetooth, particularly Bluetooth Low Energy (BLE) communication, that uses a Generic Attribute Profile (GATT) (Dian et al., 2019) to define how the data is transferred between devices. GATT has services and characteristics attributes that contain data, such as heart rate and position measurements. After connecting successfully with the GATT server hosted by the wearable, the system can obtain the GATT characteristics supported by the device.

In the proposed solution, the interest relies on the device raw characteristic, which is where the accelerometer information is. After enabling the notifications for the raw characteristic, the system will receive its values in the onCharacteristicChanged callback, whenever they change.

The communication between the microphone and the system is seamless as the sensing device is embedded in the smartphone. Still, the communication layer is responsible for managing permissions and accessing sound data.

The processing layer is where data sent by the microphone and accelerometer is processed to a comprehensive form. It involves a transformation and a filtering process, especially in the accelerometer sensor, as its data is sent raw.

In the intelligence layer, audio and motion data is analysed and actions are implemented according to it. The method to define that a fall was detected is different for each sensor. For the audio detection, the Tensor Flow machine learning platform is used, which provides a list of categories and scores for each set of audios detected. For the motion detection, the system uses a threshold method to classify a fall detected. From this information the system combines the data by calculating the confidence degree which is the condition to trigger the fault handling routine.

The fault handling routine is deployed in the user interaction layer by printing a button on the smartphone screen. If the user does not click it within a certain period of time an e-mail will be sent to their emergency contact. The message information changes according to the type of event detected (audio and/or movement) and if the user pressed the button.

4.2.1 Communication Set-up

As mentioned, the only communication link that needed to be created was the BLE between the smartphone app and the motion sensor. For that, the permissions presented on Figure 4-3 are necessary for the Fall Fusion app to have access to the data read by the accelerometer. These permissions also mean that the user needs to always have the Bluetooth and location on.

```
<uses-permission android:name="android.permission.BLUETOOTH" />
<uses-permission android:name="android.permission.BLUETOOTH_ADMIN" />
<uses-permission android:name="android.permission.BLUETOOTH_CONNECT" />
<uses-permission android:name="android.permission.ACCESS_FINE_LOCATION" />
<uses-permission android:name="android.permission.ACCESS_COARSE_LOCATION"/>
<uses-permission android:name="android.permission.ACCESS_NETWORK_STATE"/>
<uses-permission android:name="android.permission.INTERNET"/>
```

Figure 4-3: Wearable permissions

The next step is to scan the available devices and connect with the wearable using his address. Once the connection is made with the device, the app has access to the device services and characteristics. To receive accelerometer data, the raw characteristic notifications is enabled, and the accelerometer values are sent to the app whenever they change.

To access the audio data received from the smartphone microphone the Figure 4-4 permission is needed.

```
<uses-permission android:name="android.permission.RECORD_AUDIO"/>
```

Figure 4-4: Audio permissions

4.2.2 Motion Detection

The wearable device offers different types of information from the sensors embedded in it, which are: gyroscope, magnetometer, and accelerometer. Being the last the one of interest for the implemented system.

The values received from the motion sensor need a processing transformation for them to be understood. However, for copyright reasons, the processing formulas are not presented in this thesis.

After processing the motion data, the obtained values are the 3-axis coordinate systems: X, Y and Z. Figure 4-5 shows the change in the 3-axis values from when the sensor is stationary (above the line) to when it is moving (bellow the line).

