PUCRS

ESCOLA POLITÉCNICA
PROGRAMA DE PÓS-GRADUAÇÃO EM CIÊNCIA DA COMPUTAÇÃO
DOUTORADO EM CIÊNCIA DA COMPUTAÇÃO

MAICON DIOGO MUCH

RISK SITUATION DETECTOR FOR ELDERLY PEOPLE BASED ON TIME-SERIES ANALYSIS

Porto Alegre
2024

PÓS-GRADUAÇÃO - *STRICTO SENSU*

Pontifícia Universidade Católica do Rio Grande do Sul

PONTIFICAL CATHOLIC UNIVERSITY OF RIO GRANDE DO SUL
SCHOOL OF TECHNOLOGY
COMPUTER SCIENCE GRADUATE PROGRAM

RISK SITUATION DETECTOR FOR ELDERLY PEOPLE BASED ON TIME-SERIES ANALYSIS

MAICON DIOGO MUCH

Doctoral Thesis submitted to the Pontifical Catholic University of Rio Grande do Sul in partial fulfillment of the requirements for the degree of Ph. D. in Computer Science.

Advisor: Prof. Dr. César Marcon

Porto Alegre
2024

Ficha Catalográfica

M942r Much, Maicon Diogo

Risk situation detector for elderly people based on time-series analysis / Maicon Diogo Much. – 2024.
93 p.
Tese (Doutorado) – Programa de Pós-Graduação em Ciência da Computação, PUCRS.

Orientador: Prof. Dr. César Marcon.

1. elderly risk situation detection. 2. time series analysis. 3. machine learning. I. Marcon, César. II. Título.

Elaborada pelo Sistema de Geração Automática de Ficha Catalográfica da PUCRS
com os dados fornecidos pelo(a) autor(a).
Bibliotecária responsável: Clarissa Jesinska Selbach CRB-10/2051

MAICON DIOGO MUCH

RISK SITUATION DETECTOR FOR ELDERLY PEOPLE BASED ON TIME-SERIES ANALYSIS

This Doctoral Thesis has been submitted in partial fulfillment of the requirements for the degree of Ph. D. in Computer Science of the Computer Science Graduate Program, School of Technology of the Pontifical Catholic University of Rio Grande do Sul

Sanctioned on March 25, 2024.

COMMITTEE MEMBERS:

Prof. Dr. Rafael Reimann Baptista (PPGGERONBIO/PUCRS)

Prof. Dr. Fernando Gehm Moraes (PPGCC/PUCRS)

Prof. Dr. Jarbas Aryel Nunes da Silveira (PPGETI/UFC)

Prof. Dr. César Marcon (PPGCC/PUCRS - Advisor)

This work is to everyone who was part of this journey, contributing with their time, effort, motivation or simple support in difficult times.

“Não se pode criar experiência. É preciso passar por ela.”

(Albert Camus)

ACKNOWLEDGMENTS

The process of developing this thesis had the contribution of several people who were involved in parts, and in some cases from end to end, supporting, researching and dedicating their efforts to make this work successful.

I thank master's students Júlio Alexander Sieg, Vanessa Bartoski, Guilherme Schreiber who developed significant parts of this research in their master's projects. I would also like to thank Ayalon Angelo de Moraes Filho, now master, for his support and dedication to research, all members of the HealthCare System Group (HSG) research group coordinated by Professor Marcon.

I would also like to thank the scientific initiation scholarship holders Diogo Ogochi and Rodrigo Tourinho, for developing software, testing and validating stages of this thesis.

Special thanks to my advisor Prof. Dr. César Marcon for his dedication and skill in leading this research.

Also I would to thank Conselho Nacional de Pesquisa e Inovação (CNPq) to support this work through the scholarship from program Doutorado Acadêmico para Inovação (DAI) through the call 23/2018.

Lastly, I would like to thank my family for their patience and understanding of the moments I was absent and especially my wife Dinara, my reason for completing this work.

DETECÇÃO DE SITUAÇÕES DE RISCO EM IDOSOS BASEADO EM ANÁLISES DE SÉRIES TEMPORAIS

RESUMO

Pessoas em idade avançada estão mais expostas a situações de risco como quedas, alterações bruscas em sinais vitais e desmaios. Estas situações se tornam mais comuns neste estágio da vida devido à diminuição natural da capacidade do corpo de coordenar os movimentos de forma adequada. Inúmeros estudos já propuseram sistemas de monitorização da saúde desta faixa populacional analisando dados de acelerometria e/ou baseados em algoritmos de aprendizado de máquina, porém o uso destes sistemas em situações reais mostrou que esta abordagem ainda é insuficiente para que uma situação de risco possa ser diferenciada com precisão de atividades da vida diária de um idoso. Este projeto propõe o desenvolvimento de um sistema de monitoração da saúde de idosos eficaz e confiável, através da coleta contínua de séries temporais extraídas de sensores de movimento associados à sinais vitais. Estes sinais alimentam uma arquitetura de rede neural profunda do tipo Long Short-Term Memory (LSTM), capaz de interpretá-los levando em consideração não apenas o instante da coleta, mas todo o contexto pré e pós situação de risco. Esta arquitetura foi baseada na hipótese de que existe uma mudança significativa nos sinais vitais associados com uma queda real. Para esta avaliação foi criado um ambiente composto por um simulador de dispositivo wearable, um simulador de aplicativo de celular e um simulador de sistema em nuvem, muito próximo ao cenário real. Este sistema, em seu modelo final, apresentou uma acurácia geral de 97%, mostrando que a fusão de sensores em um arquitetura de análise contínua de dados contribui para o aumento da capacidade de detecção de risco em idosos.

Palavras-Chave: detecção de situações de risco em idosos, análise de séries temporais.

RISK SITUATION DETECTOR FOR ELDERLY PEOPLE BASED ON TIME-SERIES ANALYSIS

ABSTRACT

Elderly people are more exposed to risk situations such as falls, sudden changes in vital signs and fainting. These situations become more common at this stage of life due to the natural decrease in the body's ability to coordinate movements adequately. Numerous studies have proposed health monitoring systems for this population group by analyzing accelerometry data and/or based on machine learning algorithms, but the use of these systems in real situations has shown that this approach is still insufficient to accurately differentiate a risk situation from an elderly person's daily activities. This project proposes the development of an effective and reliable health monitoring system for the elderly, through the continuous collection of time series extracted from movement sensors associated with vital signs. These signals feed a deep neural network architecture of the Long Short-Term Memory (LSTM) type, capable of interpreting them taking into account not only the moment of collection, but the entire context before and after the risk situation. This architecture was based on the hypothesis that there is a significant change in vital signs associated with a real fall. For this evaluation, an environment composed of a wearable device simulator, a mobile application simulator and a cloud system simulator was created, very close to the real scenario. This system, in its final model, presented an overall accuracy of 97%, showing that sensor fusion in a continuous data analysis architecture contributes to increasing the elderly risk detection capacity.

Keywords: elderly risk situation detection, time series analysis.

LIST OF FIGURES

Figure 2.1 – Fall event represented in a triaxial accelerometer sensor, showing pre-fall, critical, and post-fall phases (Source: Author). 22
Figure 2.2 – Impact of sensor activity data from moving up and down three steps on a staircase. (Source: Author). 23
Figure 2.3 – The evolution to DNN - visually represents this progression (Source: Author). 24
Figure 2.4 – Typical Artificial Neural Network (Source: Author). 25
Figure 2.5 – Recurrent Neural Network Architecture (Source: [23]). 26
Figure 2.6 – LSTM cell with its internal structure (Source: [17]). 27
Figure 3.1 – Type and number of machine learning algorithms found in related work (Source: Author). 32
Figure 3.2 – Machine learning algorithms most cited in related works (Source: Author). 32
Figure 4.1 – Real time clinical-grade monitoring vital signs device E4 from Empatica (Source: [19]). 36
Figure 4.2 – Pilot research study location and some examples of movements collected (Source: Author). 39
Figure 4.3 – Raw sensor data from an example activity (Source: Author). 41
Figure 4.4 – Raw acc sensor data highlighting the need for filtering (Source: Author). 43
Figure 4.5 – Fast Fourier Transform (FFT) applied to acc sensor data (Source: Author). 43
Figure 4.6 – Acc data filtered with an FIR filter based on a cutoff of 5Hz (Source: Author). 44
Figure 4.7 – Acc data filtered with a median filter (Source: Author). 44
Figure 4.8 – Original sensor data and finished Kalman filtered data (Source: Author). 45
Figure 5.1 – LifeSenior wearable device (Source: Author). 53
Figure 5.2 – Flowchart of operation and data traffic of the system architecture composed of a wearable device, mobile application, and cloud service (Source: Author). 54
Figure 5.3 – System architecture simulator (Source: Author). 56
Figure 5.4 – Wearable device simulator main screen (Source: Author). 56

Figure 5.5 – App simulator plotting real-time series received from the wearable simulator and predicting fall/non-fall situations based on our proposed AI model (Source: Author). 57
Figure 5.6 – Elderly risk situation model characteristics. Our model fuses motion and vital signs data (summing seven-time series at 32 samples per second) towards enriching the volume of information about the user's real situation during a risk situation (Source: Author). 59
Figure 5.7 – User adaptation model proposal (Source: Author). 61
Figure 5.8 – LSTM architecture detailing input, LSTM, and output layers. The input has a dimension of 150x7 because we use 150 samples as a timestep and seven sensor information; the output is Fall or Non-Fall (Source: Author). 62
Figure 5.9 – Machine Learning metrics adopted for model analysis (Source: [24]). 66
Figure 5.10 – Methodology adopted to evaluate the performance of our user update model characteristic (Source: Author). 69
Figure 6.1 – Real time-series prediction system (Source: Author). 71
Figure 6.2 – Loss and accuracy graphic for full model training process (Source: Author). 71
Figure 6.3 – Blood Volume pulse correlated with accelerometer data in volunteer performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground) (Source: Author). 74
Figure 6.4 – Electrodermal Activity correlated with accelerometer data in volunteer performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground) (Source: Author). 76
Figure 6.5 – Heart Rate correlated with accelerometer data in three different volunteers performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle, and then simulate the movement of falling to the ground) (Source: Author). 77
Figure 6.6 – Temperature correlated with accelerometer data in three different volunteers performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground) (Source: Author). 78
Figure 6.7 – Loss and accuracy graphic for final model training process (Source: Author). 79
Figure 6.8 – Loss and accuracy graphic for user-adapted model training process (Source: Author). 80

LIST OF TABLES

Table 3.1 – Definition of the protocol used in systematic literature mapping. 29
Table 3.2 – Articles selected in the systematic mapping of related work. 31
Table 4.1 – Activities performed by each volunteer. 40
Table 4.2 – LifeSenior Profile columns distribution. 50
Table 5.1 – Hyperparameters and characteristics adopted in the LSTM model. . . 63
Table 5.2 – New labeling of each classification to identify only daily living activities, loss of balance, and falls, which is the main focus of this research. . . . 64
Table 5.3 – Model Performance analysis methodology. 66
Table 6.1 – Dataset columns used in the training process of the full model. 70
Table 6.2 – Full model performance on LifeSeniorProfile test data. 72
Table 6.3 – Influence of each physiological information in model training process. 73
Table 6.4 – influence of each physiological information in model accuracy using LifeseniorProfile test data. 73
Table 6.5 – Final model performance on LifeSeniorProfile test data 78
Table 6.6 – User adaptation model performance on LifeSeniorProfile specific user data. 80
Table 6.7 – Performance comparison between state-of-the-art approaches and our model. 81

LIST OF ALGORITHMS

Algorithm 5.1 – Model training algorithm 65

LIST OF ACRONYMS

ACC – Accelerometer

ADL – Activity Daily Living

AI – Artificial Intelligence

ANN – Artificial Neural Network

AVD – Activity of Daily Living

BI-LSTM – Bidirectional Long-Short Term Memory

BLE – Bluetooth Low Energy

BPM – Beats per Minute

BVP – Blood Volume Pulse

CNN – Convolutional Neural Networks

CNPQ – National Council for Scientific and Technological Development

DAI – Academic Doctoral for Innovation

DNN – Deep Neural Network

ECG – Eletrocardiogram

EDA – Electrodermal Activity

FINEP – Funding Agency for Studies and Research

FIR – Finite Impulse Responde

FFT – Fast Fourier Transform

GPU – Graphical Peripheral Units

HR – Heart Rate

HRV – Heart Rate Variability

IMU – Intertial Measuremente Unit

K-NN – K-Nearest Neighbor

LED – Light Emitting Diode

LSTM – Long-Short Term Memory

MEMS – Micro Electro Mechanical Systems

ML – Machine learning

PDE – Loss of Balance

PPG – Photopletismography

PUCRS – Pontifical Catholic University of Rio Grande do Sul

QD – Fall

RNN – Recurrent Neural Network

SVM – Support Vector Machine

TEMP – Temperature

WHO – World Health Organization

CONTENTS

1 INTRODUCTION . . . 17

1.1 MAIN OBJECTIVE . . . 18

1.2 SPECIFIC OBJECTIVES . . . 19

1.3 THESIS' STRUCTURE . . . 20

2 THEORETICAL BACKGROUND . . . 21

2.1 ELDERLY FALL SENSORS SIGNAL REPRESENTATION . . . 21

2.2 TIME-SERIES ANALYSIS MODEL THEORY . . . 24

2.2.1 RECURRENT NEURAL NETWORK (RNN) . . . 25

2.2.2 LONG SHORT-TERM MEMORY (LSTM) . . . 27

3 RELATED WORK . . . 28

3.1 RELATED WORK ON MACHINE LEARNING ELDERLY RISK FALL . . . 28

3.2 RELATED WORK ON PHYSIOLOGICAL AND MOTION SENSORS FUSION FOR ELDERLY FALL . . . 32

4 DATA COLLECTION METHODOLOGY . . . 35

4.1 PILOT TRIAL RESEARCH . . . 35

4.2 DATA COLLECTED DESCRIPTION . . . 37

4.3 DATA PREPROCESSING . . . 39

4.3.1 FORMATTING EACH FILE BASED ON ACTIVITY INTERVAL . . . 41

4.3.2 SAMPLE RATE EQUALIZATION . . . 42

4.3.3 FILTERING . . . 42

4.4 DATASET DESCRIPTION . . . 46

4.4.1 MOTION SENSORS . . . 47

4.4.2 VITAL SIGNS SENSORS . . . 48

4.4.3 PARTICIPANTS CHARACTERISTICS . . . 49

4.4.4 LIFESENIORPROFILE FORMAT . . . 49

5 ELDERLY RISK SITUATION DETECTOR METHODOLOGY . . . 51

5.1 INNOVATIONS PROPOSED IN THE ELDERLY RISK SITUATION DETECTOR MODEL . 51

5.1.1 MOTION AND PHYSIOLOGICAL SENSORS FUSED . . . 51

5.1.2 USER ADAPTATION MODEL . . . 52

5.2 CONTEXTUALIZATION . . . 52

5.3 SYSTEM ARCHITECTURE . . . 54
5.3.1 SYSTEM ARCHITECTURE SIMULATOR . . . 55
5.4 MODEL CHARACTERISTICS . . . 57
5.4.1 MOTION AND PHYSIOLOGICAL SENSORS FUSED . . . 58
5.4.2 USER ADAPTATION MODEL . . . 59
5.4.3 ARTIFICIAL INTELLIGENCE . . . 60
5.5 MODEL EVALUATION METHODOLOGY . . . 63
5.5.1 FULL MODEL PERFORMANCE . . . 67
5.5.2 INFLUENCE OF EACH PHYSIOLOGICAL SENSOR ON OVERALL ACCURACY . . . 67
5.5.3 ANALYSIS OF THE BEHAVIOR OF VITAL SIGNS DURING THE FALL . . . 68
5.5.4 MODEL WITH USER ADAPTATION ANALYSIS . . . 68
5.5.5 COMPARISON OF THE MODEL WITH SIMILAR MODELS . . . 69

6 RESULTS . . . 70
6.1 FULL MODEL PERFORMANCE . . . 70
6.2 INFLUENCE OF EACH PHYSIOLOGICAL SENSOR ON OVERALL ACCURACY . . . 72
6.3 ANALYSIS OF THE BEHAVIOR OF VITAL SIGNS DURING THE FALL . . . 73
6.3.1 ACCELEROMETER-BLOOD VOLUME PULSE INTER-SENSOR CORRELATION . . . 74
6.3.2 ACCELEROMETER-ELECTRODERMAL ACTIVITY INTER-SENSOR CORRELATION . . . 75
6.3.3 ACCELEROMETER-HEART RATE INTER-SENSOR CORRELATION . . . 76
6.3.4 ACCELEROMETER-SKIN TEMPERATURE INTER-SENSOR CORRELATION . . . 77
6.4 FINAL MODEL PROPOSAL BASED ON FUSED VITAL SIGNS RESULTS . . . 78
6.5 MODEL WITH USER ADAPTATION ANALYSIS . . . 79
6.6 COMPARISON OF THE MODEL WITH SIMILAR MODELS . . . 80
6.7 LIMITATIONS . . . 82

7 CONCLUSIONS AND FUTURE WORK . . . 83

REFERENCES . . . 85

APPENDIX A – Publication list . . . **93**

1. INTRODUCTION

Fall and risk situation detection in older adults using noninvasive devices still has crucial open research questions because we do not have a solution to solve real use cases in elderly real-life broadly. In recent years, we have experienced much research covering paramount open research questions, but almost all focus on solving parts of the problem.

The purpose of a fall detection system is to automatically detect falls and enable assistance by family or caregivers in the least invasive way possible. These characteristics impose sensor technology restrictions to solve this problem [68]. Currently, we can broadly classify available technologies in (i) environmental sensing-based systems, (ii) vision-based systems, and (iii) wearable sensor-based systems

Environmental sensing-based systems [73] work by placing sensors in the environment, such as infrared and passive infrared sensors, acoustic sensors, and sonar. This system can monitor and detect falls using non-camera devices, increasing the elderly's acceptance of most privacy laws. However, the most critical disadvantage is the need for the elderly to be in a monitored environment for the system to work.

In vision-based systems, image processing techniques are applied to camera image signals in the environment. Many algorithms for fall detection in this scenario [50][83] have excellent results, but these systems usually face problems related to privacy and elderly acceptance.

A solution that pretends to perform accurate elderly fall detection in real-life scenarios, preserving user privacy, working full time independently of the environment, and increasing elderly acceptance must be based on a wearable sensor-based system [77]. This technology has received much attention recently and is a trend research topic for elderly fall detection. In wearable-based systems usually, the sensors are embedded within a device worn by older people, which can be located on the wrist, waist, or chest. The parameters monitored by such systems are, for the most part, motion data provided by accelerometers, gyroscopes, magnetometers, barometers, and others [25].

Processing motion sensor data embedded in wearables enables us to have information about (i) movement characterization, (ii) impact detection, (iii) orientation detection, and (iv) fall detection. Nevertheless, despite this apparent problem solution, this technology alone does not provide the necessary information to differentiate an actual emergency from a simple daily living activity because signal data representations supplied by this kind of sensor in real life are irrelevant in these scenarios. Many different approaches have been explored to solve the fall detection problem using only motion sensors [2][76]; however, we have experienced significant advances in this area only with the growth of artificial intelligence in recent years [58].

Machine learning (ML) has solved many problems that researchers worldwide have explored for many years, making it possible to detect falls, activities of daily living, and risk situations based on wearable devices. However, despite this recent evolution, we still have open research questions:

1. Algorithms (ML or not) trained with datasets containing not real-life data - Most of the algorithms available show excellent accuracy, and it has been quite common to find solutions with more than 98% of the ability to detect the elderly based on motion sensors embedded in wearables. The problem is that the data used for training these algorithms are collected in simulated environments, like controlled situations in laboratories, which does not accurately represent what the algorithm will find in actual use. In practice, this algorithm usually shows false positives when used in natural environments, decreasing the reliability of these products and affecting the acceptance of the elderly;

2. Real-life datasets for training algorithms are complex to build - Supervised machine learning algorithms are the most common and applicable solution to the fall detection problem. This kind of strategy needs a lot of annotated data for the training process, so we have many available datasets with simulated data. It is not easily feasible to collect data using older people in actual falls, and we think that is also not ethical;

3. Differences in behavior between elderlies in real-life use affect the accuracy—Even having a real-life dataset to use in the training process for machine learning algorithms, we know that older people are an extremely heterogeneous population that suffers from many diseases and have different stages of mobility. This scenario directly affects the accuracy of traditional algorithms, even those developed using machine learning techniques.

To address these problems, we proposed this doctoral Thesis, which consists of developing a risk situation detector based on machine learning for older people based on time series analysis combining motion and physiological sensors embedded in a wristwatch based on a model with the capacity to learn new data from the user, adapting it to the user environment.

1.1 Main Objective

The proposed Thesis aims to develop an elderly-adapted risk situation detector based on machine learning, which will monitor risky situations in real time using subsequent techniques:

1. Context analysis - Traditional fall detection algorithms, which were mainly used before machine learning grew, are based on the advantage of detecting the peak signal in motion sensors when a fall occurs to detect it. Traditional machine learning algorithms primarily focus on techniques to detect this same point but try to reduce the false positives. Both have problems that decrease the acceptance of the elderly. To solve this problem, we propose using recurrent neural networks. This specific deep learning model considers a just data moment and the past and future data associated with one particular spatio-temporal point. In other words, the main idea is to infer a possible fall moment and analyze the associated context before and after this point to improve the accuracy. This inference is possible thanks to the memory capacity of recurrent neural networks that can include new inputs in current prediction and recent data in a manageable amount of past time;

2. Algorithm adapted to user - Algorithm adaptation to each user environment is one of the most important contributions of our research. This research proposes an innovative algorithm based on the user-adaptation concept to solve the worst problem in wearable fall detection and activity classification, i.e., the high rate of false positives. The elderly are an extremely heterogeneous population, with many different mobility degrees, diseases, and behaviors, composing conditions that make it challenging to develop a pre-trained algorithm that fits all these differences. To solve this problem, we propose an algorithm that balances pre-trained information with user information collected during use to improve the accuracy of the detectors;

3. Motion, environment, and physiological sensors fused - Traditional wearable systems focus on motion sensors, the most known to detect activities and possible falls. As we know, motion sensors do not have the total information capacity to do this job, so we explore the idea of adding new sensor types to the decision-making process. Besides motion sensor abilities, physiological sensors provide information about the user's health, which can improve the results. In parallel, since the environment and location contribute to a situation being classified as risky, we also decided to include the user location in the analysis;

4. Energy management algorithm - Based on our strategy to establish different levels of elderly risk, we had the opportunity to manage the energy spent by sensors for each level, building an innovative algorithm that manages battery energy to increase battery life and consequently increase elderly acceptance.

1.2 Specific Objectives

The specific objectives and main contributions of this Thesis are listed below:

1. To develop an elderly daily timeline detailing activities and places - Thanks to our innovative algorithm, which detects activities and locations, we can build a timeline for elderly daily life, which allows us to detect anomalies that can be classified as possible problems;

2. To explore the context before and after a fall and its influences on algorithm accuracy - The moments before and after a possible elderly fall have relevant information that usually is not considered in traditional algorithms. For example, before a fall, the user could have changes in vital signs that physiological sensors will monitor. On the other hand, after a fall, the user can maintain a fixed position, which means that it is not moving. This context will be explored to improve the accuracy of wearable activity and fall detectors;

3. To explore vital signs influences and its benefits in traditional motion sensors analysis for fall detection - The vital signs behavior during elderly risky situations, specifically in falls, is not well addressed in scientific research, as is the motion behavior. Our research aims to explore the behavior of vital signs in this context and include relevant information in our algorithm.

1.3 Thesis' Structure

This Thesis commences with Chapter 2, delving into the theoretical framework. Subsequently, Chapter 3 offers an in-depth analysis of related works. Following this, we elucidate our proposed methodology, including our Data Collection Methodology (Chapter 4) and the Proposed Model (Chapter 5). Chapter 6 showcases the experimental results, while Chapter 7 encapsulates the primary conclusions and outlines avenues for future research

2. THEORETICAL BACKGROUND

The prevalence of older individuals living independently is on the rise, coinciding with advancements in medical care that extend life expectancy, thereby fostering a global trend of older populations residing outside assisted living facilities. According to the World Health Organization (WHO), the proportion of individuals aged 60 and above is projected to nearly double from 12% to 22% between 2015 and 2020 [52]. In a related context, WHO statistics reveal that falls are the second leading cause of accidental deaths worldwide [51]. Although the consumer electronics market is flooded with wearable devices designed to detect falls and alert family members, these products often suffer from frequent false alarms due to poor user interfaces, high energy consumption, and outdated communication systems, compromising reliability. The real-time automated detection of falls using sensor data, such as triaxial accelerometers, remains a pressing research challenge [69]. The primary objective of fall detection systems is to promptly identify falls and notify family members or caregivers for timely intervention. However, accurately recognizing falls poses computational hurdles. While sudden spikes in accelerometer data can characterize falls, they also occur in various non-risk scenarios, making precise detection difficult [49]. The efficacy of fall detectors hinges on their ability to identify genuine falls while minimizing false alarms accurately.