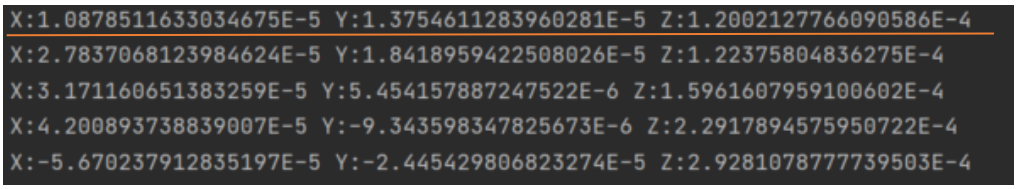


Figure 4-5: Axis values from the accelerometer

For the event detection algorithm, it is easier to have only one value to check rather than three, therefore the three accelerometer axes are transformed, according to Equation 4-1, to the magnitude, or length, of the acceleration vector ($\overrightarrow{Acc}$).

$$\left|\overrightarrow{Acc}\right| = \sqrt{X^2 + Y^2 + Z^2} \quad (m/s^2) \qquad \text{Equation 4-1}$$

The approach chosen to define a dangerous movement (possible fall event) was to consider it when the motion sensor is in a free fall situation. To define the threshold value, it was necessary to better understand how a free fall works, more specifically, how the values of Acc vary when this happens. The simplest method was to install a phone app (Physics Toolbox Accelerometer[4]) that logged the phone accelerometer data and saved it in a graphic format.

[4] More information here: https://play.google.com/store/apps/details?id=com.chrystianvieyra.android.physicstoolboxaccelerometer&hl=en_US&gl=US

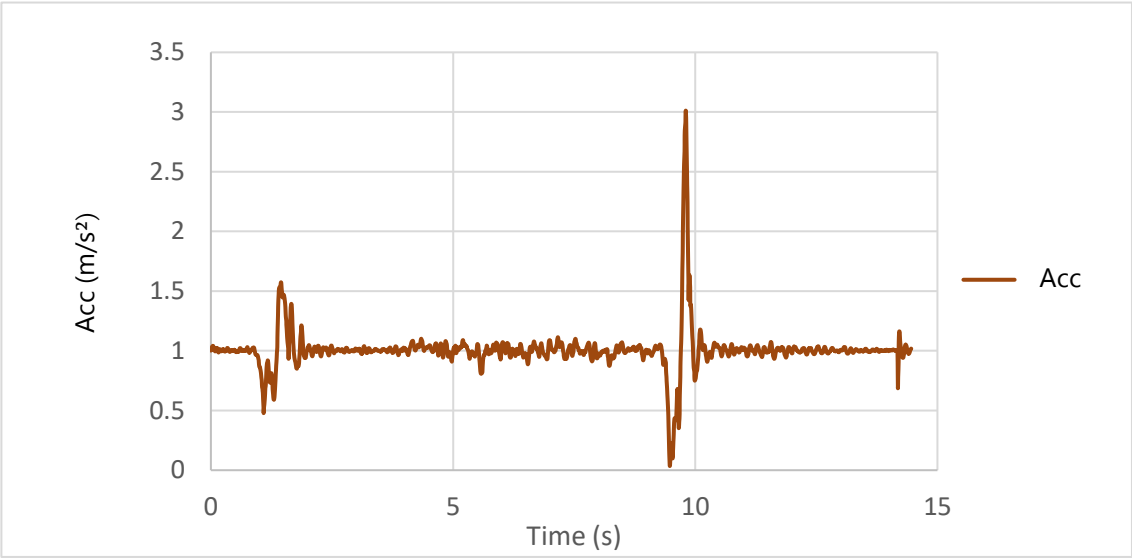


Figure 4-6: Gravitational force variation during a free fall

Figure 4-6 represents the behaviour of the acceleration magnitude (Acc) during two types of free falls: a soft and a sharp fall. The second peak, which has a value of approximately 3 m/s², represents a very sharp fall as opposed to the first peak which is a much softer fall with a peak value of approximately 1.5 m/s². Hence, 2 m/s² and 2.5 m/s² were chosen as the threshold values, as they are the values between 1.5 and 3.

A motion trust variable was created with the purpose to represent the possible fall events detected by the accelerometer. This accelerometer trust value will then affect the event detected confidence degree, which will be further explained in the Confidence Degree and Alert Actions section.