2.1 Elderly Fall Sensors Signal Representation

The rapid advancement of MicroElectroMechanical Systems (MEMS) has boosted sensors to become multi-style, integrated, high-precision, small-size, and low-priced, thus enabling their integration into wearable devices for information acquisition. These devices commonly incorporate accelerometers, gyroscopes, and pressure sensors seamlessly embedded into wristbands, necklaces, belts, and insoles. A typical wearable system comprises one or more sensors and a microcontroller, which collectively execute fall detection by acquiring, analyzing, and processing body motion data to determine the occurrence of a fall.

The key to accurately identifying a real fall based on motion sensor information is understanding how a sensor behaves during fall events. Figure 2.1 illustrates the impact resulting from a fall on a triaxial accelerometer (x, y, and z axes), from which we can observe four phases:

- **Pre-fall** - Characterized by daily living activities followed by an instability period;
- **Critical** - Marked by a sudden movement directed towards the ground;

- **Post-fall** - Usually associated with a body rest scenario;
- **Recovery** - The body position restoration, a phase absent in Figure 2.1.

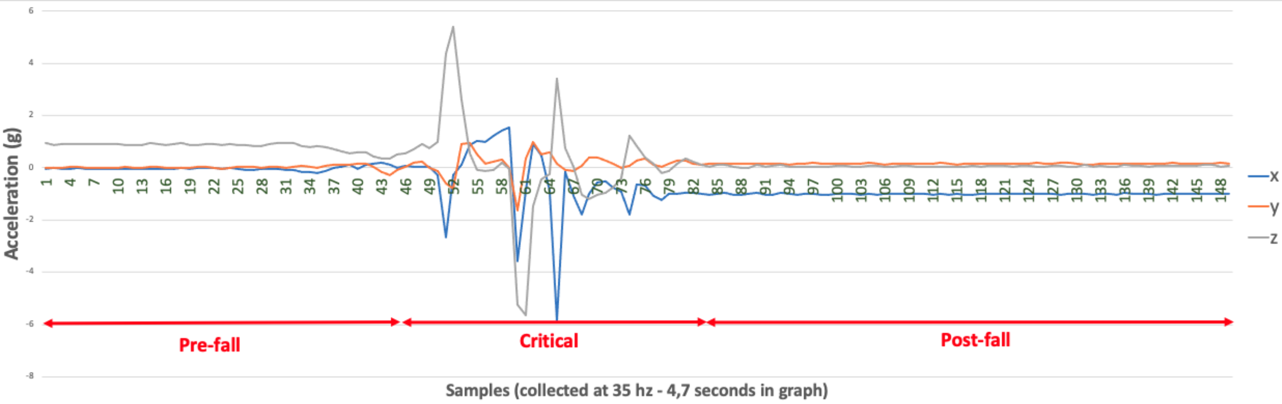

Figure 2.1 – Fall event represented in a triaxial accelerometer sensor, showing pre-fall, critical, and post-fall phases (Source: Author).

Figure 2.1 shows a "standard" curve representing motion impact in accelerometer data due to a fall. In the Pre-fall phase, the motion data is usually composed of an Activity Daily-Living (ADL) or a stable scenario followed by some instability in sensor data, indicating a start of a movement toward the ground. The critical phase comprises a strong peak of acceleration followed by a significant instability in sensors reflecting the impact on the ground. The post-fall phase follows the crucial phase in cases where older people cannot recover (Recovery phase), and the sensor data values remain stable for an extended period.

Several algorithms based on wearable accelerometers and gyroscopes have been proposed to detect falls. One common approach is to discriminate between ADL and falls by threshold values (for acceleration and angular velocity), set primarily by observational methods for both falls and ADL [21][38][78]. The advantage of the thresholding algorithm is its low computational complexity and ease of implementation. However, due to the different ways of human behavior, the recognition results of the thresholding algorithm produce significant differences and usually bad results in a real scenario.

Until now, most researchers have focused on detecting the fall by analyzing the critical phase, illustrated in detail in Figure 2.1; however, as can be seen in Figure 2.2, the representation of the critical phase in motion sensors can easily be confused with an ADL. The acceleration peak illustrated in Figure 2.2 shows that two sources of movement can generate similar behavior in the signal captured by the accelerometer. Therefore, more than a pure and simple identification of the signal morphology representing a fall is required to accurately capture its occurrence, which is usually the problem associated with a high false-positive rate in real-life fall detection.

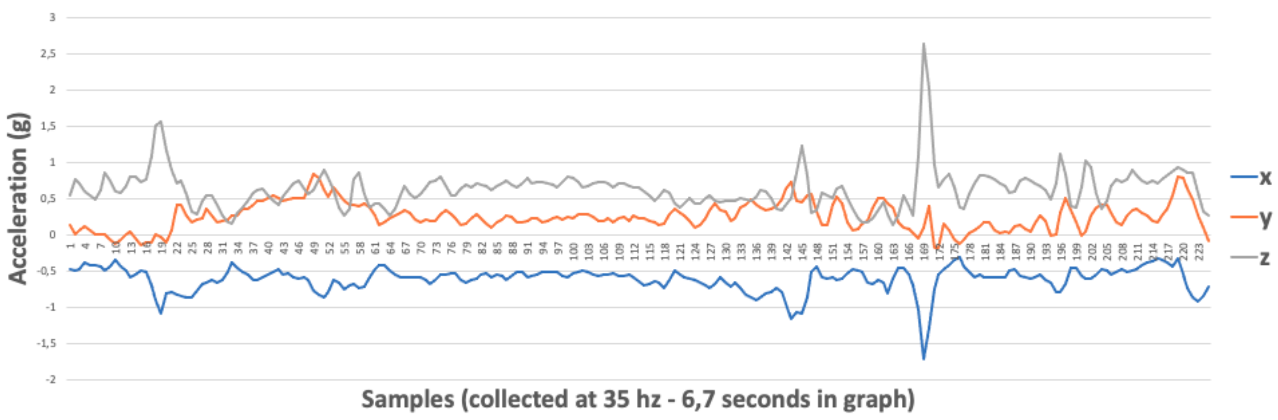

Figure 2.2 – Impact of sensor activity data from moving up and down three steps on a staircase. (Source: Author).

Several studies used machine learning as an alternative to reduce false alarms while maintaining high detection accuracy. Machine learning methods rely on a complex algorithm to get data insights for predicting output decisions. Li, Teng, and Zhang [36] described a survey identifying and categorizing machine learning into supervised and unsupervised techniques.

The supervised technique trains classifiers using pre-classified data distinguishing between falls and Activities of Daily Living (ADLs). Following this training, they are then applied to unseen data. Classical machine learning algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and K-Nearest Neighbor (K-NN) are examples of supervised learning methods widely utilized for fall detection. For instance, [65] developed a wireless gait analysis sensor system for real-time fall detection employing an SVM classifier that extracted six features for fall classification. The results demonstrated 98.8% and 98.7% fall classification accuracies for data collected from the back and belt positions, respectively.

Unsupervised algorithms employ data clustering techniques rather than relying on pre-classified data. Due to the nature of time series data, this approach is rare; however, [43] identified the nearest-neighbor algorithm as the most effective unsupervised learning technique for this type of signal.

Machine learning techniques have significantly enhanced fall detection accuracy, paving the way for extensive research. Despite promising results, these techniques still exhibit a notable rate of false positives. This issue often arises due to the prevalent use of datasets generated from fall simulation scenarios, which can bias algorithms towards seeking highly standardized behaviors, deviating from real-world usage scenarios.

Furthermore, the recent advancements in machine learning algorithms based on deep neural networks have reignited interest in this field, demonstrating promising outcomes and emerging as the preferred technique for this proposal. Chapter 3 outlines related works that applied artificial intelligence to fall detection, while the subsequent section provides a technical description of the algorithm chosen for this study.

2.2 Time-Series Analysis Model Theory

It is imperative to contextualize the tool within its broader framework to understand the proposed model, which leverages the analysis and processing of time series data through deep recurrent neural networks, specifically Long Short-Term Memory (LSTM).

Deep Neural Networks (DNN) are currently at the forefront of Artificial Intelligence (AI) algorithms; they are renowned for their remarkable capacity to enhance accuracy substantially compared to traditional models.

Figure 2.3 illustrates the evolution of neural network technology into Deep Learning within the expansive domain of AI. Machine Learning emerged to automate statistical models, such as linear regression, to refine predictions by training on data that faithfully represents the target scenario.

The term "learning" stems from the iterative process of adjusting the neurons' weights (depicted in Figure 2.4) constituting the network. These weights are fine-tuned during the training phase based on the outcomes observed in each iteration. Consequently, each neuron in the network acquires a weight, directing hidden data with analogous characteristics toward the same outcomes.

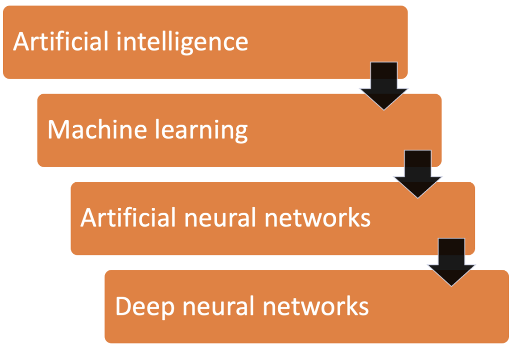

Figure 2.3 – The evolution to DNN - visually represents this progression (Source: Author).

Understanding the concept of machine learning extends to comprehending the operation of traditional ANNs, as depicted in Figure 2.4. These networks typically have three layers: input, hidden, and output. Within ANNs, the hidden layer encodes and assesses the relevance of input features in producing an output. It effectively stores information about the significance of individual inputs and their combinations, thus facilitating the network's learning process.

Deep Learning evolves artificial neural networks by augmenting the number of hidden layers. This increase in depth enhances the network's capacity for learning, albeit

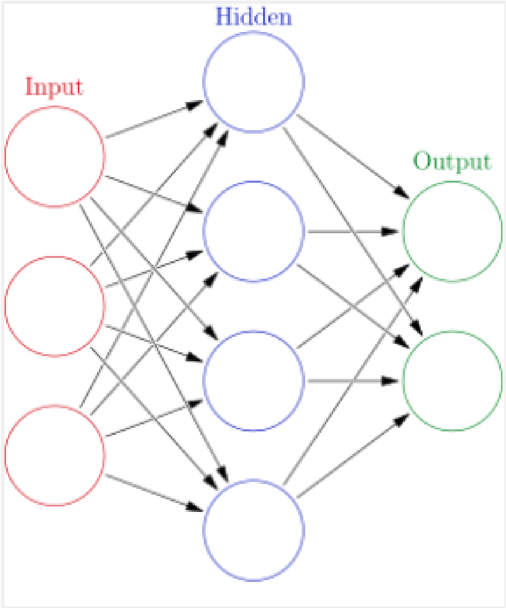

Figure 2.4 – Typical Artificial Neural Network (Source: Author).

at a higher computational cost. This computational barrier has been surmounted with Graphical Processing Units (GPUs) advancements, which enable efficient DNN processing.

2.2.1 Recurrent Neural Network (RNN)

RNN represents a specific type of neural network architecture in which the output from the preceding step serves as input for the current step. Unlike traditional neural networks, where inputs and outputs are treated as independent entities, RNNs excel in scenarios where contextual information from previous inputs is deemed crucial, necessitating the retention of past states to inform current predictions or classifications.

RNNs address this need by incorporating a hidden layer pivotal in retaining information about sequences. The hidden state within RNNs serves as a memory mechanism, preserving essential context from previous steps in the sequence. This capability enables RNNs to effectively process sequential data, making them particularly suited for tasks such as language modeling, speech recognition, and time-series prediction.

As depicted in Figure 2.5, RNNs possess a built-in "memory" mechanism that retains information from previous calculations (h0, h1, h2, ...). Unlike traditional neural networks, where each layer operates independently with its parameters, RNNs utilize the same weights and biases across all inputs and hidden layers, thereby reducing parameter complexity.

Consider a deeper network comprising one input layer, three hidden layers, and one output layer. In a conventional neural network, each hidden layer would have distinct

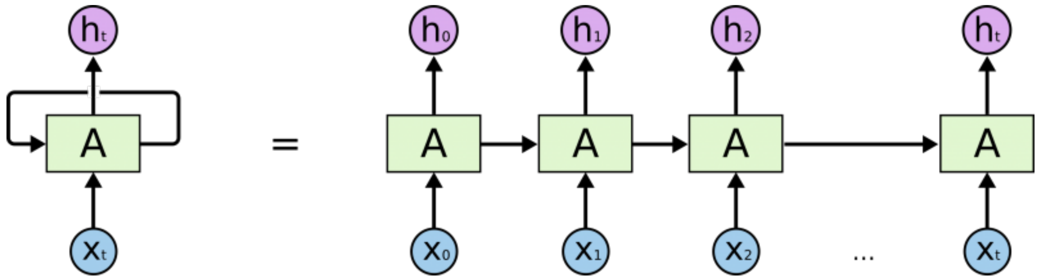

Figure 2.5 – Recurrent Neural Network Architecture (Source: [23]).

weights and biases (w1, b1), (w2, b2), and (w3, b3) for the first, second, and third hidden layers, respectively. Consequently, these layers would operate independently without retaining information from previous outputs. However, an RNN architecture transforms independent activations into dependent activations by sharing the same weights and biases across all layers. This facilitates the memorization of previous outputs by feeding each output as input to the subsequent hidden layer; therefore, the three hidden layers can be unified into a single recurrent layer, where all hidden layers share the same weights and biases.

Let h_t be the current state, h_{t-1} the previous state, and x_t the input state; then, a current state in a recurrent network cell can be expressed as:

$$h_t = f(h_{t-1}, x_t)$$

Let W_{hh} be the weight at the recurrent neuron and W_{xh} the weight at the input neuron; then, the activation function hyperbolic tangent (tanh) is expressed as:

$$h_t = tanh(W_{hh} h_{t-1} +, W_{xh} x_t)$$

Finally, let Y_t be the output and W_{hy} the weight at the output layer; then, the output is represented by:

$$Y_t = W_{hy} h_t$$

Despite the advantages of RNN topology, there are also associated disadvantages, including:

- Gradient vanishing and exploding problems;
- Difficult in training;
- Inability to effectively process very long sequences when using tanh or Rectified Linear Unit (ReLU) as activation functions.

2.2.2 Long Short-Term Memory (LSTM)

LSTM networks offer significant advantages in modeling time-series data[71] due to their specialized structure featuring three gates: input, forget, and output (Figure 2.6). These gates within LSTM networks serve distinct functions, with the "input" gate determining which information to retain and the "forget" gate determining which information to discard. This capability enables LSTM networks to dynamically adjust the balance between retaining past data and assimilating new information, as highlighted in recent literature [56][37]. Such adaptability allows the system to discern each user's behavior during wearable usage, significantly reducing false positive rates.

In time-dependent classification tasks, past and future input features hold relevance for a given period. By leveraging the capabilities of LSTM networks, this architectures can effectively capture forward long-term dependencies. First successful application of LSTM was proposed by Hochreiter [16]. LSTM architectures typically comprise a sequence input layer, multiple LSTM layers, and a single dense layer. This architecture enhances the network's understanding of complex temporal patterns and is well-suited for sequential data analysis tasks.

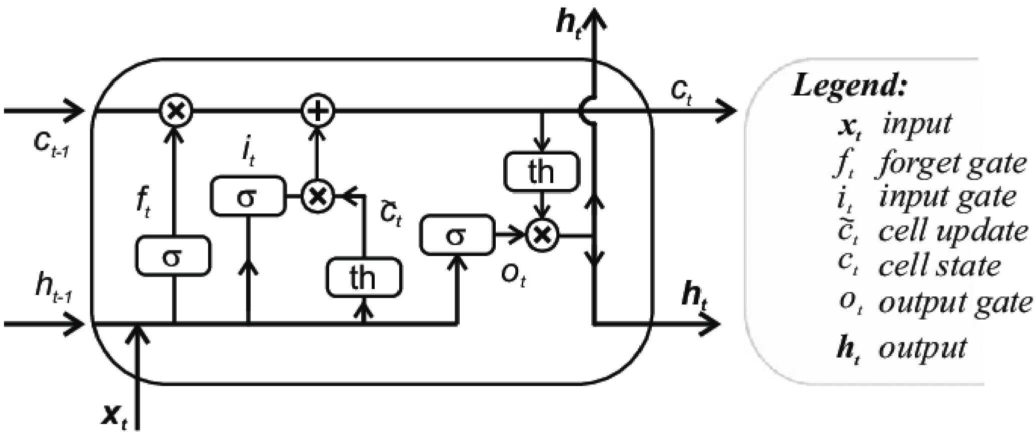

Figure 2.6 – LSTM cell with its internal structure (Source: [17]).

3. RELATED WORK

Fall detection remains an exciting area of research, with numerous approaches proposed in the literature and methods based on Machine Learning (ML) being the focus of research efforts. Section 3.1 delves into the primary ML techniques currently employed in state-of-the-art fall detection systems. This Thesis introduces a novel approach to fall detection, which involves integrating motion sensor data with vital signs commonly accessible through devices like smartwatches. While limited research explicitly addresses this relationship within the scope of our study, Section 3.2 examines the available related work in this area.

3.1 Related Work on Machine Learning Elderly Risk Fall

We conducted a systematic literature mapping to assess the research landscape regarding applying machine learning algorithms in fall detection. The aim was to identify the most commonly utilized algorithms and their effectiveness in identifying falls.

This chapter outlines the development of the systematic mapping process and presents the results obtained, which aided in defining the scope of the ongoing research. The report commences by contextualizing the research and providing vital initial considerations crucial for understanding the process. Subsequently, it details the systematic mapping process and analyzes the results.

The systematic mapping primarily focuses on the characteristics of the proposed model in this Thesis, particularly the type of wearable device used and the sensors it incorporates. Specifically, the context considers primary studies that report developing or comparing machine learning algorithms applied to fall detection by interpreting sensory data. Studies must involve at least one accelerometer sensor fixed to the user's watch position, typically the left wrist. Articles describing sensors in other formats, such as pressure or cameras, are excluded from consideration.

With these criteria in mind, a systematic mapping protocol was devised, with further details provided in Table 3.1. This protocol is a guideline for the systematic review process, ensuring consistency and rigor in the literature search and analysis.

For this research, various search string options were considered, such as:

- (ALL=(fall detection) AND (ALL=(machine learning) OR ALL=(deep learning)) AND ALL=(sensors) NOT ALL=(vision))
- (ALL=(fall detection) AND (ALL=(machine learning) OR ALL=(deep learning)) AND ALL=(sensors) NOT ALL=(camera))

Table 3.1 – Definition of the protocol used in systematic literature mapping.

Parameter	Description
Research question	What machine learning algorithms are being considered in the development of fall detectors?
Search string used	ALL = (fall detection) AND (ALL = (machine learning) OR ALL = (deep learning)) AND ALL = (sensors) NOT ALL = (vision)
Databases	Web of Science and PubMed
Acceptance criteria	1. Primary studies 2. Consider at least an accelerometer 3. Sensor attachment point: left wrist
Exclusion criteria	1. Secondary studies 2. In the identification setup, consider external sensors to the user 3. They do not make it clear which sensors are used 4. They do not make it clear which ML algorithm is used

- (ALL=(fall detection) AND (ALL=(machine learning) OR ALL=(deep learning)) AND ALL=(sensors) AND ALL=(wrist) NOT ALL=(vision))

Ultimately, we decided to select articles published from 2020 onwards. The search included articles written in English or Portuguese, with all resulting article listings being in English. These search strings were applied on the Web of Science platform, where the string: **"ALL = (fall detection) AND (ALL = (machine learning) OR ALL = (deep learning)) AND ALL = (sensors) NOT ALL = (vision)"** yielded the best results, resulting in 241 articles. Article data was exported to a spreadsheet for further processing, including the inclusion/exclusion process.

The exact search string was used on the PubMed platform to complement the search with health-focused perspectives. The search yielded 61 articles whose data were exported to the spreadsheet and subjected to the same inclusion/exclusion process.

After compiling articles from both platforms, 302 articles were selected. The initial exclusion stage involved removing duplicate articles, resulting in 256 unique articles - 46 duplicates were identified and removed from the list.

The subsequent step involved reviewing the titles of the remaining articles and applying exclusion criteria based on specific terms found in their titles. Articles containing terms such as "survey", "review", "camera sensing", "radar", or "pressure sensor" were excluded from further consideration. This step removed 37 articles, leaving 219 articles for further evaluation in subsequent steps.

Next, the inclusion and exclusion criteria were applied to the abstracts and keywords of the remaining articles, further refining the selection. This process reduced the number of articles to 121.

Articles that did not provide information about the sensors used for fall detection or the location of these sensors on the individual's body were excluded. However, articles indicating motion sensors (e.g., accelerometers and gyroscopes) applied to the wrist passed the following evaluation stage.

As the final step of the systematic mapping process, the results were carefully reviewed, and conclusions from the articles were analyzed. In this step, the inclusion and exclusion criteria were applied rigorously to identify the type of sensor used and its position on the user's body.

Among the selected articles, those that did not clearly specify the position of the sensor on the user's body were further evaluated to determine if a detailed examination of the article's content could infer the positioning of the sensor.

Upon completing this process, 57 articles met all criteria and were deemed suitable for inclusion in the study. These articles were thoroughly read and considered for the research proposed here.

In the reviewed articles, the position of the sensor on the user's left wrist was described using various terms, including "watch", "bracelet", "wristband", and simply "wrist". After careful analysis, it was determined that sensors were indeed positioned on the user's wrist in 24 out of the 57 selected articles for full reading. These 24 articles are listed in Table 3.2.

Furthermore, these 24 articles were specifically considered in evaluating machine learning algorithms. The resulting data from this evaluation is presented in the graph depicted in Figure 3.1. This graph illustrates the findings and outcomes of ML algorithms, as discussed in the selected articles, which focus on left wrist sensor placement.

The analysis of the results shows that many architectures and proposals exist to address the fall detection problem. However, it is notable that Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks emerge as the most applicable architectures, as depicted in Figure 3.2.

The recognition of CNN and LSTM architectures as the most applicable for fall detection stems from their exceptional ability to process data sequentially. CNNs excel due to their ability to translate the concept of a three-axis time series (e.g., accelerometer data in x, y, and z axes) into the framework of a three-dimensional image, where CNNs have demonstrated superior performance. On the other hand, LSTM networks are adept at processing sequential data, making them particularly suited for contextualizing sequences, a crucial aspect in analyzing time series data.

Therefore, the success of CNN and LSTM architectures in fall detection can be attributed to their respective strengths in handling sequential data, making them versatile and efficacious tools for addressing this vital healthcare challenge.

Table 3.2 – Articles selected in the systematic mapping of related work.

Ref	Year	Title	Publisher
[29]	2020	Detection of Gait Abnormalities for Fall Risk Assessment Using Wrist-Worn Inertial Sensors and Deep Learning	MDPI
[32]	2020	Deep Learning Based Fall Detection Algorithms for Embedded Systems, Smartwatches, and IoT Devices Using Accelerometers	MDPI
[47]	2020	Cluster-Analysis-Based User-Adaptive Fall Detection Using Fusion of Heart Rate Sensor and Accelerometer in a Wearable Device	IEEE
[11]	2020	Assessing the Feasibility of Augmenting Fall Detection Systems by Relying on UWB-Based Position Tracking and a Home Robot	MDPI
[82]	2020	Hardware-Based Hopfield Neuromorphic Computing for Fall Detection	MDPI
[53]	2020	Comparative Analysis of Real-Time Fall Detection Using Fuzzy Logic Web Services and Machine Learning	MDPI
[55]	2020	Wearable Computing with Distributed Deep Learning Hierarchy: A Study of Fall Detection	IEEE
[6]	2020	FPGA-based Edge Inferencing for Fall Detection	IEEE
[57]	2020	Evaluation of Feature Engineering on Wearable Sensor-based Fall Detection	IEEE
[64]	2020	Pre-Impact Fall Detection with CNN-Based Class Activation Mapping Method	MDPI
[84]	2020	Hierarchical Coherent Anomaly Fall Detection Low Bandwidth System with Combination of Wearable Sensors for Identifying Behavioral Abnormalities	IEEE
[67]	2020	Automated Development of Custom Fall Detectors: Position, Model and Rate Impact in Performance	IEEE
[85]	2021	A Machine Learning Multi-Class Approach for Fall Detection Systems Based on Wearable Sensors with a Study on Sampling Rates Selection	MDPI
[7]	2021	DeepFoG: An IMU-Based Detection of Freezing of Gait Episodes in Parkinson's Disease Patients via Deep Learning	Frontiers Media
[39]	2021	Precise Measurement of Physical Activities and High-Impact Motion: Feasibility of Smart Activity Sensor System	IEEE
[60]	2021	Machine Learning Prediction of Fall Risk in Older Adults Using Timed Up and Go Test Kinematics	MDPI
[33]	2021	Deep Convolutional and LSTM Networks on Multi-Channel Time Series Data for Gait Phase Recognition	MDPI
[79]	2022	Applying deep learning technology for automatic fall detection using mobile sensors	Elsevier
[26]	2022	Automated machine learning based elderly fall detection classification	Elsevier
[81]	2023	Toward Real-Time, Robust Wearable Sensor Fall Detection Using Deep Learning Methods: A Feasibility Study	MDPI
[34]	2023	AI based elderly fall prediction system using wearable sensors: A smart home-care technology with IOT	Elsevier
[27]	2023	Convolutional neural network for wearable fall detection systems	Elsevier

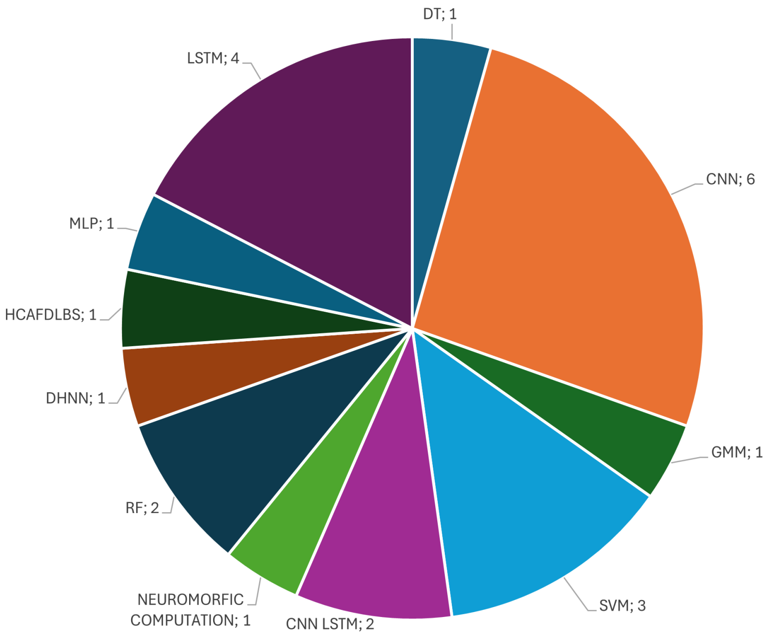

Figure 3.1 – Type and number of machine learning algorithms found in related work (Source: Author).

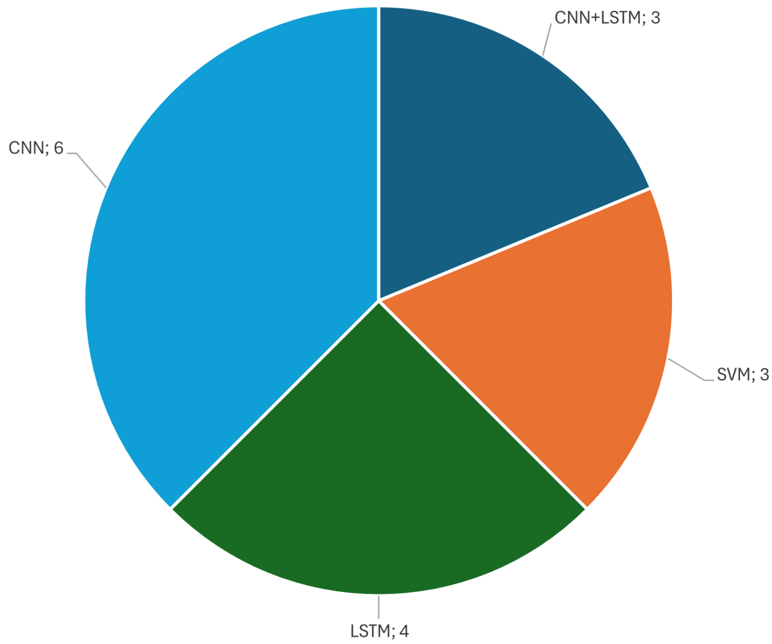

Figure 3.2 – Machine learning algorithms most cited in related works (Source: Author).

3.2 Related Work on Physiological and Motion Sensors Fusion for Elderly Fall

Establishing a relationship between physiological signals and motion sensors embedded in wearable devices during actual falls is a research area that remains to be explored in the academic environment. While accelerometry sensors, gyroscopes, magnetometers, and even pressure sensors have been extensively studied and detailed in research regarding their behavior during falls, physiological data such as heart rate, temperature, and skin electrical activity have received comparatively little attention.

Despite their potential to provide valuable insights, physiological signals about falls have yet to be thoroughly investigated in the same manner as motion sensors. This gap in research represents an opportunity to explore the synergies between physiological and motion sensor data, which could enhance the accuracy and reliability of fall detection systems. By integrating physiological signals with motion sensor data, it may be possible to develop more comprehensive and robust algorithms for detecting falls and assessing fall risk in individuals wearing wearable devices.

Therefore, further research into the relationship between physiological signals and motion sensors during falls is warranted. This research has the potential to significantly advance the field of fall detection and improve the safety and well-being of individuals, particularly those at risk of falls.

Ivascu et al. [20] reported in their article the use of vital signs monitoring to improve the decision alert system for emergency services. Their approach involved incorporating physiological information as a separate input into a multi-agent architecture proposal, which included a feature extraction phase. The main objective was to extract vital sign measurements from a local database, update the knowledge base, and integrate this information into the analysis. While their application differs from our proposal, it shares the inclusion of vital signs in the analysis process.

Similarly, Hanifi et al. [14] investigated the impact of vital signs (breathing and heartbeat) in detecting falls in patients. To mitigate false positives, they correlated this physiological data with environmental sensors, such as CW Doppler Radar. Their approach aimed to detect falls using environmental radar and validate them with a vital sign monitoring window. Preliminary results showed promising outcomes, demonstrating high vital signs monitoring and fall detection performance under real-life simulated fall scenarios.

In terms of existing datasets featuring both movement and physiological signals recorded in real-time during activities, the PPG-DaLiA dataset [59] stands out. This publicly available dataset focuses on PPG-based heart rate estimation, including physiological and motion data from wrist- and chest-worn devices of 15 subjects performing various activities under near real-life conditions. However, it is essential to note that this dataset primarily aims to develop algorithms for compensating errors in heart rate measurement using accelerometer data and does not provide fall simulations.

Through the analysis of related works, it becomes evident that the LifeSeniorProfile Dataset proposed in this Thesis fills a significant research gap in the detection of falls and risk situations in older people. It stands as a pioneering dataset that provides physiological and movement signals during daily living activities and fall simulations conducted by volunteers. This unique dataset offers valuable insights for developing and evaluating fall detection systems tailored to the needs of the elderly population.

4. DATA COLLECTION METHODOLOGY

Collecting data to develop the risk detection model in elderly patients proposed in this Thesis constitutes an essential step for analyzing the patient's context, motion behavior, and physiological sensors in critical situations compared to daily living activities. The response for each sensor is compared individually in each scenario, forming a set of data and tools capable of consolidating the proposed model.

For the data collection, we conducted a pilot trial research, which allowed us to collect and generate a motion and fall patterns database named the LifeSenior Dataset. This dataset served as a subsidy for the development of our model. This pilot research had the following specific objectives:

- Collect data from wrist signals during Activity of Daily Living (ADL);
- Collect data from wrist signals during loss of balance (pre-fall);
- Collect data from wrist signals during actual falls;
- Collect, besides traditional motion data from the Inertial Measurement Unit (IMU), data from physiological sensors, like heart rate, temperature, electrodermal activity, and blood volume pulse.

4.1 Pilot Trial Research

To collect data, volunteers willing to participate in the pilot trial research used a vital signs collector developed by the company Empatica (www.empatica.com) named E4 (Figure 4.1), positioned on the left wrist precisely like a watch. This device is recognized worldwide as a research tool, having medical grade certification in several countries worldwide, and provides accuracy in the data collected [41] [63] [10].

In addition to their sequence, the activities' characterization and performance were monitored by a physiotherapist who recorded the type of movement of each volunteer in each situation. These records, from the physiotherapist and the E4 device, formed the basis for developing the LifeSenior dataset. The present study was developed in the physiotherapy sector of Nossa Senhora da Conceição Hospital, approved by their ethical committee with identification CAAE 58855716.9.0000.5336/ Number 1.743.168.

Volunteers were recruited for convenience in the Home Care Program of Hospital Nossa Senhora da Conceição and Teaching and Research Management of Grupo Hospitalar Conceição, in the Municipality of Porto Alegre, RS, having to meet the following inclusion criteria:

Figure 4.1 – Real time clinical-grade monitoring vital signs device E4 from Empatica (Source: [19]).

- Healthy;
- Age between 18 and 40 years;
- Both genders.

Volunteers who met any of the criteria below were also considered unfit to participate in the study:

- Those with neurological diseases, such as stroke or Parkinson's disease;
- Gait disorders and musculoskeletal diseases;
- Uncorrected visual impairment;
- Inability to maintain a standing position;
- Need assistance to move around;
- Functional dependence;
- Recent orthopedic trauma.

The inclusion and exclusion criteria adopted aim to collect data from healthy adult patients without mobility problems. These criteria can be considered controversial, considering that the research's target population is an older age group with possible health and mobility problems. The study was designed in this way because, from an ethical point of view, the target population is highly vulnerable, making it unsafe to carry out a study that involves abrupt movements and simulated falls in this population group.

However, this Thesis aims precisely to develop an adaptive algorithm, making it possible to develop data collection in less vulnerable patients and subsequent use of the application in the target population.

4.2 Data Collected Description

The procedure for collecting data and developing the dataset necessary to develop the model proposed in this Thesis was applied to ten volunteers who performed twelve movement simulations, including daily activities, loss of balance, and falls. Table 4.1 resumes the activities performed by each volunteer, and these activities are represented with letters and numbers as below.

- AVD - Activity Daily Living:
  - 1. Stopped - no movement;
  - 2. Walking - walking in a straight line;
  - 3. Getting up and sitting on the chair - perform the complete movement of sitting on a seat approximately 50cm high, wait 30 seconds, and get up from the seat;
  - 4. Squatting and returning - starting from an upright posture, perform the squatting movement until rest on their heels, wait 30 seconds, and return to an upright position;
  - 5. Lying down and getting up - perform the complete movement of lying face up on a bed approximately 40 cm high, wait 30 seconds, and get up from the bed, standing upright again.
- PDE - Loss of Balance:
  - 6. Sitting and standing up - perform the complete movement of sitting on a seat approximately 50 cm high, wait 30 seconds, and when standing up, simulate the loss of balance forward and finish the upright movement;
  - 7. Standing and sitting - perform the complete movement of sitting on a seat approximately 50 cm high, simulating loss of balance due to incorrect transfer to the seat and finishing the movement upright;
  - 8. Changing direction - while initially standing still, perform a 180-degree change of direction and, in the end, simulate loss of balance to the side and complete the upright movement;

- 9. Reaching for an object on the floor - being initially stationary, moves to look for an object on the floor and, at the end, simulates loss of balance forward and ends the upright movement.

- QD - Fall:
  - 10. Obstacle - initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground;
  - 11. Cadence continuity - initially walking, simulate sliding forward, and then simulate the movement of falling onto a mattress;
  - 12. Syncope - initially standing still, relax the lower limbs to simulate falling onto a mattress.

Three types of dynamic gait preceded all movement simulations targeted by the research, adding an extra element of behavior that aims to simulate real situations. Dynamic gaits are everyday movements that have a high chance of preceding a real risk situation. These dynamic gaits are in Table4.1 with the following representation:

- A - Walk on a flat surface at an average speed of 6 meters;
- D - Gait with vertical head movements (up, down, and forward);
- G - Walking around a figure-eight obstacle.

The total number of simulations carried out by each volunteer, 36 movements, summarized in Table 4.1, generated 360 files. All movements were carried out in an area covered by 50cm x 50cm and 20mm thick EVA plates to absorb impacts and avoid discomfort. A mattress with a fall area measuring 3m x 2m and 0.30m thick will also be positioned for fall simulations. Figure 4.2 illustrates how the pilot research was developed.

The sensors in the watch used to collect data during activities form what we will call a data time series over time in this Thesis. These time series comprise movement (accelerometry) and physiological (heart rate frequency, skin temperature, electrodermal activity, and blood volume pulse) information the sensors detailed below provide.

ACCELEROMETRY (ACC) - The volunteer’s motion information is provided by a sensor called an accelerometer distributed across the three acceleration axes: x, y, and z. An accelerometer is a sensor commonly used in wearable devices to measure an object’s acceleration degree. This sensor is essential for activity analysis and fall detection, as changes in movement made by the volunteer are directly captured by it. The device used for data collection is equipped with an accelerometer that measures signals between -2g and +2g acceleration (1g = 9,8m/s2) based on 32 Hz resolution.

HEART RATE (HR) - The heart rate frequency of each volunteer was measured by a sensor called PhotoPletismoGrah (PPG). This sensor produces optical light in a specific

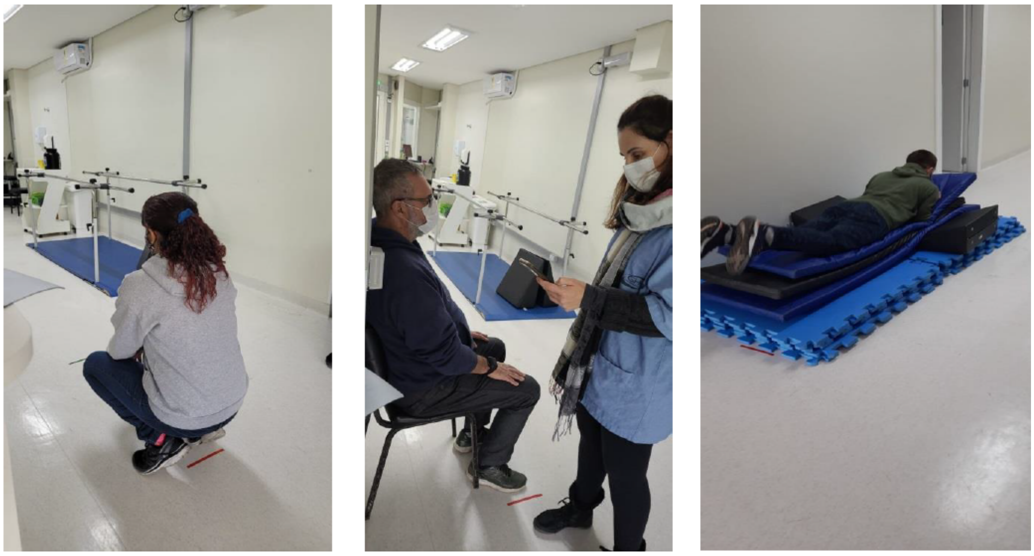

Figure 4.2 – Pilot research study location and some examples of movements collected (Source: Author).

optical wavelength and measures its refraction, which changes based on blood circulation below it in response to heart rate pulses. The heart rate is measured at a frequency of 1 Hz from 0 to 300 beats per minute.

SKIN TEMPERATURE (TEMP) - The skin temperature of each volunteer was measured using a contact sensor that works with the principle of thermal balance. This principle shows that the sensor and the skin temperature will enter a balanced temperature; the sensor measures that. The temperature is measured at a frequency of 4 Hz in a range of -40 ºC to 115 ºC.

ELECTRODERMAL ACTIVITY (EDA) - The electrodermal activity refers to electrical changes, measured at the skin's surface, that arise when the skin receives innervating signals from the brain. EDA signals are measured at a frequency of 4 Hz with a range between 0.01 and 100 uS.

BLOOD VOLUME PULSE (BVP) - A blood volume pulse measures the volume of blood passing below the sensor in either red or infrared light. It is measured at a 64 Hz resolution, ranging from -500 to +500.

4.3 Data Preprocessing

Data preprocessing is a step that occurs before model training begins and plays a vital role in adapting data to a standard that can be absorbed during the different stages of the process.

Hence, it becomes imperative to implement preprocessing procedures on data, rectifying inconsistencies and often augmenting the data to enhance its utility, thereby

Table 4.1 – Activities performed by each volunteer.

Target simulation	Dynamic gate	Time	Movement	Time	Filename	Label
AVD	A	30s	1	10s	VX_AVD_A_1	0
	D				VX_AVD_D_1	
	G				VX_AVD_G_1	
AVD	A	30s	2	10s	VX_AVD_A_2	1
	D				VX_AVD_D_2	
	G				VX_AVD_G_2	
AVD	A	30s	3	2 rep	VX_AVD_A_3	2
	D				VX_AVD_D_3	
	G				VX_AVD_G_3	
AVD	A	30s	4	2 rep	VX_AVD_A_4	3
	D				VX_AVD_D_4	
	G				VX_AVD_G_4	
AVD	A	30s	5	2 rep	VX_AVD_A_5	4
	D				VX_AVD_D_5	
	G				VX_AVD_G_5	
PDE	A	30s	6	10s	VX_PDE_A6	5
	D				VX_PDE_D_6	
	G				VX_PDE_G_6	
PDE	A	30s	7	10s	VX_PDE_A_7	6
	D				VX_PDE_D_7	
	G				VX_PDE_G_7	
PDE	A	30s	8	10s	VX_PDE_A_8	7
	D				VX_PDE_D_8	
	G				VX_PDE_G_8	
PDE	A	30s	9	10s	VX_PDE_A_9	8
	D				VX_PDE_D_9	
	G				VX_PDE_G_9	
QD	A	30s	10	10s	VX_QD_A_10	9
	D				VX_QD_D_10	
	G				VX_QD_G_10	
QD	A	30s	11	10s	VX_QD_A_11	10
	D				VX_QD_D_11	
	G				VX_QD_G_11	
QD	A	30s	12	10s	VX_QD_A_12	11
	D				VX_QD_D_12	
	G				VX_QD_G_12	

Notes: VX - X represents each volunteer;

facilitating the knowledge discovery process and yielding high-quality results. Common issues with poor data quality include missing values, noisy data, inconsistent values, attributes of diverse natures, and data redundancy. Addressing these challenges through robust preprocessing ensures that the data is suitable for subsequent analysis, leading to more accurate insights and improved decision-making outcomes.

These characteristics are not evident in the data set but can be revealed by exploratory analysis procedures. To develop the dataset used in this Thesis, we performed a series of preprocessing steps described next.

4.3.1 Formatting each File based on Activity Interval

The data collection process for each volunteer consisted of several periods that went beyond the moment the data was recorded. Upon entering the experiment site, each volunteer received the data collection device and placed it on their wrist. From this stage onwards, pairing with the system began recording all information.

Based on that, the people involved in data collection were instructed to mark the beginning and end of each activity, which is done through the device's functionality. The collection file is marked whenever the button is pressed.

Our first step in data preprocessing was to remove the original data files and maintain only interest data. Figure 4.3 shows an example of a complete register, with the initial and end points of the interest activity highlighted.

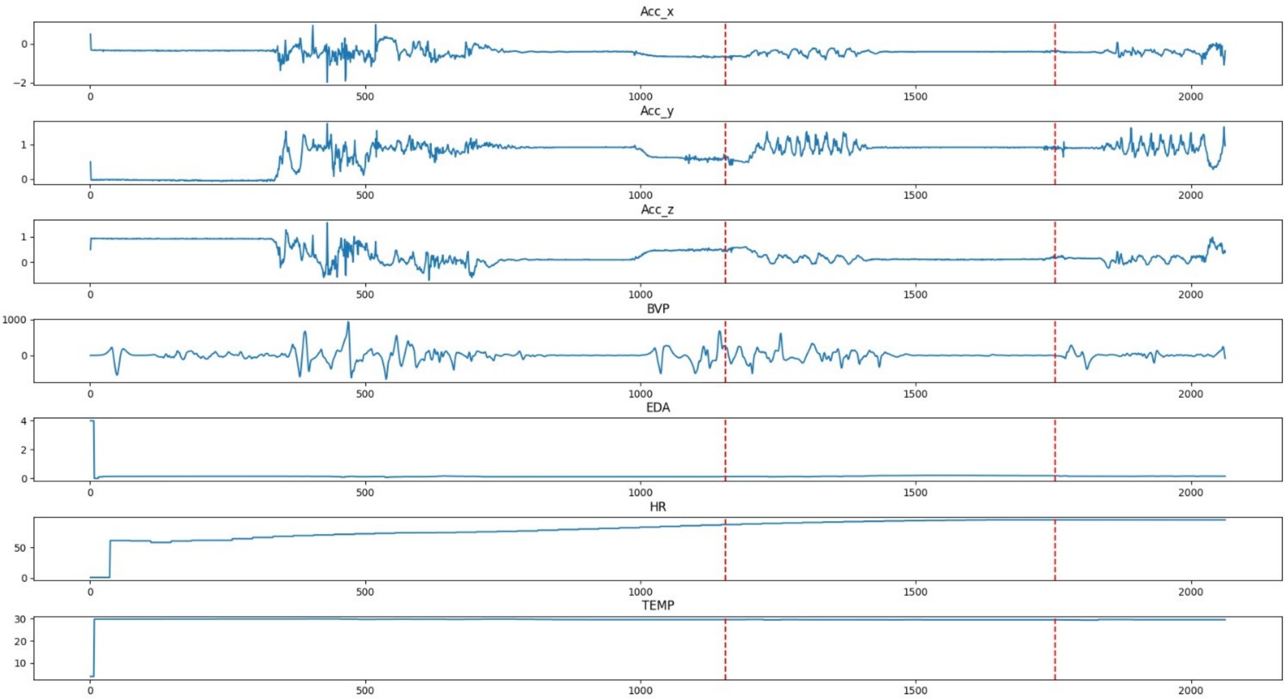

Figure 4.3 – Raw sensor data from an example activity (Source: Author).

4.3.2 Sample Rate Equalization

After the file formatting step based on the beginning and end of each activity, it was observed that each sensor, despite simultaneous collection, had different sizes in the files. This fact is due to the different sampling rates at which the device performs the collection, which can be seen below:

- Accelerometer (ACC) - 32 Hz;
- Blood volume pulse (BVP) - 64 Hz;
- Electrodermal activity (EDA) - 4 Hz;
- Heart rate (HR) - 1 Hz;
- Temperature (TEMP) - 4 Hz.

We adopted the accelerometer sampling rate (32 Hz) as the default to equalize the different sampling rates. To construct the dataset, we needed to downsample the Blood Volume Pulse parameter by 50% and upsample the other parameters. We used the value repetition technique for upsampling; all odd data were excluded for downsampling. These sampling rate customizations can also be readily applied in real-time applications, which validates the proposed technique.

4.3.3 Filtering

Filtering the signal recorded by an accelerometer is essential to remove noise recorded by the sensor; however, to calculate gait parameters correctly, choosing a suitable cutoff frequency of the filter, specifically the filter, is critical. The need for filtering accelerometry data comes from the fact that the data is characterized by fast signals and highly susceptible to noise sources. This fact was not observed in the other parameters that have slower dynamics. Figure 4.4 shows the noise components in x, y, and z data that highlight the need for filtering.

Several techniques exist to filter accelerometer data [13], most focusing on frequency cutoff points and smoothing techniques. To address this problem, we proposed a methodology based on an evaluation of the most known techniques (low pass and median) and a new technique based on Kalman filtering, in which the literature shows good results [3][31].

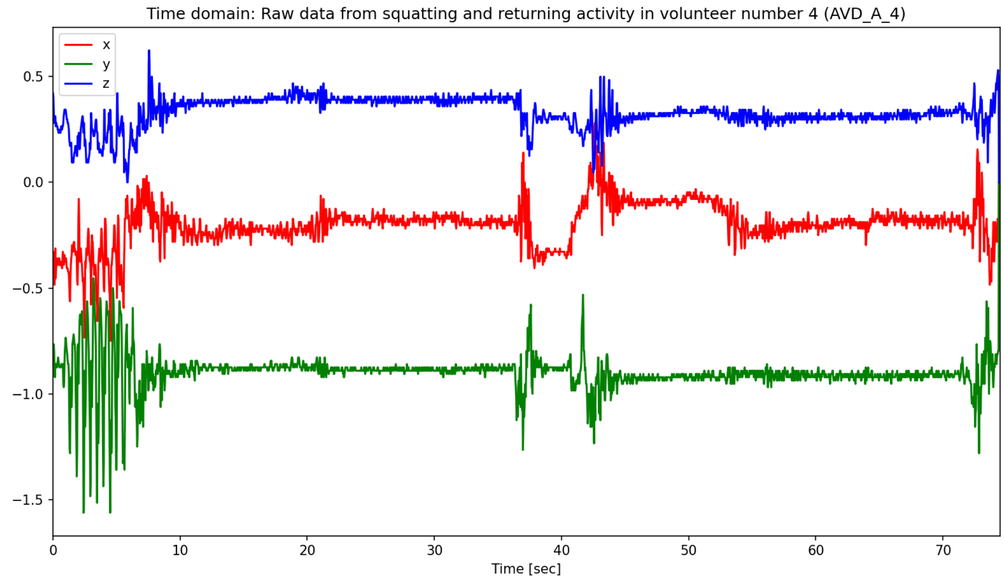

Figure 4.4 – Raw acc sensor data highlighting the need for filtering (Source: Author).