If the acc value is between the two threshold values it adds 0.5 to the accelerometer trust variable, if it is higher than 2.5 m/s² (highest threshold) it adds 1, with this being the maximum accelerometer trust value. This information is then sent to the fall detection function for further analysis. If the sensor detects no dangerous movement (Acc lower than 2 m/s²) nothing is sent to the function.

4.2.3 Audio Detection

As mentioned, the TensorFlow Lite Task Library, more specifically the audio classifier API, is used for the audio processing. The reason for choosing the Tensor Flow platform is because it is open source and easy to use for app developers. The sound classifier android sample app[5] was used as a guidance to implement the sound classification on the proposed solution.

[5] More information here: https://github.com/tensorflow/examples/tree/master/lite/examples/sound_classification/android

The audio classification starts by recording the audios detected and loading them into a tensor audio, which maintains a ring buffer to store input audio data. The audios are then classified with the tensor flow audio classifier, the YAMNet[6], which calculates a score (with a maximum value of 1) for each audio and saves it in a list for further purpose. An example of audios detected, and their scores, are shown in Figure 4-7.

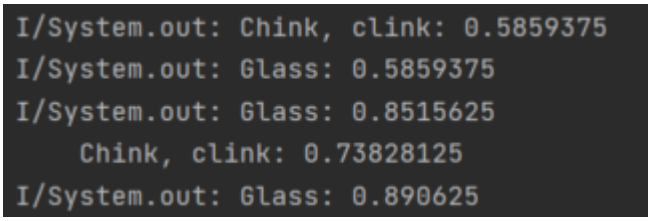


Figure 4-7: Example of sounds detected and their scores

After testing different types of sound (e.g. screaming, breaking a glass, smashing an object) and observed their scores, a value of 0.5 was chosen as the threshold and the list of sounds selected to detect a possible fall were as follows:

- Explosion
- Crying, sobbing
- Splash, splatter
- Glass
- Slap, smack
- Screaming
- Chink, clink
- Breaking
- Smash, crash
- Shatter
- Shout
- Yell
- Bang
- Crack
- Crushing

These sounds were chosen because they are often sounds that are heard during a fall, therefore they are the sounds that are considered relevant to define a possible fall event detected.

As well as the motion detection, for the audio detection an audio trust variable has been created as a representation of a possible fall detected by the microphone. This audio trust will also affect the event detected confidence degree.

[6] More information here: https://www.tensorflow.org/hub/tutorials/yamnet

If a sound score is greater than 0.5, the following changes happen: the score is added to the audio trust, an audio counter increases by one and the sound name is added to a list. For example, if the microphone detects a "screaming" with a score of 0.8 and a "breaking" with a score of 0.7, the audio trust is 1.5, the audio count is 2 and the label list has a "screaming" and a "breaking" label in it. This information is then sent to the fall detection function for further analysis. If nothing is detected (meaning the audio count is 0) nothing is sent to the function.

This process of recording, loading, classifying, and evaluating is embedded in a runnable and is therefore repeated during the operation of the app.

4.2.4 Confidence Degree and Alert Actions

The event detected confidence degree, that supports the fall event statement, is calculated based on the audio trust and the motion trust in the fall detection function. The final audio trust is also calculated in this function by dividing the audio trust received by the audio count. For example, if the audio trust received was 1.5 and the audio count was 2, then the final audio calculated trust would be 0.75.

The confidence degree is a value between 0 and 1 and is obtained with Equation 4-2.

$$Confidence\ Degree = 0.7 \times motionTrust + 0.3 \times audioTrust \quad \text{Equation 4-2}$$

$$Confidence\ Degree \in [0,1]$$

Because a fall is mainly a motion event the accelerometer has a bigger importance than the microphone, therefore he will have a greater weight in the event confidence degree. This means that if the accelerometer detects a possible fall, the system will enable the alert actions process regardless if the microphone detected something or not. The accelerometer priority does not cancel out the importance of the audio, because the confidence degree will be higher if both the accelerometer and the microphone detect a fall, compared to the accelerometer being the only one to detect it.

The confidence degree threshold selected is 0.20, because after several tests, the audio trust limit defined as relevant was higher than 0.7, so multiplying 0.7 by 0.3 gives 0.21. To have a round number, 0.2 was chosen as the confidence degree threshold value. Additionally, as previously explained, whenever the motion sensor detects a possible fall, the alert actions must be triggered. For that to happen, the confidence degree threshold must be higher than the minimum weighted motion trust which is 0.35 (*0.7×0.5)*, which therefore confirms that the confidence value of 0.2 works.

After the confidence degree calculation, the degree of confidence is then checked and if it is greater than 0.2 a fault handling routine is triggered. This means that a button is printed on the mobile phone display. A decision support message is sent to the emergency contact, under certain circumstances, detailing the event detected and the advised next steps. The process of a fall event detection is illustrated in Figure 4-8.

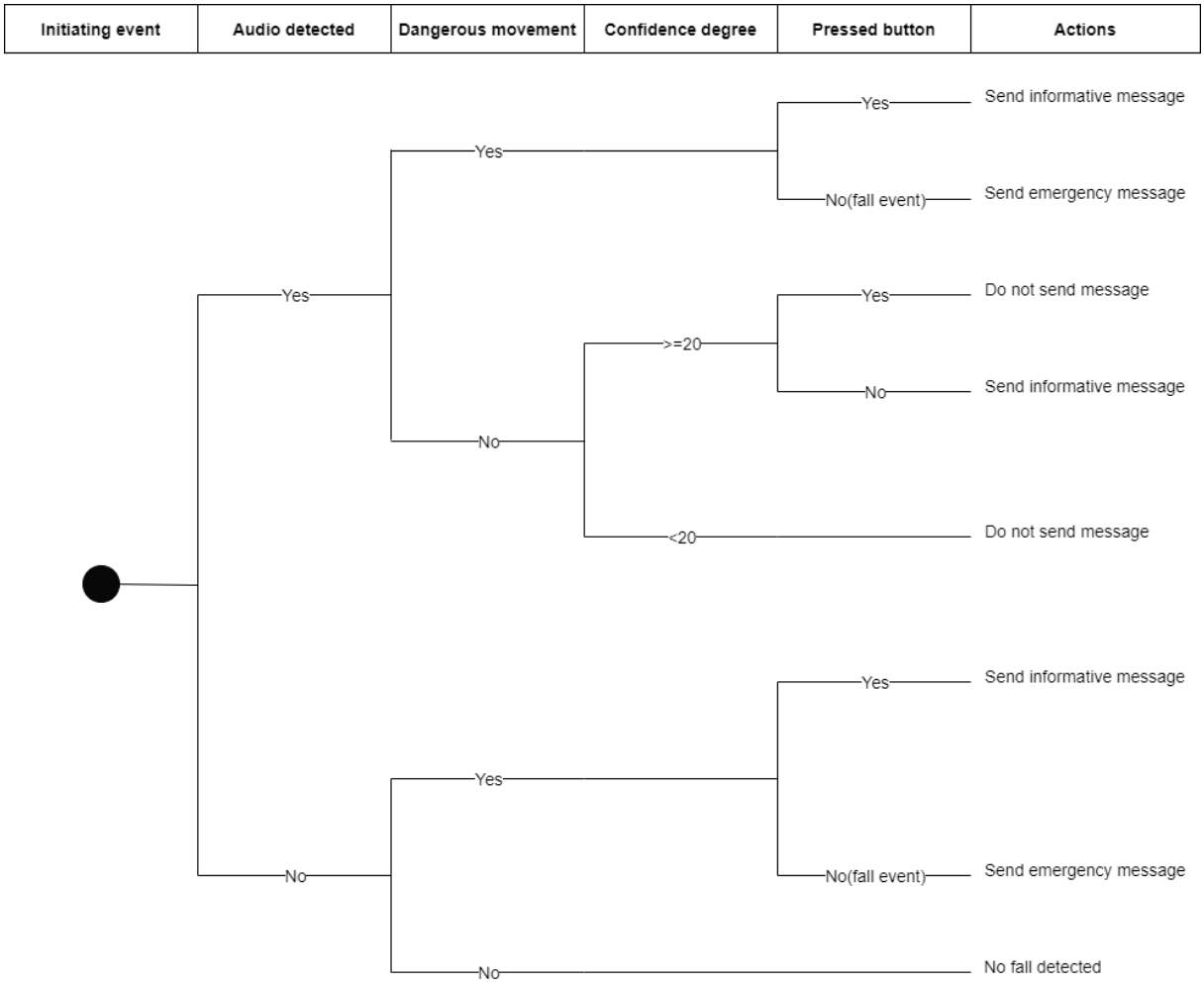


Figure 4-8: Possible fall event decision tree

As Figure 4-8 shows, if there was only a relevant sound detected then the degree of confidence must be higher than 0.2 to enable the fault handling routine. If that is the case, the button appears in the interface, but the message is only sent (in an informative format) if the button is not pressed.

The timeframe, mentioned in chapter 3, that allows to add the trust degrees of every audio and motion event detected within a certain timeframe, was also implemented using timers. Hence, if an audio and movement events are detected within the timeframe defined, their trust degrees will contribute to the confidence