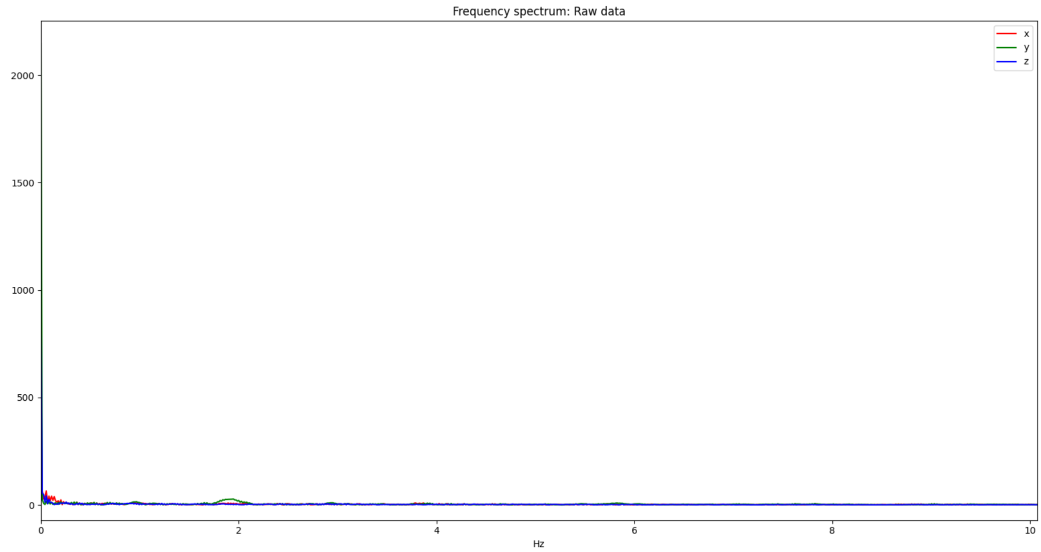

Figure 4.5 – Fast Fourier Transform (FFT) applied to acc sensor data (Source: Author).

The most traditional approach to filtering is the use of frequency filters. Figure 4.5 displays the behavior in the signal's frequency domain under analysis, demonstrating that the signal has components mostly at low frequencies.

Based on that, we proposed implementing a low-pass Finite Impulse Response (FIR) filter with a cutoff frequency set at 5 Hz. Figure 4.6 depicts the outcomes of this technique, showcasing its effectiveness within this context. As evident from the results, filtering frequencies beyond 5 Hz effectively eliminates noise components, as illustrated in Figure 4.5, which are not predominant in the dataset. This approach enhances the data quality by reducing noise interference, thus improving the reliability of subsequent analyses and interpretations.

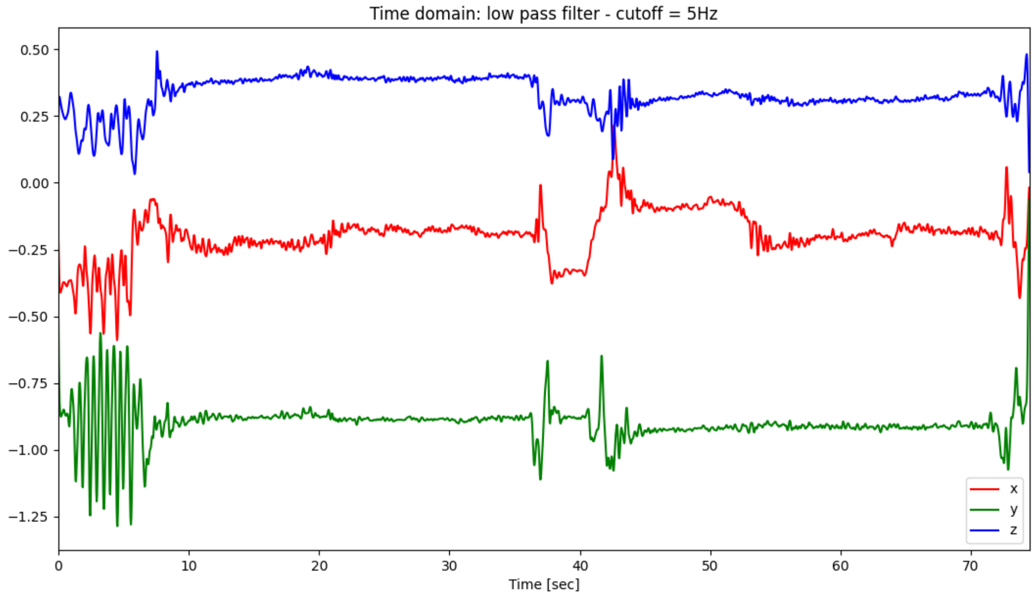

Figure 4.6 – Acc data filtered with an FIR filter based on a cutoff of 5Hz (Source: Author).

We also tried using a median filter. This filter is generally desirable when we want to remove big spikes. Nevertheless, Figure 4.7 shows that this filter is more aggressive, removing more signals than expected.

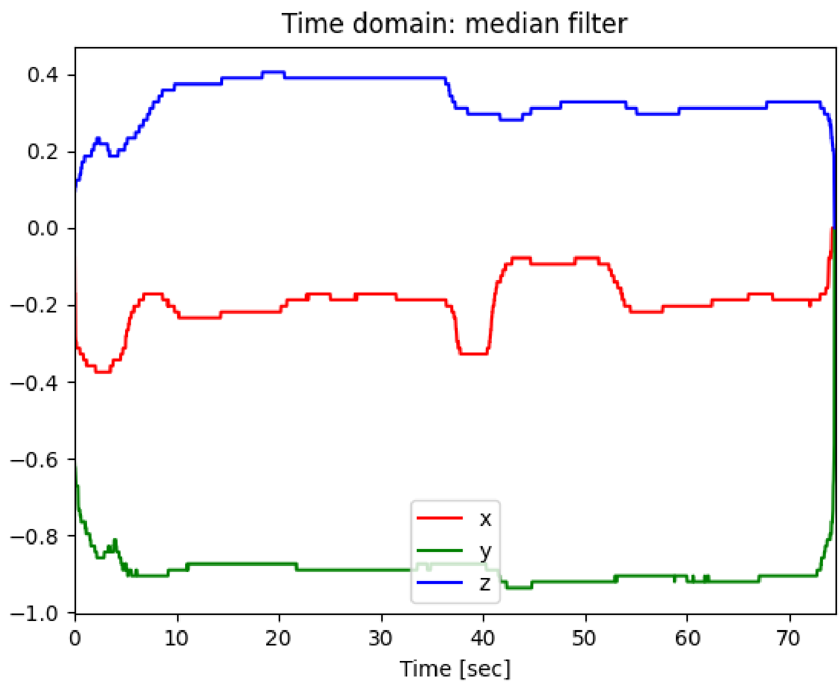

Figure 4.7 – Acc data filtered with a median filter (Source: Author).

Although the results presented are acceptable, our objective is to remove the high-frequency noise in the sampled signals as much as possible, taking care not to cause distortions. With this objective, we implemented a Kalman-type filter. A Kalman filter is a mathematical method created by Rudolf Kalman. Its purpose is to use measurements of quantities carried out over time (contaminated with noise and other uncertainties) and predict results that tend to approximate the natural values of the measured quantities and associated values.

The advantage of Kalman-type filters is that they can filter out high-frequency noise in the signal while not cutting off signal peaks, which a traditional low-pass filter would filter. We developed a series of filter parameterization variations until we reached the optimal version for our application, illustrated in Figure 4.8.

Figure 4.8 – Original sensor data and finished Kalman filtered data (Source: Author).

The Kalman Filter is an optimal linear filter primarily designed for linear systems affected by Gaussian noise. It effectively addresses two types of noise: process noise and measurement noise, both impacting the filter's gain matrix calculation. Unlike traditional filters, where the user predefines the gain matrix, the Kalman Filter dynamically calculates this matrix based on historical data, the covariance of measurements, and the covariance of the process noise.

Measurement covariance may decrease if they exhibit low levels of noise. It is essential to assess the range of variances present in the measurements. By "increasing" the measurement matrix, the influence of current observations on the estimation diminishes.

Conversely, the process noise covariance represents the covariance of the current state given the previous state (and its covariance). If the process noise covariance is increased, it implies an error in the transition between two consecutive time stamps that cannot be accounted for by the transition matrix alone and is deemed random. This adjustment acknowledges uncertainties in the system dynamics and allows the filter to adapt accordingly to achieve optimal estimation performance.

To achieve these results, we configured a filter matrix with a 6x6 size with measurement noise covariance equal to 1 and process noise covariance equal to 0.2.

4.4 Dataset Description

Falls are among the most significant risks to the health and well-being of older people becoming a significant problem in today's society. Approximately one in every three adults aged 65 years old or older falls each year, creating physical injuries and psychological harm. In addition, this problem has significant economic effects. According to the WHO, in 2030, the estimation of falls-related injuries will increase by 100%. Therefore, distinguishing between ADL and falls is a significant problem.

Aiming to provide the research environment with a new set of data with physiological information associated with data already commonly used for this type of analysis, like accelerometer and gyroscope, we developed the LifeSeniorProfile dataset [46].

Real-time tracking and detection of risky situations in older people, such as falls and sudden changes in vital signs, requires reliable, continuous, and automated monitoring systems based on relevant information. Wireless biosensors provide a great opportunity to remotely detect and monitor hazardous situations, allowing for a fast response in an emergency. Motion data is widely used to track daily activities. Physiological data can also be used for this exact purpose. However, there is yet to be a database available in the field of research in which the patient's physiological and movement information were collected simultaneously, considering daily activities and simulation of falls. LifeSeniorProfile presents a multisensor dataset for developing real-time tracking systems for the daily activities of older people. The data sensed refer to movement, using a triaxial accelerometer, and physiology, considering blood volume pulse, electrodermal activity, heart rate, inter-beat interval, and skin temperature. We collected these data from ten volunteers while performing 36 daily activities in a simulated environment.

Monitoring, detecting, and classifying activities of older people through non-invasive wearable systems is an open research area due to the similarity between movement data sensed in daily activities and risky situations, such as falls. Recently, many machine learning algorithms, especially those that explore deep layers of neural networks [40][37][62], have tried to search for hidden details of motion data of accelerometers, gyroscopes, barometers, and magnetometers to identify features that filtering and thresholding algorithms cannot identify. Despite the promising results, even these high-performance algorithms hardly reveal a real risk capable of achieving a false positive rate close to zero.

Accelerometers are the most common motion sensors used to identify human activities, providing real-time relative acceleration in a given direction, which varies according to available freedom degrees. In the rest state, the accelerometers share quasi-static values, and at excessive movement, they provide an acceleration peak. This behavior is adequate for developing a low-precision thresholding algorithm to detect fall situations and identify elderly risk situations. On the one hand, this algorithm is ineffective since many risk-free activities also have the same data signature. On the other hand, the foundation is the same for many fall detection systems developed in various research. Over the years, many studies have tried to improve these results by adding different motion sensors, but this problem is still an open research area.

Our primary motivation for this work is based on the direct correlation between accidental falls and vital signs [75]; this correlation is not explored in most of the research data available to develop systems that explore risk situations for older people. Integrating vital signs with motion signals offers a considerable advantage for identifying, detecting, and classifying daily activities and fall risks. However, this integration is rarely addressed in the available works [44].

This work provides a dataset of multisensory information, which includes, in addition to traditional movement sensors, some physiological sensors collected during activities of daily living and risky situations. We designed this database to analyze changes in vital signs caused by daily activities and falls. These data enable us to explore the fusion of physiological and movement data and classify all sensors based on their importance in detecting daily activities and falls, allowing us to give weight to each element sensed.

Some datasets are available for research in this area, but almost all are based only on motion sensors. We propose a novel approach bringing up important vital signs correlated with motion data during simulated daily living activities and risk situations.

In addition to the proposed dataset's pioneering nature in correlating vital signs with motion sensors, the proposal to use a device already widely clinically validated for research and certified by several regulatory agencies in the health area makes the LifeSeniorProfile dataset unique.

We developed this dataset to record natural and provoked human actions, such as a fall, using several sensors that enable us to gather information from multiple points of view about each human action. We planned to include a triaxial accelerometer to detect human movement and insert sensors of temperature, EDA, and PPG to extract vital signs.

4.4.1 Motion Sensors

All datasets evaluated presented data on daily activities and falls collected through motion sensors, primarily accelerometers. The main reason for focusing on motion sensors is that most activities usually vary significantly in the sensing signal. For example, a fall is registered by a sequence of peaks and valleys in an accelerometer signal.

An accelerometer is an electromechanical device that measures the change in velocity over time [54]. Acceleration measurements can be static, such as the force of gravity, or dynamic, caused by motion. In general, accelerometers translate an external acceleration signal into a displacement of their moving mass, called inertial mass. An accelerometer reports a drop as an abrupt change in values, represented by peaks and valleys [9]; a graph generated by an accelerometer during a fall shows the pre-fall, critical, and post-fall phases. Within the crucial phase, it is still possible to identify the free fall, impact, and adjustment [61].

On the one hand, a high peak of acceleration followed by inactivity is a solid indicator to detect falls; on the other hand, more information is needed to avoid false alarms. For example, lying on a bed satisfies this accelerator sequence, making a fall detection system with exclusive use of this approach somewhat limited. Therefore, we structured this dataset by collecting vital signs to analyze how this information can be composed with motion information to decide about a daily activity or a fall.

4.4.2 Vital Signs Sensors

The temperature sensor enables us to identify body changes that may indicate simple disorders, such as a fever crisis, or more severe disorders that can compromise the functioning of vital organs. If the body temperature exceeds 42ºC, the individual is at risk of dying. The temperature sensor, combined with a motion sensor, can help to identify the cause of a fall or fainting.

EDA is the term used to define autonomous changes in the electrical properties of the skin. For this reason, the EDA sensor works by identifying electrical changes on the surface of the skin, allowing the monitoring of episodes of stress, anxiety, and the neurological state of an individual since it is much more susceptible to human emotions than just the analysis of heart rate [8].

The PPG sensor uses an optical technique to identify blood volume changes in the microvascular tissue bed under the skin due to the pulsatile nature of the circulatory system [4]. The sensor system comprises a light source and a red and infrared light-emitting diode (LED) detector. The PPG sensor monitors light intensity changes through reflection or tissue transmission [72]. Studies report that through PPG, it is possible to estimate signals non-invasively, such as an electrocardiogram (ECG), heart pulse rate, saturation [48], respiratory rate [22], and blood pressure [35].

4.4.3 Participants Characteristics

The dataset consists of data from 10 volunteers with an average age of 36 years; all of them meet the acceptance criteria, 60% male with average weight and height of 85kg and 1.74m, respectively. Regarding female volunteers, the average weight and height were 72kg and 1.65m. Further information about the volunteers was preserved for confidentiality reasons provided in the consent form for participation in the research.

4.4.4 LifeSeniorProfile Format

LifeSeniorProfile consists of 36 different activities simulated by ten volunteers for a total of 360 simulations. The dataset is organized into a division by activity (36 folders), where within each activity, each volunteer performs ten different simulations once. Details of each activity's execution have already been presented in Section 4.2.

All files in the dataset are in .csv format, and the formatting of each file name follows the pattern:

$$< VX > \_ < TARGET - SIMULATION > \_ < DYNAMIC - GATE > \_ < MOVEMENT > .csv$$

- VX - The letter V always indicates the volunteer, and the X varies from 1 to 10 to indicate which volunteer performed the simulation;
- TARGET-SIMULATION - The target simulation is a group of everyday activity volunteers. They can assume the names AVD (activity daily living - 15 simulations), PDE (Loss of Balance - 12 simulations), and QD (Fall - 9 simulations);
- DYNAMIC-GATE - Three dynamic gate simulations precede each MOVEMENT. This field can assume the names A (walk on a flat surface at average speed for 6 meters), B (gait with vertical head movements: up, down, and forward), or G (walk around an obstacle forming the number 8);
- MOVEMENT - This part of the file indicates which movement was simulated and can assume values between 1 and 12 (more details about each movement can be seen in Section 4.2).

Each file in the dataset follows the specific structure detailed in Table 4.2.

The first three columns refer to the accelerometry signal distributed between its axes (x, y, and z). The fourth column stores the physiological parameter Blood Volume

Table 4.2 – LifeSenior Profile columns distribution.

acc_x	acc_y	acc_z	BVP	EDA	hr	temp	label
...	...	...	...	...	...	...	...

Pulse (BVP), followed by EDA. The sixth column stores the heart rate (hr) and the volunteer's body temperature. The last column (number 7 - label) stores the movement that is being simulated. It is essential to highlight that all sensors are equalized at the same sampling rate (32 Hz) and that each file has a different number of lines because the simulations also have different execution times; however, to avoid classification overlap, each line of the dataset is identified individually, instead of there being a unique classification for the file.

The format described above was proposed to facilitate processing by artificial intelligence algorithms since the training input and definitive use are easily given in frames (lines) of the dataset, and each one has both the values of x (sensors) and y (expected output).

5. ELDERLY RISK SITUATION DETECTOR METHODOLOGY

Over the last few years, many researchers have proposed different architectures to overcome the fall detection problem using noninvasive wearables in older people. In a timeline scenario, the first fall detectors based on wearable devices sensing motion data proposed threshold-based algorithms [9] to identify the peak values from the accelerometer sensor that represent a fall. Still, researchers verified that this topology is unsuitable outside a laboratory environment due to the high rate of false positives. Researchers started to aggregate new motion sensors into accelerometers to decrease the high rate of false fall detections, like a gyroscope, magnetometer, and barometric pressure [18]. Other researchers also tried to fuse motion and vital signs data but considered vital signs only as complementary information to the fall detector [30]. With the recent development of deep learning algorithms, the reliability of fall detection has evolved to the desired quality standards, opening up a significant area of research.

The methodology proposed for this research was developed to obtain a risk detection model for use in real elderly monitoring devices. To do this, we carried out the following: data collection, clinical study, analysis of the collected data, development of the AI algorithm, analysis related to the influence of the proposed innovations, and, finally, creation of a simulator to perform system performance tests.

5.1 Innovations Proposed in the Elderly Risk Situation Detector Model

Continuing the legacy of research carried out in this area and based on the analysis of related work, we developed a model for detecting risk situations in older people, focusing on falls, one of the biggest problems in this population group who live alone.

5.1.1 Motion and Physiological Sensors Fused

Vital signs are paramount health indicators for detecting and monitoring medical conditions [12]. Any deviation from an individual's reference range can be a significant warning sign, signaling potential health concerns. Various indicators, such as skin temperature fluctuations, sudden heart rate spikes, reduced oxygen saturation levels, or changes in blood pressure associated with specific movements, can signal the onset of a risk situation. Stressful events, such as falls among older individuals, often trigger alterations in vital signs [28].

Since the relationship between vital signs and actual falls remains unexplored in existing literature, we recognized this as a valuable research opportunity for investigating how vital signs behave in such scenarios. We initiated the LifeSeniorProfile project to collect vital sign data during daily activities and fall simulations; leveraging this dataset, we conducted thorough data analysis to gain insights into the behavior of vital signs in various contexts, particularly during fall events. Subsequently, we utilized this knowledge to develop an innovative elderly risk situation detection model. By integrating vital signs into our fall detection algorithm, we gained a significant advantage in accurately identifying and detecting actual falls. This integration is a crucial innovation of our proposed model, offering enhanced capabilities in distinguishing genuine fall events from other activities or false alarms. Our approach fills a critical gap in the existing literature and, by incorporating vital sign data as valuable input, paves the way for more effective fall detection systems.

5.1.2 User Adaptation Model

Our model is based on an LSTM network, which is an extended structure of the RNN [16] that has been used for a lot of fall detection past research [37][80]. Despite the excellent ability of this network in processing data time series, when we train generalized machine learning models from human data, the common problem is that the distributions of the data may vary from one participant to another due to individual differences. Two participants with the same fall characteristics may have different vital signs behavior, which causes internal covariate shifts among datasets and inequality in feature representation. To solve this problem, we propose a user adaptation LSTM structure that adapts their capacity to the user environment through a validation train phase in the first use. The main idea behind this proposal is to provide a way to fit user environment, routine, and behavior to the initial generalist model, trying to increase the model's performance in each user.

5.2 Contextualization

Understanding the context in which this research is linked is necessary to explain the model we propose in this Thesis. The development of this Thesis is the final phase of a project that began in 2015, called Lifesenior - Continuous Monitor of Emergency Situations, developed at PUCRS under the coordination of Professor Doctor César Marcon and supported by the Financiadora de estudos e pesquisas (FINEP).

Lifesenior (Figure 5.1) is an elderly monitoring system capable of alerting people or healthcare systems about any abnormal situation detected. The system consists of a traditional wearable watch-type device connected via Bluetooth to a cellular device running an application developed specifically for the project. The application is responsible for receiving the data processed on the wearable device and processing and making notifications whenever necessary. Initially, the device was designed with a radio frequency connection operated by the manufacturer Sigfox [66]; however, during the development of the project, there were changes in technology and technical instability of the service, leading to a change in the project that altered the topology of the device to have a connection Bluetooth and connection system via cell phone and no longer a direct connection to cloud servers.

In addition to the features above, Lifesenior has an array of monitoring sensors designed to enhance the system's information-gathering capabilities, thereby improving the accuracy of detections. Among these sensors, PPG stands out, enabling the calculation of vital parameters such as heart rate, breathing rate, oxygen saturation, and even blood pressure. Additionally, the system incorporates a temperature sensor to monitor body temperature and motion sensors, including accelerometers and gyroscopes, to detect movement patterns and postural changes. This comprehensive suite of sensors empowers Lifesenior to gather rich and diverse data, enabling robust analysis and precise detection of potential risk situations, such as falls, thereby enhancing users' overall safety and well-being.

The main objective of this Thesis is to develop a reliable model for detecting risky situations in older people. The model should be capable of mainly identifying falls with a low rate of false positives.

Figure 5.1 – LifeSenior wearable device (Source: Author).

In addition to the context of the LifeSenior project, this Thesis was developed with the support of the Doutorado Acadêmico para Inovação (DAI) program within call 23/2018 of the National Council for Scientific and Technological Development (CNPq), submitted by the student and being awarded a research grant throughout the doctoral research. The project submitted to the DAI program was a partnership between the doctoral student, the PUCRS university, and the company TOTH LIFECARE and aimed to develop parts related to the LifeSenior software.

5.3 System Architecture

Figure 5.2 details our proposed system architecture, which will serve as a platform for the risk detection model in older people; this architecture covers a wearable device with Bluetooth Low Energy (BLE) communication, Lifesenior application, and cloud service.

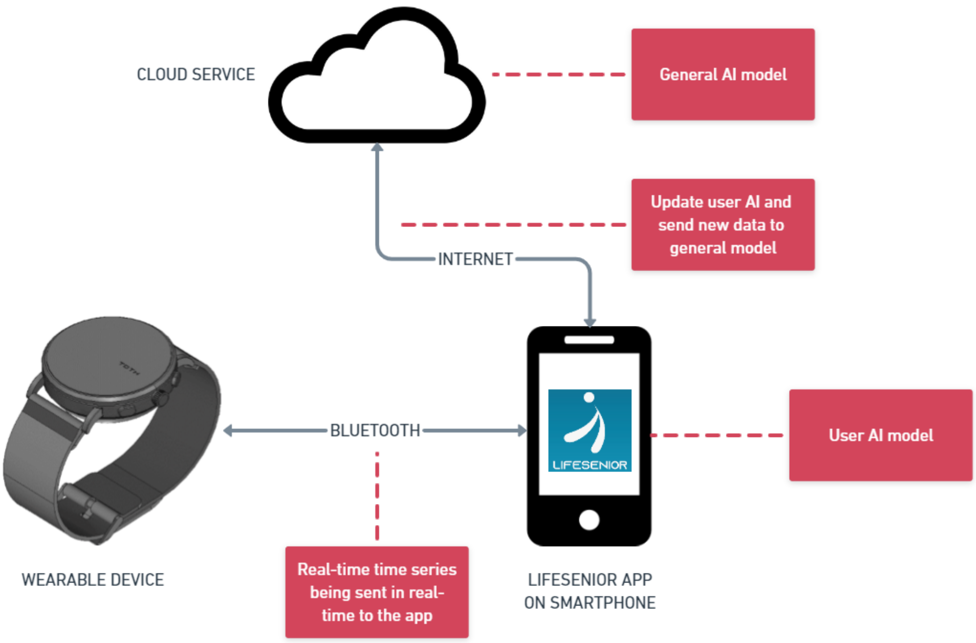

Figure 5.2 – Flowchart of operation and data traffic of the system architecture composed of a wearable device, mobile application, and cloud service (Source: Author).

The wearable device was designed to resemble a traditional watch, improving the acceptance of older people. However, the wearable is much more complex than a simple watch. Inside the wearable case, dedicated circuits acquire vital user signs through a PPG sensor; besides, the wearable covers a complete motion system focused on learning the user's biological activity and detecting anomalies. The wearable device is most critical in this system architecture because it performs the measures with a medical classification in a noisy and dynamic environment. It provides a way to continuously monitor vital signs and motion information from users, not in a diagnostic character but continuously, to send data uninterruptedly for processing in a mobile application using BLE.