degree. In the current implementation, once a relevant event is detected, the system allows the alert actions to immediately process that event. So, the system does not consider events detected later, but which are still within the timeframe, for the alert actions process.

As mentioned, if the confidence degree is bigger than 0.2, a button and a message will appear in the phone screen, as shown in Figure 4-9.

Figure 4-9: Alert button interface

The next actions will depend on the type of sound and movement detected and if the user pressed the button as shown in the decision tree of Figure 4-8. On certain situations an emergency (Figure 4-10) or an informative e-mail (Figure 4-11) will be sent to the emergency e-mail address.

falldetection18@gmail.com
para mim

We believe a fall has happened and our advice is to call your elder or call the hospital directly.
Degree of confidence (trust) of a fall: 54%
Audio confirmations: Glass
Dangerous movements: yes
The elder did not pressed the alert button.

Figure 4-10: Emergency example message

In the message of Figure 4-10, there was a glass sound detected, which means a glass was broken, and a dangerous movement detected. To support the user decision, the degree of confidence is mentioned (in the form of a percentage for easier understanding) and the message also mentions that the user has not pressed the alert button and is therefore an emergency.

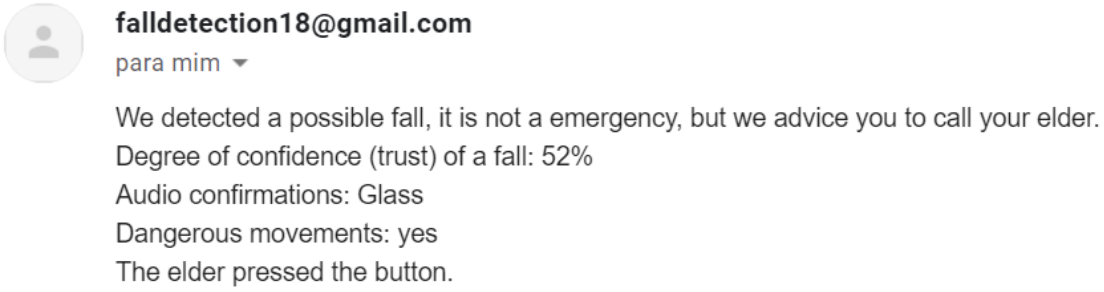


Figure 4-11: Informative example message

Figure 4-11 situation is very similar to Figure 4-10, the only difference is that the user pressed the alert button to cancel for help. Therefore, it is not an emergency, but the system advice is to call the relative, nevertheless.

4.3 Results and Discussion

In this section, the performance of the proposed system is evaluated with 7 types of daily activities and one fall event. Each activity was performed 10 times, making a total of 70 sample tests.

The fall event activity included sound and/or movement experiments and a fall event classification was defined as the printing of the alert button (Figure 4-9) on the phone screen. The motion sensor was placed in the tester's chest and the phone was near the sensor, so the Bluetooth connection wasn't lost.

Some of the audio samples used were from the collection of sound clips drawn from YouTube, available on Audio Set from Google [7].

The experiments have four possible outcomes:

- **true positive** (TP) is defined as an event which the system detected a fall when a fall has happened.
- **false negative** (FN) is defined as an event which the system did not detect a fall when a fall has happened.
- **true negative** (TN) is defined as an event which the system did not detect a fall when a fall did not happen.
- **false positive** (FP) is defined as an event which the system detected a fall when a fall did not happen.

The system performance is calculated as Equation 4-3 shows.

$$System\ Performance = \frac{TP + TN}{Total\ Experiments} \times 100 \qquad \text{Equation 4-3}$$

[7] available here: https://research.google.com/audioset/dataset/index.html

Table 4-1: Proposed system performance

Activities experiments	Number of experiments	True positive (TP)	False negative (FN)	True negative (TN)	False positive (FP)	Performance	System Performance
Falling	10	7	3			70%	83%
Sitting/Getting up	10			7	3	70%	
Laying down	10			8	2	80%	
Walking	10			10		100%	
Going downstairs	10			7	3	70%	
Doing the dishes	10			10		100%	
Watching Tv	10			9	1	90%	
Total	**70**	**7**	**3**	**51**	**9**		

The results of the experimental data are shown in Table 4-1. A total of 7 out of 10 falls were detected whereas 3 of the falls were not detected because the confidence degree was not higher than the threshold. This may have been because the fall was very soft, or because no sound was heard evidencing a fall.

It is important to mention that most of the fall's experiments were correctly detected due to the motion sensor, even though sounds were also played. This means that the system recognizes a dangerous movement better than an alarming sound. It may be due to the Tensor Flow audio classification method or because of the event processing method. As referred in the previous section, when a dangerous movement is detected the confidence degree is greater that the limit and the fault handling routine is immediately triggered. This causes for the system to ignore the following events detected, but the confidence degree is changed with those events, nevertheless. This does not compromise the system as the alert button creates extra redundancy in the system and all detected events are presented to the emergency contact so he can make the most informed decision possible.

The 9 false positives happened because, either the subject moved too fast, or the audio was misclassified, and the system mistook that for a fall. The higher false positives are in the sitting/getting up and going downstairs experiments, which is reasonable because, in the first case, the person can sit too abruptly making the motion sensor shake, which causes the sensor to send free fall values (Figure 4-5). In the second case, a scream from a movie on the Tv can also confuse the audio sensor by classifying it as a "screaming" sound.

From Equation 4-3, the system performance was calculated resulting in a value of 83%, which is a good starting point for a prototype app. The performance calculation is merely a representative value of the viability of the implemented fall detection app, it is not intended to be a comparison with other works since they have different methodologies and testing environments.

4.4 Community Validation

A paper (Michel et al., 2022) based on this thesis was submitted and accepted for presentation at the workshop "Health and health-related data: the foundation for eHealth" organised at the I-ESA 2022[8] conference. Being reviewed by two independent experts in interoperability for enterprise systems and applications, it sets another important means of validation of the work developed.

The Fall Fusion app is being incorporated in the Citizen Hub application (available in the Android App store), which is developed in the Smart4Health project to allow users to collect and manage their health-related data through wearable devices. The Citizen Hub application is also used in the Smart Bear[9] project, as a means to monitor posture and daily activities to understand their impact on lower back health and balance disorders. The sensors delivered to the project participants[10] are shown in Figure 4-12, where the Citizen Hub app is installed in the smartphones distributed in the sensors pack. The fall fusion functionality is only available on the developer branch but will soon be available on the public branch of the Android store.