As a part of this system architecture, we have a mobile application that receives user data in real-time, sent by the wearable, and is responsible for processing and running our proposed model to detect risky elderly situations. The mobile app communicates with a cloud service over the internet to send new training data with their respective classifications made by the user to the generalist model and receive updated models adjusted to the user's reality.

5.3.1 System Architecture Simulator

Aiming to operationalize all the steps foreseen in the proposed architectural system and taking into account that at the time of development of this research, the tools foreseen in the initial project (wearable devices, application, and cloud system) were not yet available to researchers, it was decided to develop a complete simulation of the architecture in a computational environment capable of filling this research gap, but at least validating all stages of the research, so that when the physical architecture is available, it would be easily connected to the results achieved.

This simulation environment allows us to simulate the stages of receiving events from sensors positioned on the wearable device (wearable simulator) and the interpretation of these events by machine learning algorithms positioned on the server (APP simulator). Additionally, commands coming from the App Simulator can be evaluated, as well as their effects on reducing the wearable's energy consumption and the variation of events transmitted from the wearable to the App Simulator. The simulated architecture flowchart is detailed in Figure 5.3 and comprises a wearable device simulator, App simulator, and cloud simulator.

The wearable device simulator is fed with data from previously selected and standardized datasets, and its sampling rate is adequate with the power commands coming from the App Simulator. As the datasets have temporal information, the wearable simulator can pass on to the App Simulator the precise times that events occur to evaluate if an older adult is being monitored. Periodically, the App Simulator can automatically communicate with the Cloud Simulator and retrain the neural network, with the new data recorded by the wearable, updating the neural network weights. This command can also be done manually by the simulator operator.

The implementation of the simulated environment is composed of two applications/modules developed in Python. An application implements the operation of the wearable, receiving data from the datasets and communicating with the App Simulator - sending this data and receiving commands. The other application implements the App Sim-

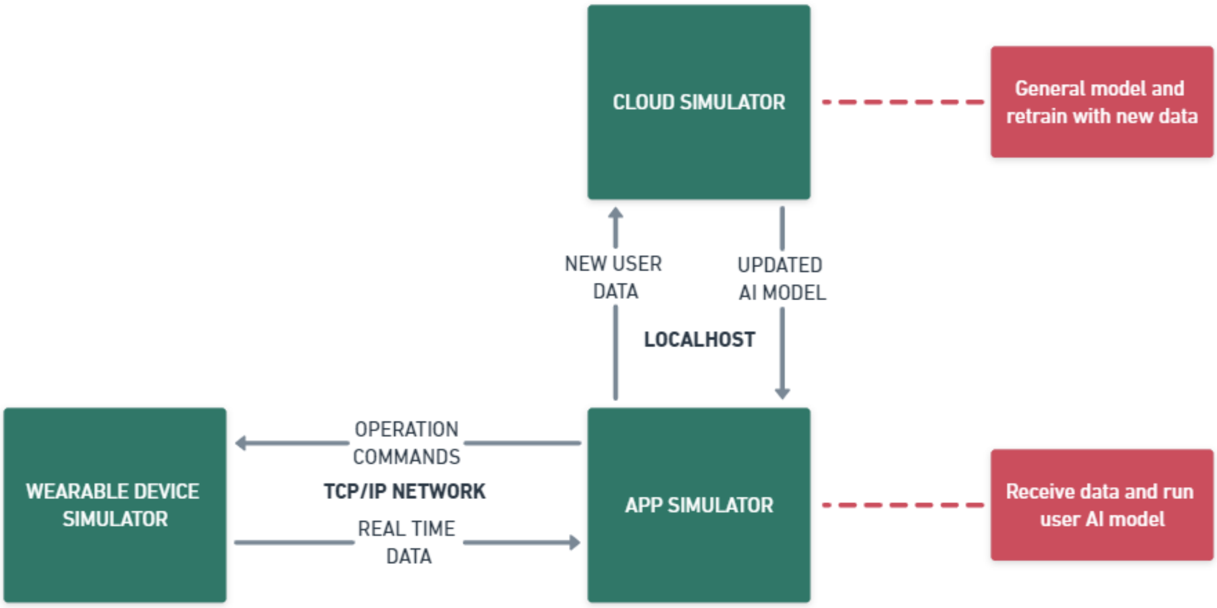

Figure 5.3 – System architecture simulator (Source: Author).

ulator, which receives data from the wearable and inserts it into the machine learning algorithm that detects falls, risk situations, and daily activities. According to the detected events, the App Simulator sends commands to the wearable. It should be noted that for this work, the objective is only to identify falls, and it is not necessary to explore other identifications, as well as commands for the wearable device.

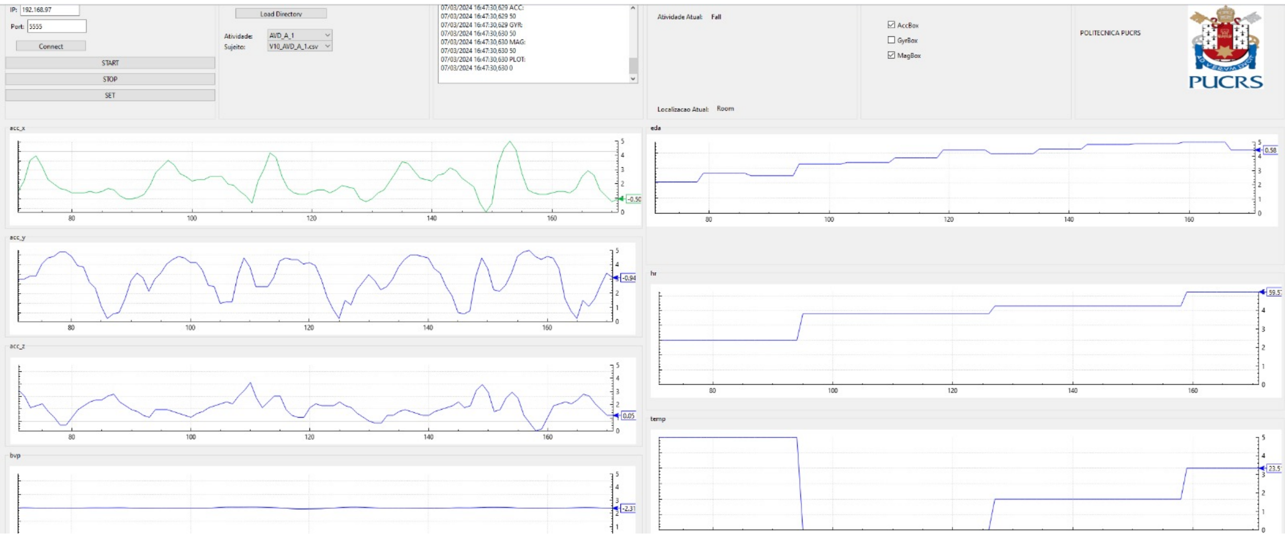

Figure 5.4 – Wearable device simulator main screen (Source: Author).

Communication between the wearable and the concentrator application in the real environment takes place via BLE; in the simulator, it is carried out via the TCP protocol. In both modules, it is possible to see the data being sent/received and the commands in real-time. Figure 5.4 shows the application screen that simulates the wearable, while Figure 5.5 illustrates the App simulator.

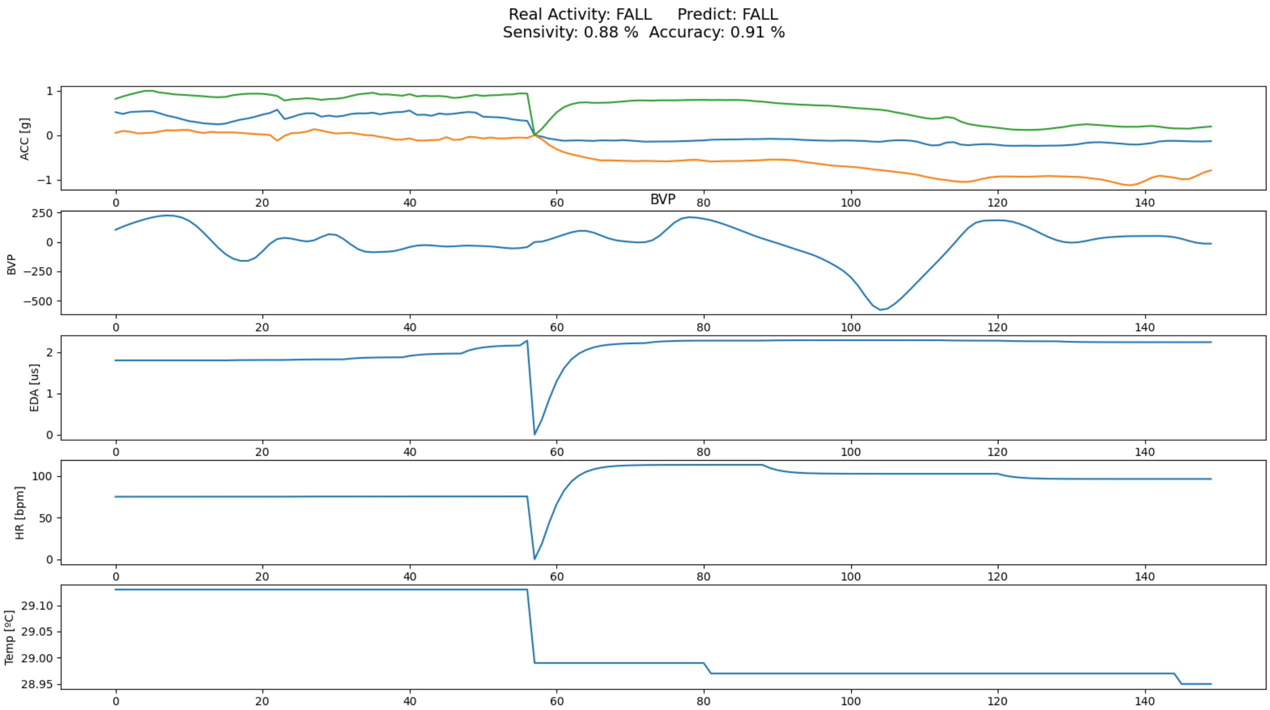

Figure 5.5 – App simulator plotting real-time series received from the wearable simulator and predicting fall/non-fall situations based on our proposed AI model (Source: Author).

The simulation referring to the cloud system (Cloud Simulator) was implemented locally in the App Simulator, being operated through commands exchanged between the two simulations. The objective is to send new data collected during the User Adaptation Model phase to the Cloud Simulator for a retraining and network adjustment stage.

5.4 Model Characteristics

This Thesis presents a model capable of expanding the discussion on the topic through the exploration of two new concepts: evaluating the influence and advantage of associating information from physiological vital signs, such as heartbeat, temperature, electrical activity of the skin, and volume pulse, an approach that is already commonly used in most models explored so far, which is based on the processing of motion sensors; explore a model capable of adjusting to user behavior through a personal training stage able to improve the accuracy of the detector.

5.4.1 Motion and Physiological Sensors Fused

To identify risk situations, the system proposed in this Thesis is based on a hypothesis that there is a significant change in the behavior of the user's vital signs before, during, and after an actual fall. If captured correctly, these variations in vital signs can and should help validate a risk situation usually detected more easily by movement sensors.

The theory proposed here is still poorly addressed in the literature, and it is impossible to fully affirm that this hypothesis is valid only through scientific research. Despite the lack of information regarding the behavior of vital signs during a fall, our objective is to analyze whether hypothetical changes generate relevant information to improve the accuracy of detecting a fall without increasing the number of false positives.

Unlike the behavior of vital signs, the result of a fall and daily activities on movement sensors is already consolidated in the literature [9], contributing to this Thesis's deeper investigation into clarifying the behavior of vital signs in risk situations.

Information such as fluctuations in skin temperature, a sudden increase in heart rate, and a peak in EDA due to a nervous moment are some of the hypotheses we explore in this Thesis. Integrating vital signs information into a traditional fall detection algorithm could give an enormous advantage in increasing the model's accuracy.

Since the proposed hypothesis does not have significant evidence in the literature, the first stage of the system development methodology was data collection, described in detail in Chapter 4. One of the concerns during the research was the quality of the vital signs collected during the study. Usually, wearable watch-type devices have a poor commitment to the veracity of the information passed on, given that their use is primarily recreational. To overcome this problem, we acquired a specific device for research data collection in the watch format, capable of simulating actual future use and providing reliable medical-grade vital signs information.

Data collection occurred in a population range lower than the elderly, as the process involved falls and abrupt movements, which would not be ethically correct for older people. However, another feature of the model proposed here was developed for this problem, which is the ability of the model to adjust to the user based on a more generalist model. After data collection, we proceed with the pre-processing and data preparation steps detailed in Chapter 4, culminating in developing the risk situation detection model, detailed below.

The model proposed here is based on artificial intelligence, specifically LSTM recurrent neural networks. This model was adopted thanks to its great capacity for processing time series, memory capacity, and context analysis. It was highlighted in the analysis of related works as an architecture most suitable for this type of application.

The model generally works as described in Figure 5.6; it was built to receive and process the three axes from the accelerometry sensor (motion data) in real time and four physiological signals (heartbeat, blood volume pulse, electrodermal activity, and temperature). This data comes from the wearable at a rate of 32 samples per second, and we have a new prediction of a Fall or Non-Fall situation at every 150 samples or 4.68 seconds. This prediction window, which we call timestep, is the time window we consider for a prediction. This interval was chosen based on an empirical view of common sensor data representing falls; larger and smaller window sizes were also analyzed without performance gains.

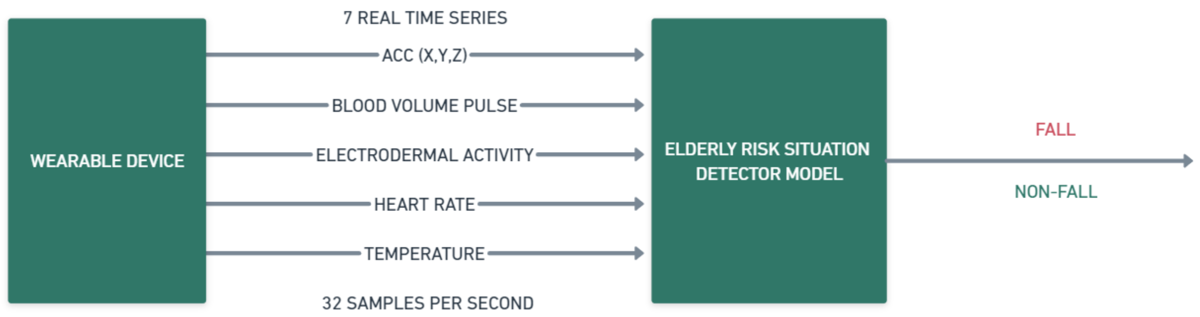

Figure 5.6 – Elderly risk situation model characteristics. Our model fuses motion and vital signs data (summing seven-time series at 32 samples per second) towards enriching the volume of information about the user's real situation during a risk situation (Source: Author).

5.4.2 User Adaptation Model

The main problem detected in models with only simulated content operating in real scenarios is not detecting a fall when it happens (what we call true positive); however, the system identifies non-real falls (false positives) [1]. Commonly, some activities of daily living are erroneously reported as falls, thus reducing the user's confidence.

The leading cause of this problem is the high heterogeneity in the behavior of this type of device user. The device can be used by older people with mobility problems, chronic diseases that affect movement [15], elderly with low or high degrees of activity, and other variables that affect the performance of fall detection algorithms.

Analyzing the problem, we concluded that the best solution would be to train a model that covered all these behavioral and environmental variations. This approach encounters a limitation when the raw material for a model of this type is the dataset; accessing or collecting data for this population group is extremely difficult.

To address this challenge, we propose the "User Adaptation Model", which progresses from a generalized solution to one capable of adapting to the user's specific environment and behaviors. Figure 5.7 illustrates the detailed operation of this model, which involves the following steps:

- Training the Model with Available Data - The model initially undergoes training using available data, primarily sourced from the LifeSeniorProfile dataset. The accuracy of this initial training is assessed, and if satisfactory, the model advances to the next stage;
- User Training Phase - A user training phase is initiated upon the user's first use of a wearable device. During this phase, users perform coordinated movements guided by the application, mirroring those executed by volunteers while creating the LifeSeniorProfile dataset. Notably, falling movements are excluded from this phase due to safety considerations. The application annotates the collected data, which is then transmitted to the cloud system for retraining. Given that false positives are a primary concern, users provide feedback by classifying instances of false alarms. We retrain the model using this user data and deploy the updated version to the application;
- Continuous Check Phase - The model enters continuous check mode following the initial user training phase. If the model outputs a "FALL" situation, the user is prompted to confirm this classification. The confirmed data, along with the classification, are then submitted to the cloud for further retraining;
- Retraining the Model with New User Data - All new data received by the cloud system, including confirmed classifications, are aggregated with existing data and subjected to a model retraining phase.

Following these iterative steps, the User Adaptation Model continuously refines its accuracy and adaptability, ultimately providing users with a personalized and reliable fall detection solution.

5.4.3 Artificial Intelligence

This Thesis proposes constructing and using an AI model based on recurrent neural networks, specifically LSTM, where data input is done directly through time series. This model is supervised learning; for training, it is necessary to input data previously classified by a domain expert. This data collection and classification stage was fully developed during the construction of the LifeSeniorProfile dataset.

LSTM provides a high capacity for modeling time-series data [71] thanks to its structure containing three gates: input, forget, and output. LSTM uses the "input" and

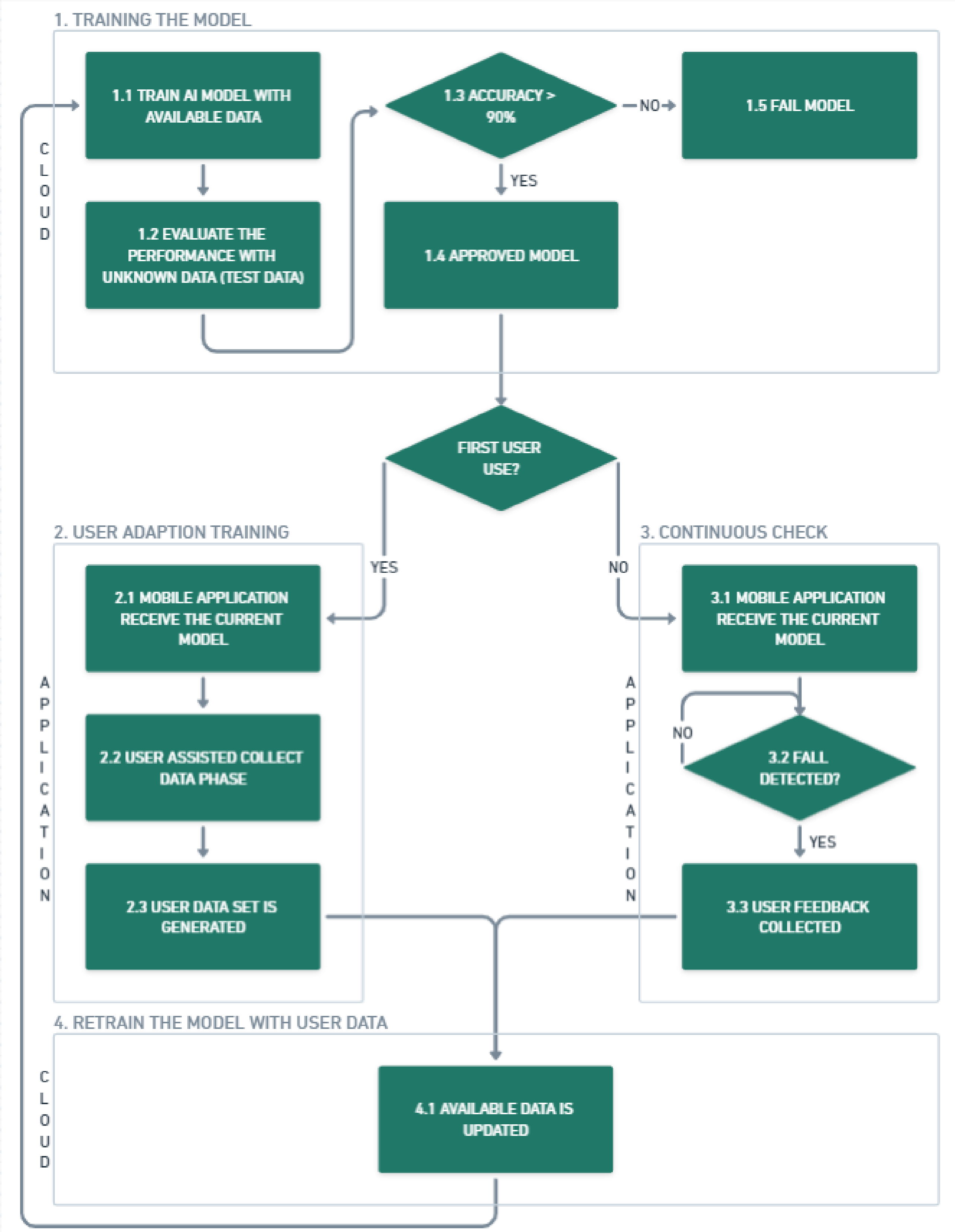

Figure 5.7 – User adaptation model proposal (Source: Author).

"forget" gates to decide which information to remember and drop. This skill makes it possible to modulate the ratio between remembering old data and learning new information, as reported in recent articles [56][37], helping the system identify each user's natural behavior during LifeSenior use. This unique feature from LSTM is decisive in understanding the real emergency applicable to each user, decreasing the false positive rate hugely.

Regarding the time-dependent classification task, the context around specific input joint features can be helpful information. Let A be information from the sensors and B be the time step (we use 150 samples for window timestep in 32 Hz sampling that produces 4.68 s of window frames), so the deep neural network proposed for this application uses continuous time-series of motion and physiological sensors as A × B input dimension. The dense layer output turns the output vector into an equal-length probability matrix, and the class that receives the highest probability is chosen.

Figure 5.8 details the proposed architecture, which allows the continuous analysis of the temporary series generated by the sensors without the need to carry out manual feature engineering.

The architecture proposed here is the result of an extensive analysis of different topologies that included changing the size of the viewing windows, ranging from windows smaller than 1 second to windows of more than 10 seconds, and changing the number of LSTM cells from using a single cell to the final number of cells proposed here.

Varying the size of the viewing window has a direct impact on the real representation of a fall. Analyzing a 1-second window does not make sense in real life, while a very large window makes the point of interest less significant. The time windows adopted was the one that presented the best results.

Similarly, the number of LSTM cells adopted in this architecture was the one that presented the best results when the network was subjected to test data. Simpler architectures had extreme difficulty in classifying unseen data. To avoid overfitting, we chose to use a Dropout of 10%.

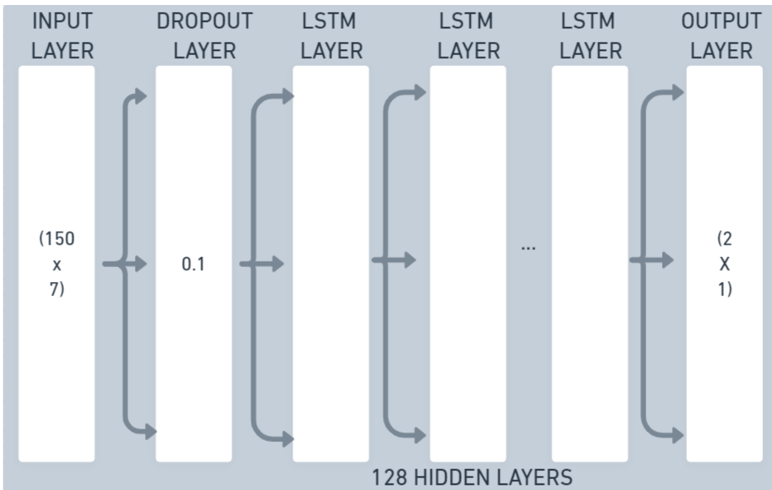

Figure 5.8 – LSTM architecture detailing input, LSTM, and output layers. The input has a dimension of 150x7 because we use 150 samples as a timestep and seven sensor information; the output is Fall or Non-Fall (Source: Author).

The training phase encompasses 252 simulated movements associated with coherent simulated vital signs, divided into 189 daily living situations and 63 falls. We used 70% of the dataset for training and 30% for tests. Table 5.1 summarizes the characteristics and hyperparameters of the proposed deep neural network.

Table 5.1 – Hyperparameters and characteristics adopted in the LSTM model.

Information	Value
Dropout	0.1
Learning Rate	0.0001
Epochs	2000
Training Steps	50000
Batch Size	128

The proposed model was developed to achieve performance based on available data. Notably, the volume of data used to train the model is small due to the difficulty of collecting larger data. However, we understand that despite this fact, the proposal validates the concept addressed in the research.

The model also has a simplicity characteristic due to the low volume of data available. During the research, more complex models were created that achieved a higher degree of accuracy but suffered from the overfitting effect; that is, the model was overfitted to the training data, presenting low classification capacity on unseen data.

5.5 Model Evaluation Methodology

To evaluate the performance of the proposed model, we carried out a series of experiments to analyze whether the hypothesis proposed in this Thesis is true. The basis of our analysis is the collection of data carried out during the research that culminated in the formation of the LifeSeniorProfile dataset, a set of data that made fall simulations and daily activities monitored by a motion sensor and physiological sensors collected by a wearable device available to the academic environment. of the watch type with a degree of medical accuracy, something not yet available in the academic environment.

As this research aims to detect elderly falls and not individually evaluate which specific activity the user is carrying out, we changed to the LifeSeniorProfile format detailed in Table 5.2. This change consists of classifying activities only into daily living activities (ADL), loss of balance (PDE), and falls (QD) and no longer discriminating individually on which activity is being developed.

As discussed in Chapter 4, the LifeSeniorProfile dataset had 360 files in total, and based on our new division, we have 150 AVDs, 90 QDs, and 120 PDEs. To perform the train, test, and update model process, we divide the dataset into three categories:

Table 5.2 – New labeling of each classification to identify only daily living activities, loss of balance, and falls, which is the main focus of this research.

Target simulation	Dynamic gate	Time	Movement	Time	Filename	Label
AVD	A	30s	1	10s	VX_AVD_A_1	0
	D				VX_AVD_D_1	
	G				VX_AVD_G_1	
AVD	A	30s	2	10s	VX_AVD_A_2	0
	D				VX_AVD_D_2	
	G				VX_AVD_G_2	
AVD	A	30s	3	2 rep	VX_AVD_A_3	0
	D				VX_AVD_D_3	
	G				VX_AVD_G_3	
AVD	A	30s	4	2 rep	VX_AVD_A_4	0
	D				VX_AVD_D_4	
	G				VX_AVD_G_4	
AVD	A	30s	5	2 rep	VX_AVD_A_5	0
	D				VX_AVD_D_5	
	G				VX_AVD_G_5	
PDE	A	30s	6	10s	VX_PDE_A6	2
	D				VX_PDE_D_6	
	G				VX_PDE_G_6	
PDE	A	30s	7	10s	VX_PDE_A_7	2
	D				VX_PDE_D_7	
	G				VX_PDE_G_7	
PDE	A	30s	8	10s	VX_PDE_A_8	2
	D				VX_PDE_D_8	
	G				VX_PDE_G_8	
PDE	A	30s	9	10s	VX_PDE_A_9	2
	D				VX_PDE_D_9	
	G				VX_PDE_G_9	
QD	A	30s	10	10s	VX_QD_A_10	1
	D				VX_QD_D_10	
	G				VX_QD_G_10	
QD	A	30s	11	10s	VX_QD_A_11	1
	D				VX_QD_D_11	
	G				VX_QD_G_11	
QD	A	30s	12	10s	VX_QD_A_12	1
	D				VX_QD_D_12	
	G				VX_QD_G_12	

Notes: VX - X represents each volunteer; 0 - represents and Daily living activity (AVD); 1- represents a Fall (QD) and 2 - represents a Loss of Balance (PDE);

- Update data - We segregated one complete volunteer with all 36 activities to be used after the model training process to simulate adapting the model to the user. This complete volunteer was not part of either the model training process or the testing process, reimaining 324 files for train an test phase;

- Train data - From the remaining 324 files, we randomly separated 252 files to be used in the training phase.

- The remaining 72 files were used as model test data to verify accuracy.

It is important to emphasize that the number of predictions depends not on the number of files but on the size of each file and, specifically, the size of the timestep used. For example, in a 45-second file, we have 1440 samples (32 samples/second x 45 seconds), and nine classifications will be made (1440/150 = 9) due to the window size being 150 samples.

All the experiments were performed on a local workstation using Python as a programming language in the Visual Studio Code platform. Standard Python modules such as Tensorflow, Pandas, and Numpy were utilized at different stages of the experimentation. The workstation had a 20 GB main memory and an NVIDIA TITAN XP with 20 GB RAM capacity.

The model training process is detailed in algorithm 5.1. The training process consists of ordering all training files into a single file, where each line is classified among the three possible LABEL variations. At each training step, the three-dimensional tensor (batch size, timestep, num-sensors) is fed with training data into the artificial intelligence architecture until the number of total iterations is reached.

```
function Train(trainingConfigParameters)
netconfig ← trainingConfigParameters
dropout ← 0.1
lstm[num-units] ← 128
data ← files
while train-step < cfg-iterations do
   inputtensor[batchsize, timestep, num-sensors] ← data
   lstm ← inputtensor, labels
   compute → loss, accuracy
end while
return model
```

Algorithm 5.1 – Model training algorithm detailing steps involved.

Aiming to automate the evaluation process, we developed a series of logs capable of detailing the necessary information from the model. For all model analyses, we perform detailed monitoring and calculations as follows. During the training phase, the information stored was:

- Sensors - each file contains the sensors used to train the model. This information is relevant, as several models were trained with different combinations;

- Training steps - loss and accuracy were accounted for in each training step of the proposed models. Each training step represents a forward and backward in the network with a part of the dataset. For our model, we use a size of (128, 150, SENSORS) where 128 is the batch size, 150 is the timestep, and SENSORS is the number of sensors used for training that vary according to each configuration.

Figure 5.9 depicts the metrics adopted to analyze the proposed models. The metrics analysis culminates in the Precision, Recall, and F1-score information, which gives a finer-grained idea of how well the classifier is doing instead of just looking at overall accuracy.

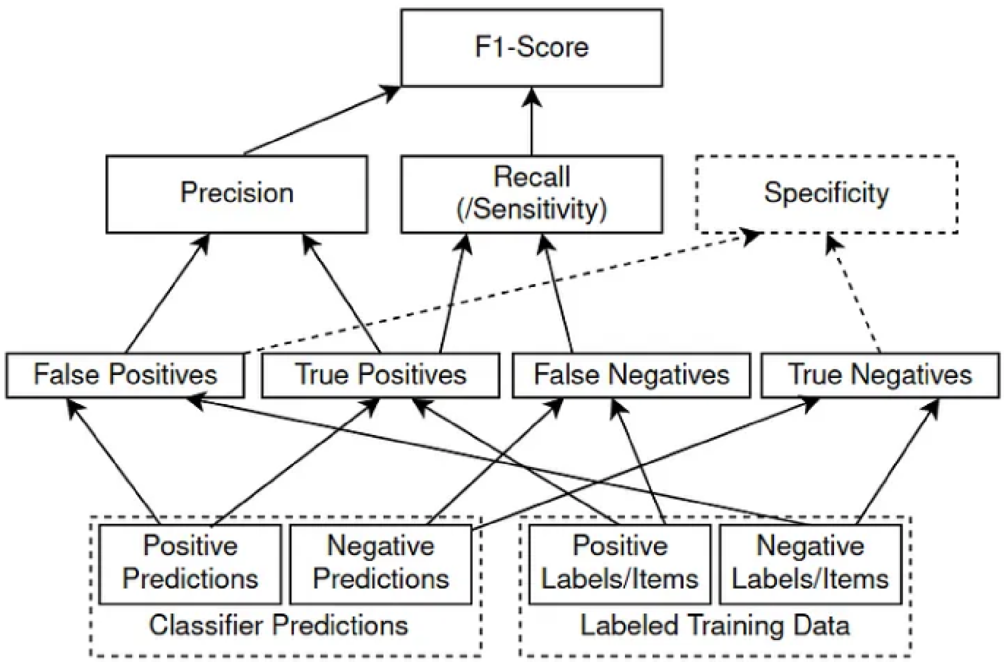

Figure 5.9 – Machine Learning metrics adopted for model analysis (Source: [24]).

We need to start calculating the True Positives, True Negatives, False Positives, and False Negatives classifications to achieve this information. Table 5.3 shows the methodology adopted for this process, and the result can be seen below. For this analysis, we consider Falls (QD) as Positives and Activity Daily Living (AVD) or Loss of Balance (QD) as negative classifications.

Table 5.3 – Model Performance analysis methodology.

	Labeled training data		
Classifier predictions	Falls (True)	Non-Falls (False)	Total
Positive	a	b	a+b
Negative	c	d	c+d
Total	a+c	b+d	a+b+c+d

Considering Table 5.3, we obtain the following considerations for Accuracy, Precision, Specificity, and F1-Score:

- Accuracy is the probability of the model providing correct results, being positive in falls and negative in non-falls. Expressed another way, the probability of true positives and true negatives as a proportion of all results and is calculated as (a+d)/(a+b+c+d), also expressed as (a+d)/N, where N is the total amount of samples;
- Precision measures how many positive predictions are correct (true positives). The formula for it is a/(a+b);
- Recall/Sensitivity measures how many positive cases the classifier correctly predicted over all the positive cases in the data. It is sometimes also referred to as Sensitivity. The formula for it is a/(a+c);
- Specificity measures how many negative predictions are correct (true negatives). The formula for it is d/(d+b);
- F1-Score is a measure combining precision and recall, generally described as the harmonic mean of the two. Harmonic mean is another way to calculate an "average" of values, generally described as more suitable for ratios (such as precision and recall) than the traditional arithmetic mean. The formula used for the F1-score in this case is 2 x ((Precision x Recall) / (Precision + Recall)).

This model's performance was evaluated in the following ways, and the results are in Chapter 6.

5.5.1 Full Model Performance

The complete model predicts fall and non-fall situations using all available information as input: three axes of accelerometry, blood volume pulse, electrodermal activity, heart rate, and temperature.

Exploring the performance of the complete model is essential to extract information regarding whether or not the performance of the risk situation detection model improved due to the inclusion of vital signs data, our proposal theory.

5.5.2 Influence of Each Physiological Sensor on Overall Accuracy

Based on the hypothesis of this Thesis that vital signs can carry information that improves the quality of fall detection and reduces the number of false positives, we carried out an individual analysis of the performance of each physiological information associated with the traditional fall detection model. which only considers accelerometry data. This analysis allows the most significant information to be identified while it is possible to list relevant information. The following combinations were evaluated:

- ACC - only the three accelerometry axes, an architecture commonly used for fall detection;
- ACC+BVP - accelerometry data fused with blood volume pulse information;
- ACC+EDA - accelerometry data fused with electrodermal activity;
- ACC+HR - accelerometry data fused with heart rate;
- ACC+TEMP - accelerometry data fused with skin temperature.

5.5.3 Analysis of the Behavior of Vital Signs During the Fall

One of our most important objectives is to address the behavior of the vital signs during fall and non-fall situations. To clarify this behavior and generate evidence that can contribute to new research, we collected data that culminated in the LifeSeniorProfile dataset, with relevant information to develop this analysis.

We analyzed all the data collected and sought to identify situations that could characterize behavior identifiable by algorithms, with the results covered in the following chapter.

5.5.4 Model with User Adaptation Analysis

To evaluate the performance of the proposed model's adaptation functionality to the user's environment, we conducted a training simulation by the user, collecting new information to update and retrain the model.

This simulation is detailed in Figure 5.10. It consists of starting from the complete model explored in Section 5.5.1 and updating the model's training data with the new data from the newly trained volunteer. After updating the data, retraining was carried out, generating a new model evaluated with new data from the volunteer himself.

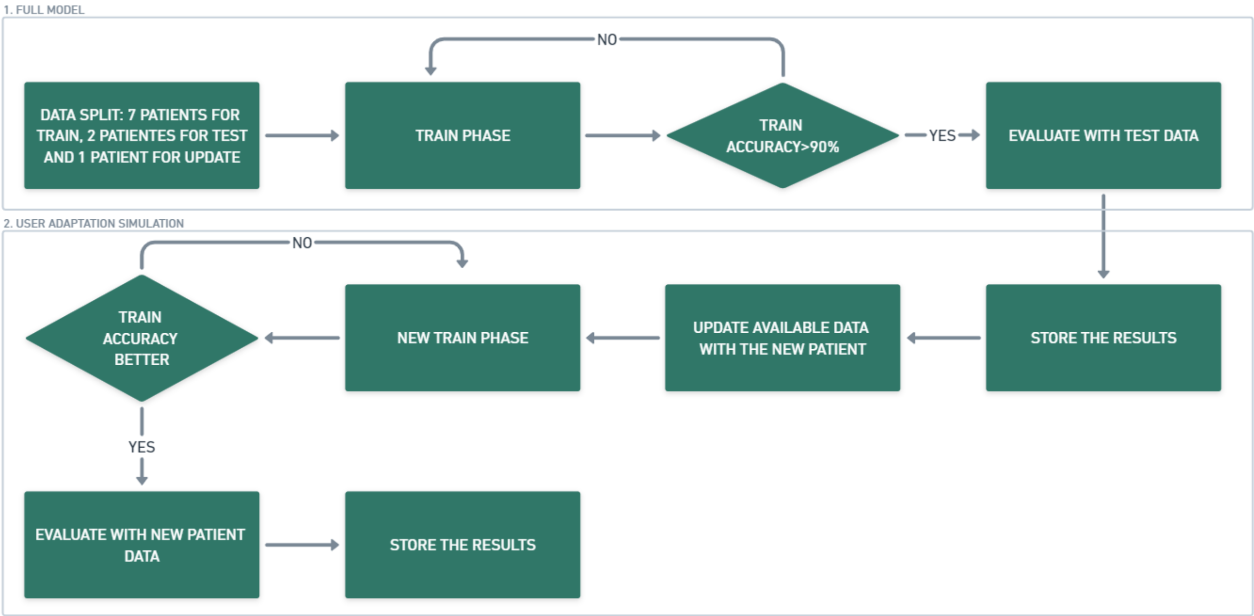

Figure 5.10 – Methodology adopted to evaluate the performance of our user update model characteristic (Source: Author).

5.5.5 Comparison of the Model with Similar Models

We also analyzed, in the same way, the proposed model's performance, comparing it to the current state of the art in this usage scenario. Based on our related work research detailed in Section 3.1, we focused on comparing models with similar characteristics, and the results can be seen in the next chapter.

6. RESULTS

The hypothesis proposed in this thesis and detailed in the methodology considers two new factors: the inclusion of information regarding vital signs in the model and the model's ability to adjust to user behavior.

The construction of a truly effective model for fall detection using a wearable device correlating information on vital signs and movement imposes some limitations, such as the heterogeneity of this type of information in this population range (explored in more detail in Section 6.3), the difficulty in accessing data in large quantities and the difficulty in accessing data collected in real situations from patients in this population group. These limitations significantly harm any research in this area (I believe that it is one of the reasons why it is still an open research subject); however, with the development of the collections carried out during the doctoral research and assembly of the LifeSenior-Profile dataset, it was possible to put the concept proposed here, generating the results described in the following sections.

In all test cases below, we use a real simulation of the model in practice to evaluate its performance with test data. This analysis is slightly different from the traditional approach, where data not known by the network (test data) is passed for direct classification. To do this, we send the test data set through a stream at 32 Hz to be classified every 150 samples (4.68s), generating a new prediction. All predictions were tallied and analyzed as detailed in Section 5.5, and an example of the screen that shows the time series and predictions can be seen in Figure 6.1.

6.1 Full Model Performance

In its full version, the model consists of training using all available sensors associated with the classification imposed in the development of the dataset. These inputs and outputs can be observed in Table 6.1.

Table 6.1 – Dataset columns used in the training process of the full model.

X							Y
acc_x	acc_y	acc_z	bvp	eda	hr	temp	label

For this training process, we used a total of 431542 inputs classified individually as falls (QD), daily activities (ADL), and loss of balance (PDE). We used a timestep of 150 samples and a batch size of 128 for a total of 50,000 timesteps, which caused the model to be trained for 2000 epochs. In Figure 6.2, we can see the loss and accuracy during

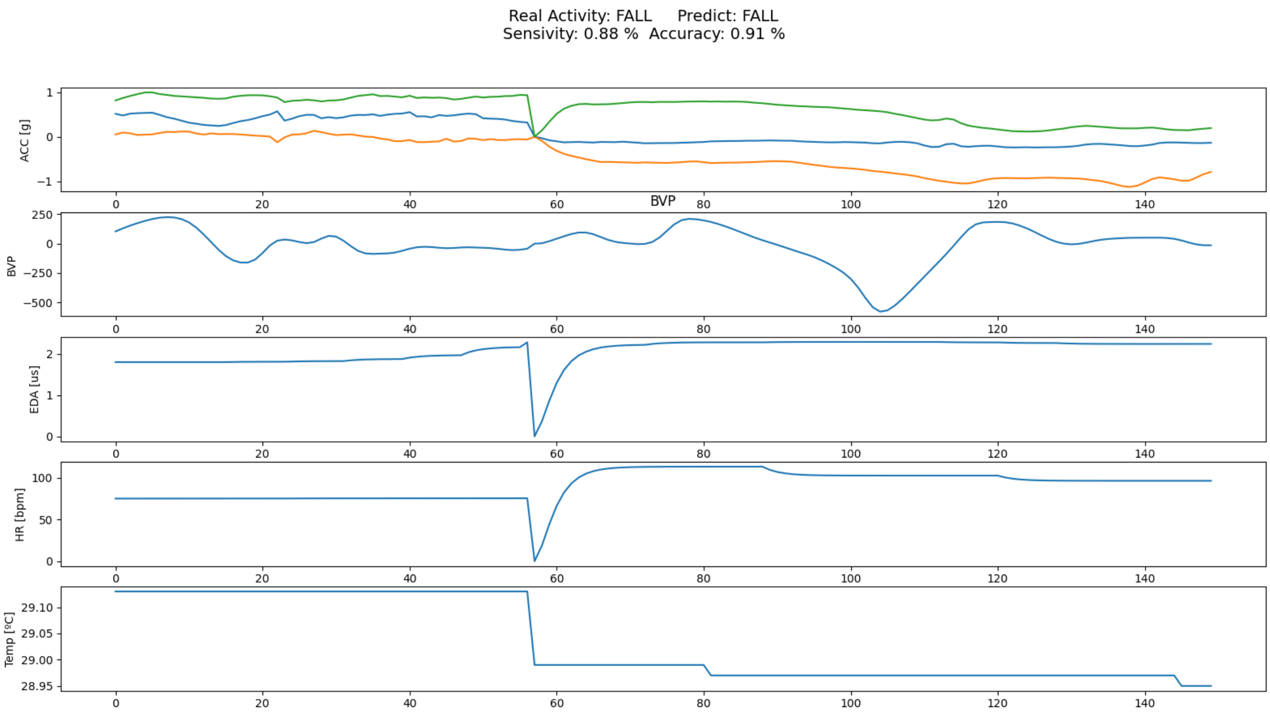

Figure 6.1 – Real time-series prediction system (Source: Author).

the training process until it reaches 50,000 steps. We achieve in this model a final train accuracy was **0.9373** and the final train loss was **0.156289**.

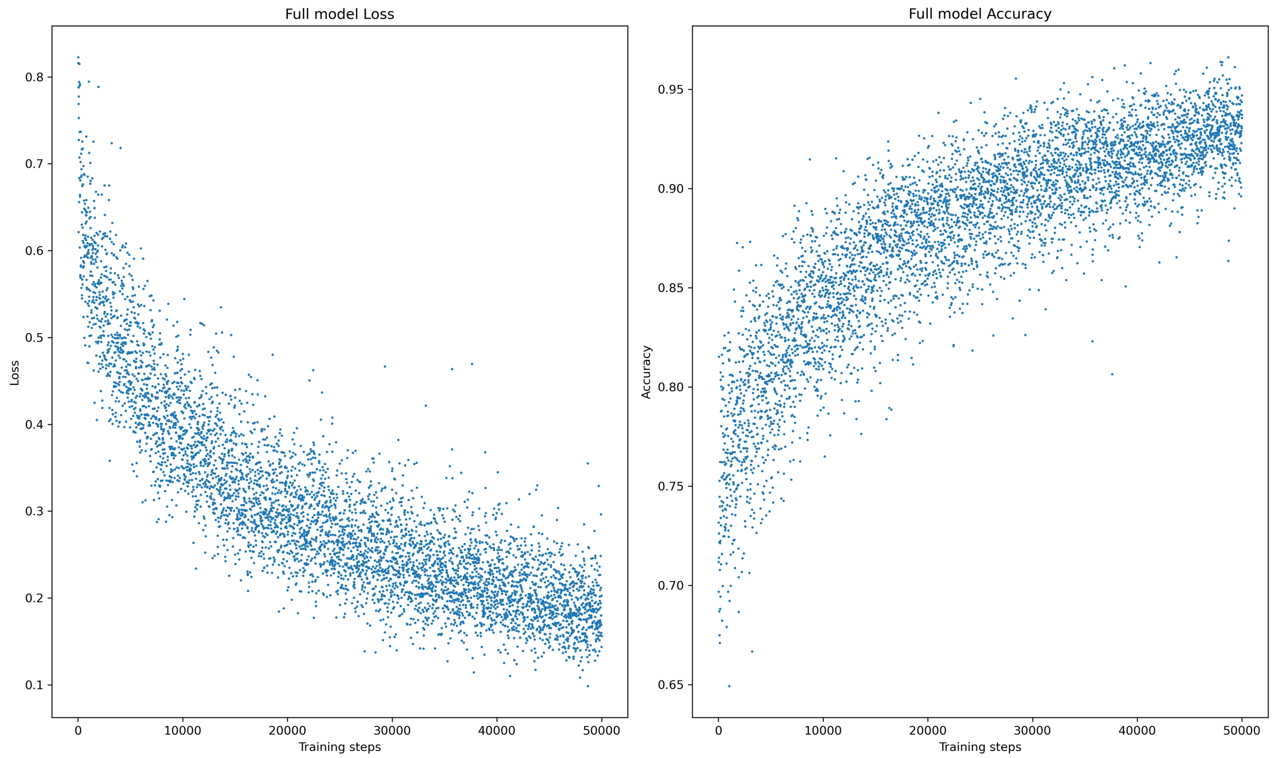

Figure 6.2 – Loss and accuracy graphic for full model training process (Source: Author).

The performance results of this model using test data in real-time are summarized in Table 6.2.

Table 6.2 – Full model performance on LifeSeniorProfile test data.

Model version	Accuracy	Specificity	Precision	Recall/Sensitivity	F1-Score
Full	0.76	0.76	0.10	0.94	0.19

Based on the results outlined in Table 6.2, it is evident that the constructed model exhibits a high sensitivity to detecting falls in the test data, achieving a rate of 94%. However, this high sensitivity comes at the expense of a high incidence of false positives. In other words, the model tends to predict falls in instances where no falls have occurred, leading to a significant number of erroneous predictions. This behavior aligns with what happens in practice, showing that simply adding vital signs information to the model cannot alleviate the problem. In the following sections, we will continue exploring this problem.

6.2 Influence of Each Physiological Sensor on Overall Accuracy

Aiming to detail the influence of each physiological sensor added to the model to identify its impact on the overall accuracy, we proceed with an individualized training process, always correlating the traditional accelerometry model with a physiological signal.

We begin our individualized analysis with the traditional model, which counts as input-only accelerometry data and has as output the classification between Fall (QD), Daily Activity (ADL), and Loss of Balance (PDE). After that, we correlate each physiological sensor with the traditional model.

For this training process, we used 431542 inputs classified individually as QD, ADL, and PDE. We used a timestep of 150 samples and a batch size of 128 for a total of 50,000 timesteps, which caused the model to be trained for 2000 epochs. Table 6.3 and Table 6.4 summarize the train accuracy and performance using test data, respectively.

It is possible to observe that adding physiological information from the blood volume pulse and electrodermal activity parameters adds valuable information to the model and improves fall detection accuracy. The correlation with the Heart Rate and Temp parameters was not performed as the data from these signals show a high variability that could not be related to non-fall and fall activities, as will be detailed in Section 6.3 below.

The growth in accuracy during training shows that the model converges more efficiently as we associate information that contributes to the classifications already pre-

Table 6.3 – Influence of each physiological information in model training process.

Model	Sensors	Final Loss	Final train accuracy
ACC	acc_x, acc_y, acc_z	0.4469	0.7877
ACC+BVP	acc_x, acc_y, acc_z, bvp	0.310961	0.874271
ACC+EDA	acc_x, acc_y, acc_z, eda	0.233567	0.911667

Table 6.4 – influence of each physiological information in model accuracy using Lifesenior-Profile test data.

Model	Sensors	Accuracy	Specificity	Precision	Recall	F1-Score
ACC	acc_x, acc_y, acc_z	0.95	0.96	0.27	0.49	0.35
ACC+BVP	acc_x, acc_y, acc_z, bvp	0.98	0.99	0.97	0.91	0.94
ACC+EDA	acc_x, acc_y, acc_z, eda	0.91	0.97	0.79	0.54	0.64

established by the accelerometry data. Both BVP and EDA show convergence in behavior, contributing significantly to improving the model's accuracy, with evidence detailed below.

6.3 Analysis of the Behavior of Vital Signs During the Fall

To analyze the inter-sensor correlation between motion and vital signs, we used the accelerometer as a base sensor to identify a volunteer's movement, daily activities, loss of balance, and fall. We looked for variations in the other sensors at the points where the events were identified on the accelerometer graph.