Figure 4-12: Smart Bear sensors pack

It is very interesting to incorporate the Fall Fusion app into the Smart Bear project, because it works with people over 65 years old, who are very prone to falls and, therefore, the app can be very useful for these people.

[8] More information here: https://i-esa2022.webs.upv.es/index.htm
[9] More information here: https://www.smart-bear.eu
[10] The Smart Bear project has a pilot study in Madeira until mid-2023

5

Conclusions and Future Work

The motivation for the present study was the potential that IoT systems can create in today's society. Especially in the older population, as they are more susceptible to debilitating conditions. For this reason, it is vital to continuously bring new forms of technology that enable a more independent and healthy life.

Beside the technology development, it is tremendously important to increase the use of it, which is often linked to concerns and doubts created by situations like false or missed alarms. It was precisely this mistrust that this thesis tried to solve or at least diminish.

To solve the problem described in the research question, a hypothesis was formulated, where the concepts of data fusion and redundancy are firstly introduced, which are related to data management, decision support, fault handling and event classification.

With the background research established, it was possible to develop the proposed methodology for trustworthy IoT systems. A system with a number of redundant data sources for a meaningful data fusion and a proper event classification with a significant degree of confidence calculated. Where the degree of confidence technique was the innovative work approach, which is a value that represents the reliability the system has on the event detected classification. Its value depends on the combined information received by the system's data sources. The principle is, the higher events number detected, from the different data sources, the higher is the degree of confidence and, therefore, higher is the trust on the system.

As healthcare is a large domain with many applications of interest, this dissertation focused on the detection of falls, inside home environments, which is also a novel point of this thesis, because usually work related to system reliability is very directed towards industrial systems rather than people. Hence, a fall detection phone application using sensor fusion and methods to create extra redundancy was developed. The data sources chosen were from a phone microphone (audio) and from an accelerometer (motion) sensor embedded in a

wearable. This choice of sensor combination being also innovative, considering the current offer of sensors present in a fall detection system.

The system suffered some changes due to challenges encountered during its development, such as the Upright values that could not be read correctly and therefore the device was impossible to use. The final solution becomes a fall detection app with two different sensors, one wore around the neck (motion sensor) and the other on an everyday item (microphone smartphone). An alert button and an automated message system are also implemented, which introduces extra redundancy and therefore increases the trust on the system.

The tests results show that the system has a performance of 83% and the detection of more than one event by both or one of the sensors has a higher degree of confidence than if it was one event detected. This proves that having a number of redundant data sources for a meaningful data fusion improves the system reliability and therefore the trust on the system, as foreseen in the work hypothesis.

It would be interesting to further develop the concepts of event synchronism and database in the conceptual methodology, in a sense of creating an history of events that could be accessed and weighted in the fused data. Validating the conceptual methodology in more scenarios and applications areas would also be interesting.

As future work, the system performance could be increased by training the machine learning audio classifier more and by turning the system cross platform, being accessible also in iOS applications. Instead of the research projects motion wearable, a more commercial accelerometer sensor could be used in future applications.

Regarding the system workflow, an improvement could be a buzzer that alerted the user in case the Bluetooth connection was lost. A buzzer to catch the user attention to the alert button could also be an improvement, as well as alert messages sent to the emergency contact's mobile phone instead of the email.

This solution was validated only in a laboratory environment and partially implemented and validated in the Smart Bear project. With future work it will be possible to test in a more real scenario with elderly population, which is the focus of this work. The feedback from this implementation will also contribute tremendously for improvements to be made in the future.

It is very important to continuously improve the methods that ensure the system trustworthiness and therefore the use of it. Especially in elderly population, where this type of system allows a more independent living while ensuring the security and wellbeing of the system users.

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