6.3.1 Accelerometer-Blood Volume Pulse Inter-sensor Correlation

We noticed that the Blood Volume Parameter (BVP) strongly correlated with the events recorded by the accelerometer. Figure 6.3 shows the collision with an obstacle.

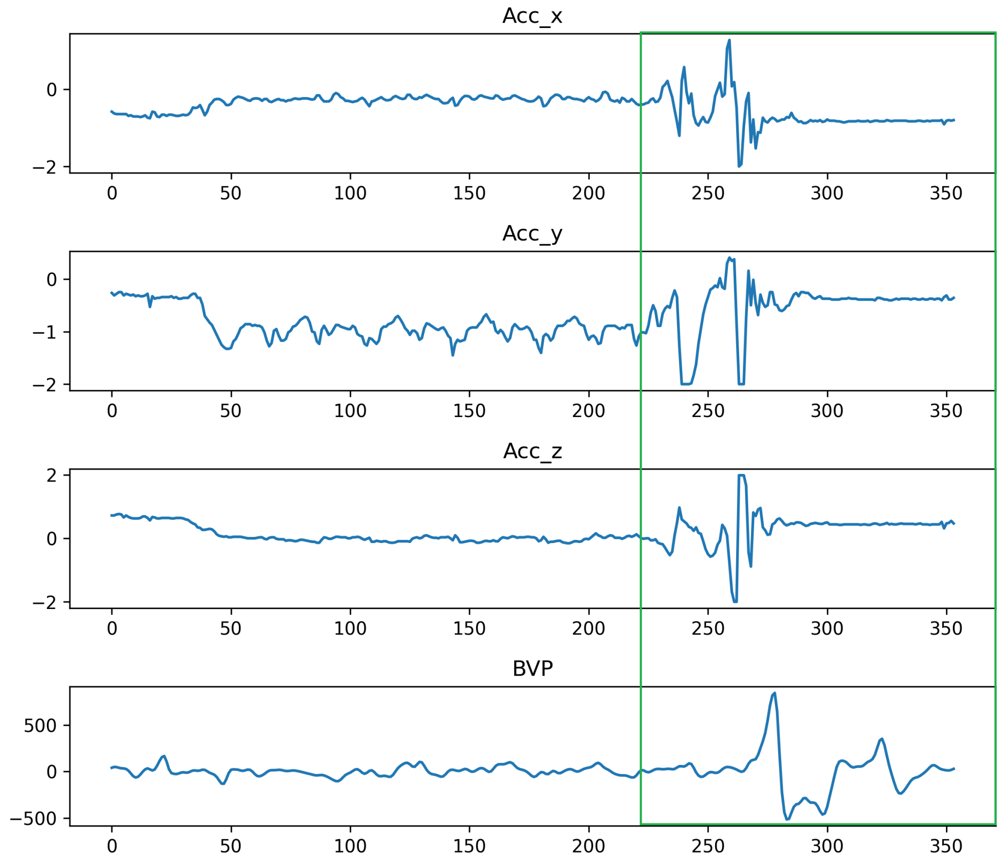

Figure 6.3 – Blood Volume pulse correlated with accelerometer data in volunteer performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground) (Source: Author).

The BVP is reported in μV and is expected to show the graph a deflection and peak with every heartbeat. Physiologically, it measures the volume of blood passing the sensor below the watch. This measure is done by the PPG sensors in either red or infrared light.

In LifeSeniorProfile, we have a total of 90 fall simulations. In at least 62 (68%) of them, we have significant changes in Blood Volume Pulse, such as those highlighted in Figure 6.3 during and immediately after the fall.

This change can be interpreted in several ways. Physiologically, BVP can be affected by heart rate, heart rate variability (HRV, which is the interval between heartbeats), and respiration rate. Certain emotions can trigger the release of hormones, such as epinephrine and norepinephrine, raising blood flow and muscle oxygen. Blood volume can also change due to widening or contraction of blood vessels. These emotions can then be interpreted using BVP, as the blood flow will be affected.

From the point of view of the model developed based on artificial intelligence, these variations associated with signal peaks manifested in the accelerometry signal contribute to the identification of an actual fall, as they will contribute to differentiating a real fall from a daily activity from an abrupt movement. In comparative terms, only in 19% of the daily activity simulations and 16% of the loss of balance simulations did we have significant changes in the blood volume pulse directly correlated with a significant peak in accelerometer data, showing that this parameter is relevant for the proposed model.

We cannot also rule out that these variations are technical, such as the displacement of the watch on the volunteer's wrist or a greater incidence of light between the volunteer's wrist and the base of the watch (which would affect the reading of the PPG sensor), despite the watch being buckled to avoid these problems in all volunteers.

Despite the apparent high correlation between the variation in blood volume pulse and the moment of the fall, it is essential to point out that a considerable volume (28%) of volunteers did not show this variation during the fall simulation. We attribute this fact to each person's natural and individual behavior, highlighting the need for a model that can adapt to the user's natural behavior, described in Section 6.5.

6.3.2 Accelerometer-Electrodermal Activity Inter-sensor Correlation

Electrodermal activity (EDA) assesses the naturally occurring changes in the electrical properties of human skin and is a noninvasive way to measure the human nervous system in real-time. EDA is a marker of sympathetic network activity and reflects the activity of the sympathetic nerve on sweat glands.

By measuring the EDA sensor, it is possible to indirectly estimate the behavior of the volunteer's nervous system, but it is well accepted in academia [5]. As seen in Figure 6.4, right after the point marked on the accelerometer as a fall, there is a significant variation in the skin's electrical activity. This variation occurred in 78 of the 90 falls simulated in LifeSeniorProfile (86%) but manifested in several ways. The vast majority (75.6%) of the variations presented were variations aimed at increasing the EDA signal, however in 24.3% there was a decrease in EDA after the fall and in 19% of the simulations the signal remained stable.

From the proposed model's point of view, integrating the EDA signal into the model brings benefits in most cases. Since the data indicates an oscillatory behavior during the fall, this behavior contributes to the intelligence-based model's artificial absorption of this variation as a confirmation of the fall.

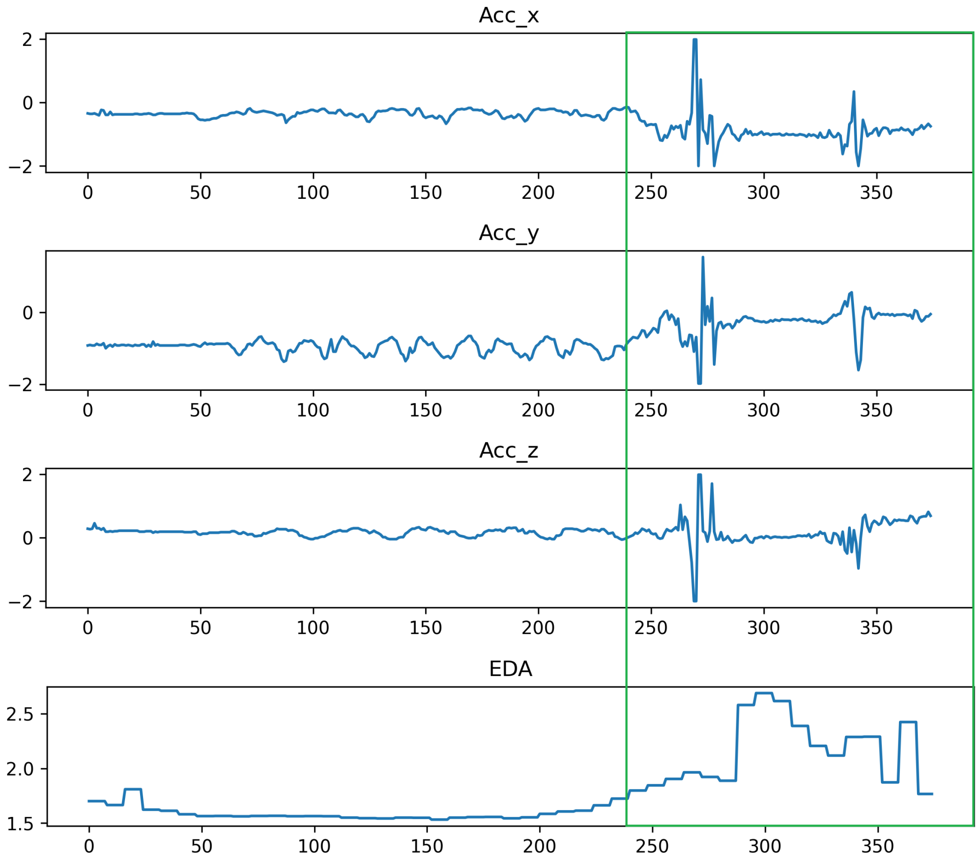

Figure 6.4 – Electrodermal Activity correlated with accelerometer data in volunteer performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground) (Source: Author).

Comparing these numbers with the execution of daily activities (ADL), it is possible to observe that this behavior is not present in 82% of activities, contributing to the hypothesis that the use of this sensor provides valuable information to the model.

However, this behavior is more present in loss-of-balance activities (PDE); significant peaks in the accelerometry signal do not accompany it.

6.3.3 Accelerometer-Heart Rate Inter-sensor Correlation

The PPG sensor acquires the heart rate, and its signal represents the number of heartbeats per minute (bpm). Analyzing the 90 fall simulations available in LifeSeniorProfile, it was not possible to find a behavior that would contribute to increasing accuracy in fall detection since, as can be seen in Figure 6.5, the behavior is completely random, no correlation was found with the recorded drop.

In all simulations, we had a completely stable signal, an increase in heart rate, and a decrease in heart rate, with none of the behaviors standing out. Likewise, no behav-

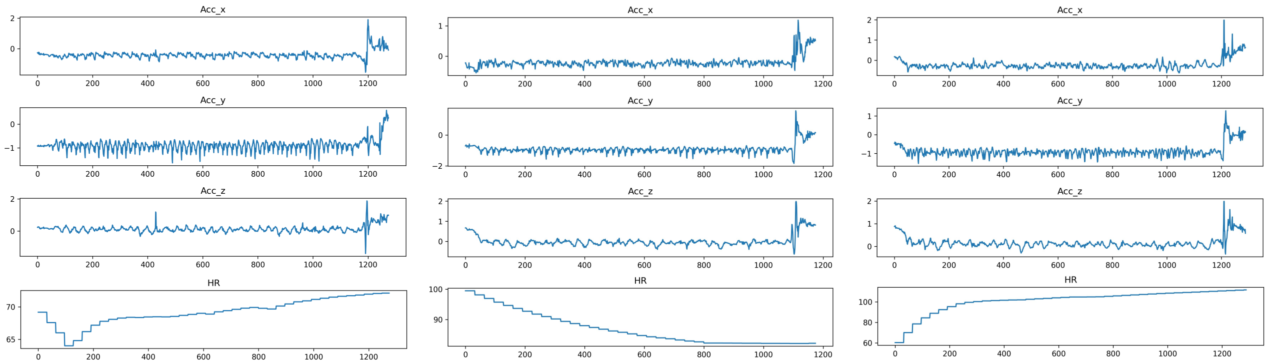

Figure 6.5 – Heart Rate correlated with accelerometer data in three different volunteers performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle, and then simulate the movement of falling to the ground) (Source: Author).

ior could be interpreted as a valid pattern in the simulations of daily activities (ADL) and loss of balance (PDE).

These results, in a way, are not surprising since the heart rate (HR) is a signal that has a slow transition behavior; that is, the effects of a fall tend to be represented in the heart rate late, around 1 to 2 minutes depending on the algorithm implemented in the device. In this scenario, it would only make sense to include this information in the model if an increased window size was used (around 3840 samples to cover the two minutes projects with the 32 Hz rate - as a comparison, the current model works with a window of 150 samples which comprises less than 5 seconds at 32 Hz).

6.3.4 Accelerometer-Skin Temperature Inter-sensor Correlation

We also correlated, in the same way, the accelerometry with the volunteer's skin temperature data during the execution of all LifeSeniorProfile activities, paying greater attention to moments of falling. Based on this analysis, it is possible to see that there is no direct relationship between the drop and the behavior of skin temperature. As seen in Figure 6.6, where we have an example of three patients performing the same activity, the temperature behavior is completely random from the point of view of fall detection. We also analyzed all activities classified as non-falling and found the same behavior.

The nature of the temperature signal behavior can justify these results. The sensor used in the collection device is of the contact type, having naturally associated with its operation a latency arising from the need for thermal balance between the watch's metal and the skin in contact with it. This balance takes some time to stabilize; therefore, a possible variation, possibly towards a decrease in temperature, would only be noticed a considerable time after the drop.

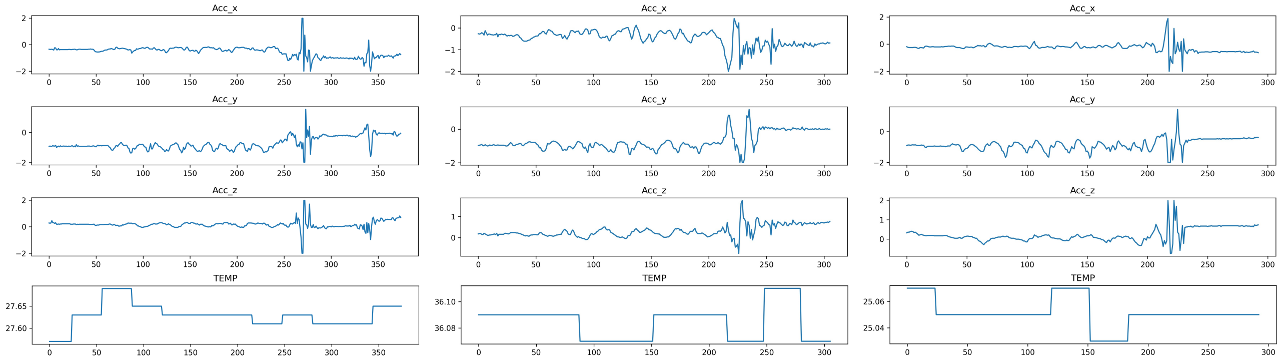

Figure 6.6 – Temperature correlated with accelerometer data in three different volunteers performing a fall simulation (Obstacle: initially walking, simulate the collision of the lower limbs with an obstacle and then simulate the movement of falling to the ground) (Source: Author).

Therefore, it can be concluded that the temperature vital sign contributes little to the proposed model and can be easily removed from the analysis without compromising accuracy.

6.4 Final Model Proposal based on Fused Vital Signs Results

Based on the results detailed in the previous sections, we propose the final model for detecting risk situations in older people. In addition to the accelerometry signals, which have already shown their importance for models of this type, the data indicate that the physiological signal blood volume pulse and electrodermal activity have behavior that can help validate a fall.

Based on this analysis, we propose that the movement sensor (accelerometer) be associated with BVP and EDA physiological signals.

We analyzed the performance of this proposal, and from the graph in Figure 6.7 it is possible to observe that the model migrates to an accuracy close to 90% in a much shorter time than in other models (around train step 5000 it is already possible observe an accuracy of 85% of the model, a fact that was achieved only close to training step 20,000 for other models.), showing that it has training data that tends to make the model converge faster. The final train accuracy was **0.951146**, and the final loss was **0.158591**.

The metrics of the model in operation with real-time data through the wearable simulator are detailed in Table 6.5.

Table 6.5 – Final model performance on LifeSeniorProfile test data

Model version	Accuracy	Specificity	Precision	Recall/Sensivity	F1-Score
Final	0.97	0.99	0.90	0.84	0.87

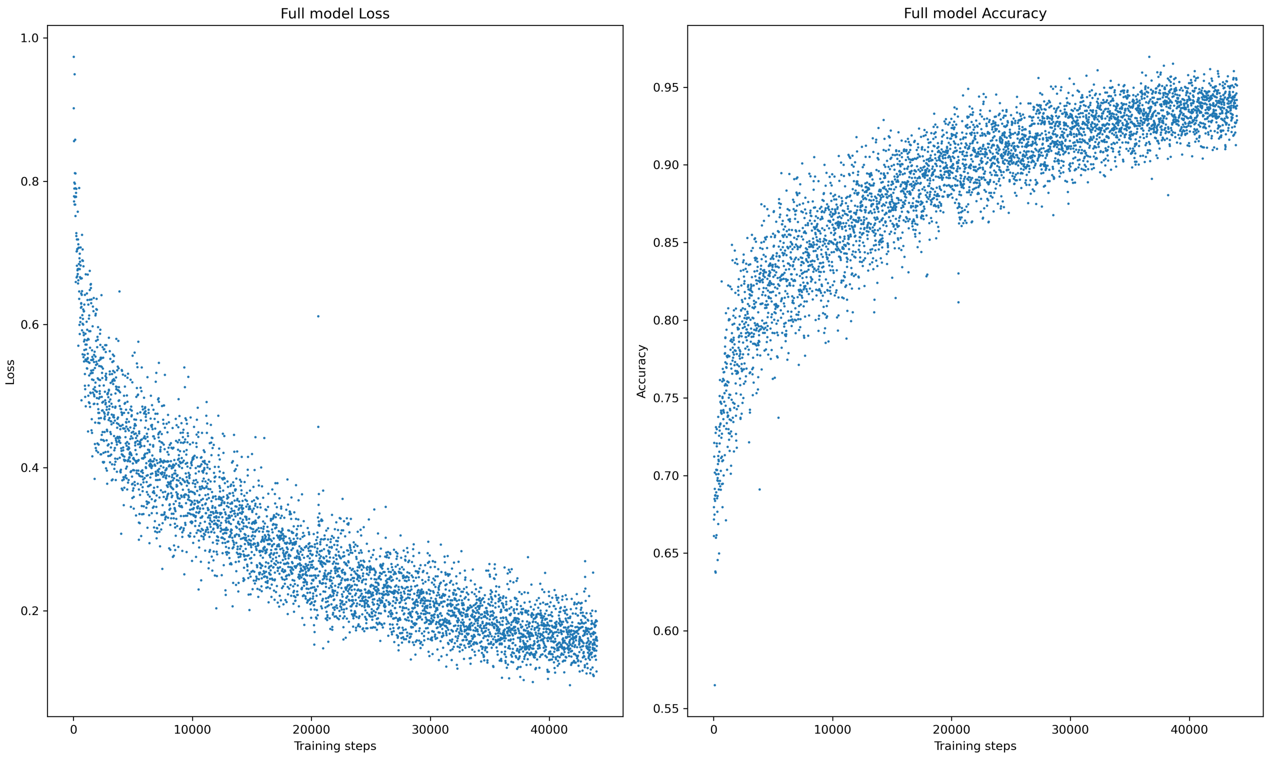

Figure 6.7 – Loss and accuracy graphic for final model training process (Source: Author).

6.5 Model with User Adaptation Analysis

As the previous sections have proven, the hypothesis that the behavior of vital signs is much more heterogeneous than the behavior of signals expected for movement sensors is fulfilled. Interpersonal behavior is highly variable, which tends to harm the models developed in the laboratory in real-use situations.

As detailed in the methodology, we simulate a model capable of adapting to user behavior through a training process during the first use and through confirmation by the user whenever a fall is detected. This generates a collaborative model that aims to enrich training data with real information, which is difficult to reproduce in simulated environments.

To simulate this behavior, we start from the final model proposed in Section 6.4 and evaluate its performance in detecting data from a new user with data not seen by the model. This new user performed the simulation of each activity twice, one used for training and the other used for testing the model. We evaluate the performance of the test data using the model from Section 6.4, and after collecting the results, we perform training with the new data. Later, we used the same test data in the latest model to evaluate whether the data from that user contributed to the improvement of the specific model for him and the general model.

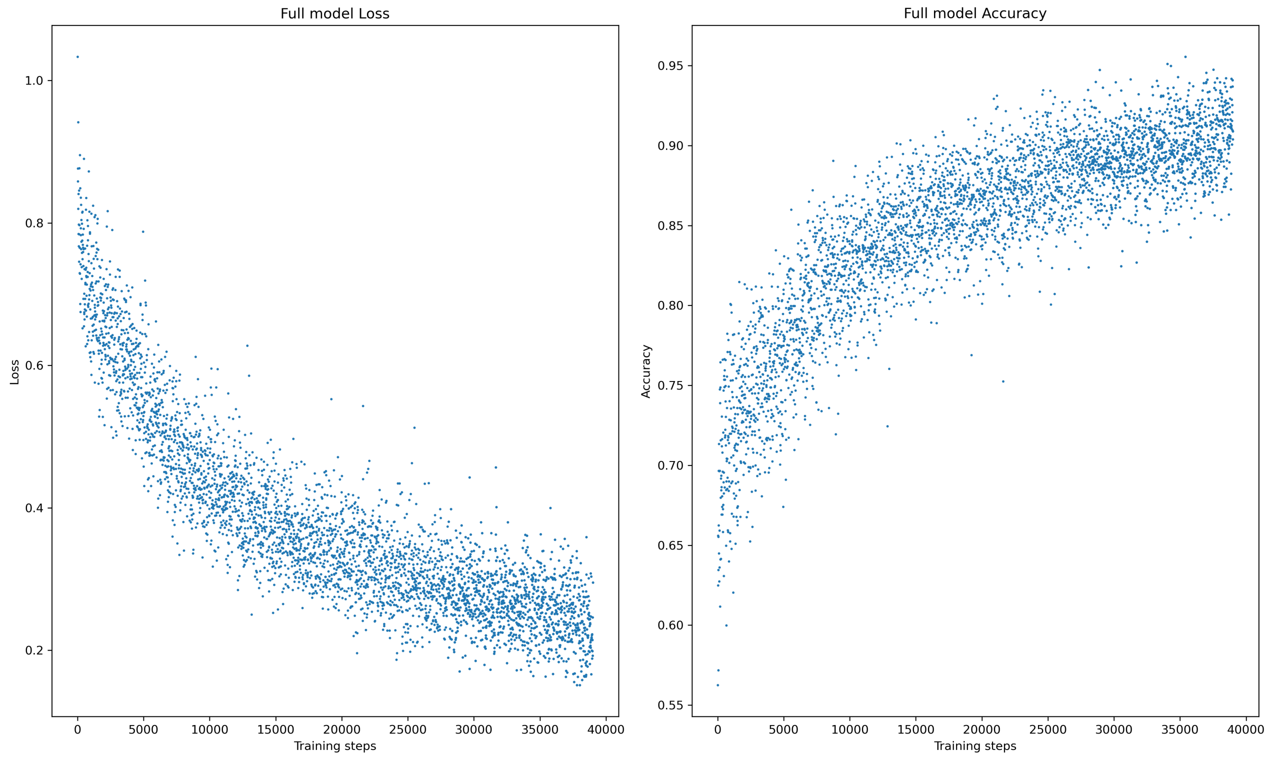

Figure 6.8 – Loss and accuracy graphic for user-adapted model training process (Source: Author).

In Figure 6.8, we can see that this model converged usually, as expected, without any significant increase in general accuracy. But, how can be seen in Table 6.6 the accuracy taking in account fall detection probability increase a lot when we tested this model using only data test from him (b), compared with previous model testing same data (a).

Table 6.6 – User adaptation model performance on LifeSeniorProfile specific user data.

Model version	Accuracy	Specificity	Precision	Recall	F1-Score
a) Final model with new data	0.85	0.93	0.44	0.33	0.38
b) User adapted with new data	0.91	0.92	0.58	0.85	0.69
c) User adapted with test data	0.69	0.94	0.98	0.63	0.77

In Table 6.6, we can also see that the increment of new data did not cause any harm to the overall performance of the model, as can be seen in part (c), where the model was tested with the same general test data used in the previous steps.

6.6 Comparison of the Model with Similar Models

We have demonstrated a more generalized and detailed architecture of the risk detection model, which is a closer representation of real-life fall situations. Our model shows significant results and proved to be relevant in its area. The proposed model is a pioneer in using vital signs and correlated movement data to increase fall detection accuracy. The relation between recent articles and our model can be seen in Table 6.7.

Comparatively, Yhdego et al. [81] obtained an F1-score of 97% through a mixed model composed of a feature extractor feeding an LSTM, followed by a linear classifier. However, the article proposes using only accelerometry data, a type of sensor that produces non-differentiable signals in real life.

Also, Kulurkar et al. [34] obtained an F1-Score of 98% using MobiAct Dataset [74], a know available dataset for fall detection. Analyzing this article, we can see that, besides these excellent results, the model could identify a fall only with 0.85 precision, 0.66 recall, and 0.862 accuracy when they simulated data streaming. This is important to understand why our Accuracy and F1-Score do not achieve values near 100% as other studies.

Khawnuan et al. [27] similarly explored a model based on convolutional neural networks applied to the tFall [42] and SisFall [70] datasets, obtaining significantly better metrics than other techniques on the same datasets.

Table 6.7 – Performance comparison between state-of-the-art approaches and our model.

Reference	Classes	F1 Score	Accuracy
[81]	3	0.97	0.98
[34]	9	0.98	0.99
[27]	9	0.9915	0.9915
Proposed	**5**	0.87	0.97

Analyzing these recent works comparatively, it is possible to observe that the metrics achieved were far superior to the model proposed in this thesis. The following factors can explain this:

- Data Streaming: a fall simulation in LifeSeniorProfile comprises a series of different gait simulations that aim to approximate the actual behavior of a pre-fall situation. However, these simulations do not fall but are part of the process. Depending on the window size, it is possible to "see" only one pre-crash period, which generates a correct classification of the model as non-crash but is counted as a false prediction due to the file belonging to a file initially classified as a drop. For example, LifeSeniorProfile has files where it is possible to have up to 8 different windows, and only one has information regarding the fall. This limitation considerably lowers the F1-Score, a fact that can be improved in future works;

- low volume of data: LifeSeniorProfile is the first dataset version of this research. We think there is space to increase it with more data and make it a more relevant dataset in this research area. Unfortunately, it was developed during the world pandemic, and acquiring more data was impossible. As a result, we believe that the low volume of data significantly harmed the results achieved. For a model based on deep learning, a high volume of data is necessary for the best performance to be achieved.

6.7 Limitations

The proposal model in this thesis has some limitations that need to be taken into consideration:

- Emulated falls: One of the critical limitations of our work, and most of them available in the literature, is that the datasets utilized for experimentation are emulated fall datasets. Our model proposes a user adaptation phase that aims to reverse the proportion between simulation and real-life over time; however, it is necessary to recognize that the basis is a simulated model;
- Limited number of volunteers - as the number of volunteers performing the simulated movements is not higher than other datasets, the researcher needs to consider specific algorithms; some insights can be the product of a poor number of collections and not from the algorithm performance;
- Age of volunteers - the average age of volunteers is lower than that of the elderly, generating a loss of specific characteristics found only in older adults. This choice prevents older adults from getting injured, even with the falls being controlled and assisted by a medical team. Since the subjects were young and healthy, will the model remain equally efficient for the elderly population, which is the target population? Will the user adaptation model be sufficient to convert this simulated scenario into another population range for an elderly user? These questions need further investigation, thus opening doors for future research directions;
- Artificial Intelligence hyperparameters: The current configuration of the proposed model is aimed at a small database. The researcher must be careful when expanding this model, as adjusting the dropout layers, batch size, and number of LSTM layers may be necessary.

7. CONCLUSIONS AND FUTURE WORK

In this work, we have presented a novel methodology for improving the accuracy of a risk situation detector in elderly people, associated with the development of an innovative dataset with motion and physiological sensors correlated and collected in a joint way.

Our model achieves significant results in real-time stream data, which is more difficult than traditional static analysis of test data. It shows that the correlation of vital signs with accelerometry data is relevant for detecting risk situations in the elderly. The initial results are promising and open doors for further experimentation.

This work can be used to build new models or improve the proposed associations between vital signs, sensors, and other possible combinations, helping to increase the quality of older people's lives.

We believe that the work could have advanced by connecting the device used in the collection to the App simulator developed. This would have made it possible to receive the collected time series in real-time, better evaluating the capacity of the model to adapt to the user and the variation present in the signals while performing different fall simulations or daily activities. This step will remain a proposal for future work that can be developed in additional research.

We agree that the data used in this work do not exactly reflect the target population of the developed system, however, it is expected that the system's adaptability will be able to cushion these differences over time and through retraining.

Our training process took into account the use of a specialized device, which has sensors certified for medical-grade use. It is known that the reality of a device to be used on humans in a real scenario is much lower and so we explored the concept of adaptability of the algorithm, in an attempt to compensate for these adversities, having achieved satisfactory results.

Through this research, it was also possible to conclude that the physiological signals of heartbeat and skin temperature do not produce relevant information for the model when using significantly small monitoring windows to detect a fall (high-speed signal). The behavior of these signals has a slower variation dynamic, mainly due to the technologies used for monitoring, which means that their influence is exerted on the signals in an interval well ahead of the moment of the fall. A workaround for this problem would be to use larger observation windows, but detections would be significantly slower as a side effect.

For future work, we are considering expanding the LifeSeniorProfile dataset to include more volunteers and increase its heterogeneity, aiming to contribute more relevant data to the academic environment.

For future research using this as a basis, we recommend connect a real wearable sending in real time data to app simulator and analyze the results considering simulations performed in real time.

All content developed during this research, including data processing scripts, source code adopted in the proposed model and the complete dataset produced during this thesis are available in a public domain [45].

REFERENCES

[1] Abbate, S.; Avvenuti, M.; Cola, G.; Corsini, P.; Light, J.; Vecchio, A. “Recognition of false alarms in fall detection systems”. In: Proceedings of the IEEE Consumer Communications and Networking Conference (CCNC), 2011, pp. 23–28.

[2] Abdelhedi, S.; Bourguiba, R.; Mouine, J.; Baklouti, M. “Development of a two-threshold-based fall detection algorithm for elderly health monitoring”. In: Proceedings of the IEEE International Conference on Research Challenges in Information Science (RCIS), 2016, pp. 1–5.

[3] Alfian, R. I.; Ma’arif, A.; Sunardi, S. “Noise reduction in the accelerometer and gyroscope sensor with the kalman filter algorithm”, *Journal of Robotics and Control (JRC)*, vol. 2–3, 2021, pp. 180–189.

[4] Allen, J. “Photoplethysmography and its application in clinical physiological measurement”, *Physiological measurement*, vol. 28–3, 2007, pp. 1–40.

[5] Amin, R.; Faghih, R. T. “Physiological characterization of electrodermal activity enables scalable near real-time autonomic nervous system activation inference”, *PLoS computational biology*, vol. 18–7, 2022, pp. 1–28.

[6] Bharathkumar, K.; Paolini, C.; Sarkar, M. “Fpga-based edge inferencing for fall detection”. In: Proceedings of the IEEE Global Humanitarian Technology Conference (GHTC), 2020, pp. 1–8.

[7] Bikias, T.; Iakovakis, D.; Hadjidimitriou, S.; Charisis, V.; Hadjileontiadis, L. “Deepfog: an imu-based detection of freezing of gait episodes in parkinson’s disease patients via deep learning”, *Frontiers in Robotics and AI*, vol. 8, 2021, pp. 1–8.

[8] Blain, S.; Mihailidis, A.; Chau, T. “Assessing the potential of electrodermal activity as an alternative access pathway”, *Medical Engineering & Physics*, vol. 30–4, 2008, pp. 498–505.

[9] Bourke, A.; O’Brien, J.; Lyons, G. “Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm”, *Gait & Posture*, vol. 26–2, 2007, pp. 194–199.

[10] Campanella, S.; Altaleb, A.; Belli, A.; Pierleoni, P.; Palma, L. “A method for stress detection using empatica e4 bracelet and machine-learning techniques”, *Sensors*, vol. 23–7, 2023, pp. 1–16.

[11] Capra, M.; Sapienza, S.; Motto Ros, P.; Serrani, A.; Martina, M.; Puiatti, A.; Bonato, P.; Demarchi, D. “Assessing the feasibility of augmenting fall detection systems by

relying on uwb-based position tracking and a home robot", *Sensors*, vol. 20–18, 2020, pp. 1–22.

[12] Chester, J.; Rudolph, J. "Vital signs in older patients: age-related changes", *Journal of the American Medical Directors Association*, vol. 12–5, 2011, pp. 337–343.

[13] Fridolfsson, J.; Börjesson, M.; Buck, C.; Ekblom, Ö.; Ekblom-Bak, E.; Hunsberger, M.; Lissner, L.; Arvidsson, D. "Effects of frequency filtering on intensity and noise in accelerometer-based physical activity measurements", *Sensors*, vol. 19–9, 2019, pp. 1–12.

[14] Hanifi, K.; Karsligil, M. "Elderly fall detection with vital signs monitoring using cw doppler radar", *IEEE Sensors Journal*, vol. 21–15, 2021, pp. 16969–16978.

[15] Hashim, H.; Mohammed, S.; Gharghan, S. "Accurate fall detection for patients with parkinson's disease based on a data event algorithm and wireless sensor nodes", *Measurement*, vol. 156, 2020, pp. 1–18.

[16] Hochreiter, S.; Schmidhuber, J. "Long Short-Term Memory", *Neural Computation*, vol. 9–8, 11 1997, pp. 1735–1780.

[17] Hrnjica, B.; Bonacci, O. "Lake level prediction using feed forward and recurrent neural networks", *Water Resources Management*, vol. 33–7, 2019, pp. 2471–2484.

[18] Huynh, Q.; Nguyen, U.; Tran, S.; Nabili, A.; Tran, B. "Fall detection system using combination accelerometer and gyroscope". In: Proceedings of the Second International Conference on Advances in Electronic Devices and Circuits (EDC 2013), 2013, pp. 52–56.

[19] Inc., E. "Empatica e4 - real time clinical grade monitoring system". Source: https://www.empatica.com/research/e4/, 29 feb 2024.

[20] Ivașcu, T.; Negru, V. "Activity-aware vital sign monitoring based on a multi-agent architecture", *Sensors*, vol. 21–12, 2021, pp. 1–29.

[21] Jantaraprim, P.; Phukpattaranont, P.; Limsakul, C.; Wongkittisuksa, B. "Improving the accuracy of a fall detection algorithm using free fall characteristics". In: Proceedings of the International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2010, pp. 501–504.

[22] Jarchi, D.; Salvi, D.; Tarassenko, L.; Clifton, D. A. "Validation of instantaneous respiratory rate using reflectance ppg from different body positions", *Sensors*, vol. 18–11, 2018, pp. 1–18.

[23] Junior, J. "Redes neurais recorrentes — lstm". Source: https://medium.com/@web2ajax/redes-neurais-recorrentes-lstm-b90b720dc3f6, 29 feb 2024.

[24] Kanstrén, T. “A look at precision, recall, and f1-score”. Source: https://towardsdatascience.com/a-look-at-precision-recall-and-f1-score-36b5fd0dd3ec, 29 feb 2024.

[25] Karar, M.; Shehata, H.; Reyad, O. “A survey of iot-based fall detection for aiding elderly care: Sensors, methods, challenges and future trends”, *Applied Sciences*, vol. 12–7, 2022, pp. 3276–3291.

[26] Kausar, F.; Awadalla, M.; Mesbah, M.; AlBadi, T. “Automated machine learning based elderly fall detection classification”, *Procedia Computer Science*, vol. 203, 2022, pp. 16–23.

[27] Khawnuan, U.; Sittiwanchai, T.; Yodpijit, N. “Convolutional neural network for wearable fall detection systems”, *Science, Engineering and Health Studies*, vol. 86–C, 2023, pp. 1–9.

[28] Kim, H.-G.; Cheon, E.-J.; Bai, D.-S.; Lee, Y. H.; Koo, B.-H. “Stress and heart rate variability: a meta-analysis and review of the literature”, *Psychiatry investigation*, vol. 15–3, 2018, pp. 1–11.

[29] Kiprijanovska, I.; Gjoreski, H.; Gams, M. “Detection of gait abnormalities for fall risk assessment using wrist-worn inertial sensors and deep learning”, *Sensors*, vol. 20–18, 2020, pp. 1–21.

[30] Koshmak, G. A.; Linden, M.; Loutfi, A. “Evaluation of the android-based fall detection system with physiological data monitoring”. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 1164–1168.

[31] Kownacki, C. “Optimization approach to adapt kalman filters for the real-time application of accelerometer and gyroscope signals’ filtering”, *Digital Signal Processing*, vol. 21–1, 2011, pp. 131–140.

[32] Kraft, D.; Srinivasan, K.; Bieber, G. “Deep learning based fall detection algorithms for embedded systems, smartwatches, and iot devices using accelerometers”, *Technologies*, vol. 8–4, 2020, pp. 1–17.

[33] Kreuzer, D.; Munz, M. “Deep convolutional and lstm networks on multi-channel time series data for gait phase recognition”, *Sensors*, vol. 21–3, 2021, pp. 1–15.

[34] Kulurkar, P.; kumar Dixit, C.; Bharathi, V.; Monikavishnuvarthini, A.; Dhakne, A.; Preethi, P. “Ai based elderly fall prediction system using wearable sensors: A smart home-care technology with iot”, *Measurement: Sensors*, vol. 25, 2023, pp. 1–11.

[35] Kurylyak, Y.; Lamonaca, F.; Grimaldi, D. “A neural network-based method for continuous blood pressure estimation from a ppg signal”. In: Proceedings of the IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2013, pp. 280–283.

[36] Li, C.; Teng, G.; Zhang, Y. “A survey of fall detection model based on wearable sensor”. In: Proceedings of the International Conference on Human System Interaction (HSI), 2019, pp. 181–186.

[37] Li, H.; Shrestha, A.; Heidari, H.; Le Kernec, J.; Fioranelli, F. “Bi-lstm network for multimodal continuous human activity recognition and fall detection”, *IEEE Sensors Journal*, vol. 20–3, 2019, pp. 1191–1201.

[38] Li, Q.; Stankovic, J.; Hanson, M.; Barth, A.; Lach, J.; Zhou, G. “Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information”. In: Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks (BSN), 2009, pp. 138–143.

[39] Liu, H.-P.; Chuang, Y.-M.; Liu, C.-H.; Yang, P. C.; Fuh, C.-S. “Precise measurement of physical activities and high-impact motion: Feasibility of smart activity sensor system”, *IEEE Sensors Journal*, vol. 21–1, 2020, pp. 568–580.

[40] Mauldin, T.; Canby, M.; Metsis, V.; Ngu, A.; Rivera, C. “Smartfall: A smartwatch-based fall detection system using deep learning”, *Sensors*, vol. 18–10, 2018, pp. 1–19.

[41] McCarthy, C.; Pradhan, N.; Redpath, C.; Adler, A. “Validation of the empatica e4 wristband”. In: Proceedings of the Internation Student Conference (ISC), 2016, pp. 1–4.

[42] Medrano, C.; Igual, R.; Plaza, I.; Castro, M. “Detecting falls as novelties in acceleration patterns acquired with smartphones”, *PloS one*, vol. 9–4, 2014, pp. 1–9.

[43] Medrano, C.; Plaza, I.; Igual, R.; Sánchez, Á.; Castro, M. “The effect of personalization on smartphone-based fall detectors”, *Sensors*, vol. 16–1, 2016, pp. 1–14.

[44] Mohan, D.; Al-Hamid, D. Z.; Chong, P. H. J.; Gutierrez, J.; Li, H. “Fall prediction in elderly through vital signs monitoring–a fuzzy–based approach”, *IEEE Internet of Things Journal*, vol. 1–1, 2024, pp. 1–12.

[45] Much, M. D. “Eldery risk situation detector for elderly people based on time-seris analysis”. Source: https://github.com/maicondiogomuch/RiskSituationDetector, 29 feb 2024.

[46] Much, M. D.; Sieg, J.; de Moraes Filho, A.; Bartoski, V.; Schreiber, G.; Marcon, C. “Lifeseniorprofile: A multisensor dataset for elderly real-time activity track”.

In: Proceedings of the International Conference on Health Informatics (HEALTHINF), 2023, pp. 453–460.

[47] Nho, Y.-H.; Lim, J. G.; Kwon, D.-S. “Cluster-analysis-based user-adaptive fall detection using fusion of heart rate sensor and accelerometer in a wearable device”, *IEEE Access*, vol. 8, 2020, pp. 40389–40401.

[48] Nitzan, M.; Romem, A.; Koppel, R. “Pulse oximetry: fundamentals and technology update”, *Medical Devices: Evidence and Research*, vol. 1–1, 2014, pp. 231–239.

[49] Noury, N.; Fleury, A.; Rumeau, P.; Bourke, A.; Laighin, G.; Rialle, V.; Lundy, J.-E. “Fall detection-principles and methods”. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007, pp. 1663–1666.

[50] Núñez-Marcos, A.; Azkune, G.; Arganda-Carreras, I. “Vision-based fall detection with convolutional neural networks”, *Wireless communications and mobile computing*, vol. 2017, 2017, pp. 1–16.

[51] Organization, W. H. “Falls”. Source: https://www.who.int/news-room/fact-sheets/detail/falls, 29 feb 2024.

[52] Organization, W. H. “Ageing and heath”. Source: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health, 29 feb 2024.

[53] Pandya, B.; Pourabdollah, A.; Lotfi, A. “Comparative analysis of real-time fall detection using fuzzy logic web services and machine learning”, *Technologies*, vol. 8–4, 2020, pp. 1–12.

[54] Piccinno, A.; Hemmatpour, M.; Ferrero, R.; Montrucchio, B.; Rebaudengo, M. “A review on fall prediction and prevention system for personal devices: Evaluation and experimental results”, *Advances in Human-Computer Interaction*, vol. 2019–1–12, 2019.

[55] Qian, X.; Chen, H.; Jiang, H.; Green, J.; Cheng, H.; Huang, M.-C. “Wearable computing with distributed deep learning hierarchy: a study of fall detection”, *IEEE Sensors Journal*, vol. 20–16, 2020, pp. 9408–9416.

[56] Queralta, J.; Gia, T.; Tenhunen, H.; Westerlund, T. “Edge-ai in lora-based health monitoring: Fall detection system with fog computing and lstm recurrent neural networks”. In: Proceedings of the International Conference on Telecommunications and Signal Processing (TSP), 2019, pp. 601–604.

[57] Ramachandran, A.; Ramesh, A.; Karuppiah, A. “Evaluation of feature engineering on wearable sensor-based fall detection”. In: Proceedings of the International Conference on Information Networking (ICOIN), 2020, pp. 110–114.

[58] Rastogi, S.; Singh, J. "A systematic review on machine learning for fall detection system", *Computational intelligence*, vol. 37–2, 2021, pp. 951–974.

[59] Reiss, A.; Indlekofer, I.; Schmidt, P. "PPG-DaLiA". Source: https://archive.ics.uci.edu/dataset/495/ppg+dalia, 29 feb 2024.

[60] Roshdibenam, V.; Jogerst, G.; Butler, N.; Baek, S. "Machine learning prediction of fall risk in older adults using timed up and go test kinematics", *Sensors*, vol. 21–10, 2021, pp. 1–18.

[61] Saleh, M.; Abbas, M.; Prudhomm, J.; Somme, D.; Le Bouquin Jeannès, R. "A reliable fall detection system based on analyzing the physical activities of older adults living in long-term care facilities", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, 12 2021, pp. 1–1.

[62] Santos, G.; Endo, P.; Monteiro, Kayoand Rocha, E.; Silva, I.; Lynn, T. "Accelerometer-based human fall detection using convolutional neural networks", *Sensors*, vol. 19–7, 2019, pp. 1–12.

[63] Schuurmans, A. A.; De Looff, P.; Nijhof, K. S.; Rosada, C.; Scholte, R. H.; Popma, A.; Otten, R. "Validity of the empatica e4 wristband to measure heart rate variability (hrv) parameters: A comparison to electrocardiography (ecg)", *Journal of medical systems*, vol. 44, 2020, pp. 1–11.

[64] Shi, J.; Chen, D.; Wang, M. "Pre-impact fall detection with cnn-based class activation mapping method", *Sensors*, vol. 20–17, 2020, pp. 1–12.

[65] Shibuya, N.; Nukala, B.; Rodriguez, A.; Tsay, J.; Nguyen, T.; Zupancic, S.; Lie, D. "A real-time fall detection system using a wearable gait analysis sensor and a support vector machine (svm) classifier". In: Proceedings of the International Conference on Mobile Computing and Ubiquitous Networking (ICMU), 2015, pp. 66–67.

[66] Sigfox. "What is sigfox". Source: https://www.sigfox.com/what-is-sigfox/, 29 feb 2024.

[67] Silva, J.; Gomes, D.; Sousa, I.; Cardoso, J. "Automated development of custom fall detectors: Position, model and rate impact in performance", *IEEE Sensors Journal*, vol. 20–10, 2020, pp. 5465–5472.

[68] Singh, A.; Rehman, S.; Yongchareon, S.; Chong, P. "Sensor technologies for fall detection systems: A review", *IEEE Sensors Journal*, vol. 20–13, 2020, pp. 6889–6919.

[69] Subramaniam, S.; Faisal, A. I.; Deen, M. J. "Wearable sensor systems for fall risk assessment: A review", *Frontiers in digital health*, vol. 4–1, 2022, pp. 1–20.

[70] Sucerquia, A.; López, J.; Vargas-Bonilla, J. “Sisfall: A fall and movement dataset”, *Sensors*, vol. 17–1, 2017, pp. 1–14.

[71] Sülo, I.; Keskin, S.; Dogan, G.; Brown, T. “Energy efficient smart buildings: Lstm neural networks for time series prediction”. In: Proceedings of the International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML), 2019, pp. 18–22.

[72] Tamura, T.; Maeda, Y.; Sekine, M.; Yoshida, M. “Wearable photoplethysmographic sensors—past and present”, *Electronics*, vol. 3–2, 2014, pp. 282–302.

[73] Taramasco, C.; Rodenas, T.; Martinez, F.; Fuentes, P.; Munoz, R.; Olivares, R.; De Albuquerque, V.; Demongeot, J. “A novel monitoring system for fall detection in older people”, *IEEE Access*, vol. 6–1, 2018, pp. 43563–43574.

[74] Vavoulas, G.; Chatzaki, C.; Malliotakis, T.; Pediaditis, M.; Tsiknakis, M. “The mobiact dataset: Recognition of activities of daily living using smartphones”. In: Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and E-health (ICT4AWE), 2016, pp. 143–151.

[75] Waleed, N. A.; Jarjees, M. S. “A review study for elderly fall and vital signs monitoring systems”. In: Proceedings of American Institue of Physics Conference (AIP), 2023, pp. 240–244.

[76] Wang, F.-T.; Chan, H.-L.; Hsu, M.-H.; Lin, C.-K.; Chao, P.-K.; Chang, Y.-J. “Threshold-based fall detection using a hybrid of tri-axial accelerometer and gyroscope”, *Physiological measurement*, vol. 39–10, 2018, pp. 1–10.

[77] Warrington, D.; Shortis, E.; Whittaker, P. “Are wearable devices effective for preventing and detecting falls: an umbrella review (a review of systematic reviews)”, *BMC public health*, vol. 21, 2021, pp. 1–12.

[78] Weiss, A.; Shimkin, I.; Giladi, N.; Hausdorff, J. “Automated detection of near falls: algorithm development and preliminary results”, *BMC research notes*, vol. 3–1, 2010, pp. 1–8.

[79] Wu, X.; Zheng, Y.; Chu, C.-H.; Cheng, L.; Kim, J. “Applying deep learning technology for automatic fall detection using mobile sensors”, *Biomedical Signal Processing and Control*, vol. 72, 2022, pp. 1–9.

[80] Xu, J.; He, Z.; Zhang, Y. “Cnn-lstm combined network for iot enabled fall detection applications”, *Journal of Physics: Conference Series*, vol. 1267–1, 2019, pp. 1–7.

[81] Yhdego, H.; Paolini, C.; Audette, M. “Toward real-time, robust wearable sensor fall detection using deep learning methods: A feasibility study”, *Applied Sciences*, vol. 13–8, 2023, pp. 1–17.

[82] Yu, Z.; Zahid, A.; Ansari, S.; Abbas, H.; Abdulghani, A.; Heidari, H.; Imran, M.; Abbasi, Q. “Hardware-based hopfield neuromorphic computing for fall detection”, *Sensors*, vol. 20–24, 2020, pp. 1–16.

[83] Zerrouki, N.; Harrou, F.; Houacine, A.; Sun, Y. “Fall detection using supervised machine learning algorithms: A comparative study”. In: Proceedings of the International Conference on Modelling, Identification and Control (ICMIC), 2016, pp. 665–670.

[84] Zhou, J.; Zhao, Y. “Hierarchical coherent anomaly fall detection low bandwidth system with combination of wearable sensors for identifying behavioral abnormalities”, *IEEE Access*, vol. 8, 2020, pp. 137683–137691.

[85] Zurbuchen, N.; Wilde, A.; Bruegger, P. “A machine learning multi-class approach for fall detection systems based on wearable sensors with a study on sampling rates selection”, *Sensors*, vol. 21–3, 2021, pp. 1–23.

APPENDIX A – PUBLICATION LIST

[1] Much, M. D., Marcon, C., Hessel, F., & Cataldo Neto, A. (2021, July). LifeSenior–A Health Monitoring IoT System Based on Deep Learning Architecture. In International Conference on Human-Computer Interaction (pp. 293-306). Cham: Springer International Publishing, United States.

[2] de Moraes Filho, A., Schreiber, G., Sieg, J., Much, M., Bartoski, V., & Marcon, C. (2023). Methods to Estimate Respiratory Rate Using the Photoplethysmography Signal. (HEALTHINF), Portugal.

[3] Much, M. D., Sieg, J., de Moraes Filho, A., Bartoski, V., Schreiber, G., & Marcon, C. (2023). LifeSeniorProfile: A Multisensor Dataset for Elderly Real-time Activity Track. (HEALTHINF), Portugal.

Pontifícia Universidade Católica do Rio Grande do Sul
Pró-Reitoria de Pesquisa e Pós-Graduação
Av. Ipiranga, 6681 – Prédio 1 – Térreo
Porto Alegre – RS – Brasil
Fone: (51) 3320-3513
E-mail: propesq@pucrs.br
Site: www.pucrs.br