UNICA

UNIVERSITÀ
DEGLI STUDI
DI CAGLIARI

Ph.D. Degree In
MATEMATHICS AND COMPUTER SCIENCE

Cycle XXXV

Title Of The Ph.D. Thesis

Locomotion Traces Data Mining for Supporting Frail People with Cognitive Impairment

Scientific Disciplinary Sector
INF/01 INFORMATICA

Ph.D. Student	**Samaneh Zolfaghari**
Supervisor	**Prof. Daniele Riboni**
Co-Supervisor	**Prof. Diego R. Recupero**

Final Exam. Academic Year 2021/2022
Thesis Defence: April 2023 Session

To my parents, Tarlan and Ahmad, and
my beloved spouse, Mohsen,
for their endless love and support

Acknowledgments

Undertaking this Ph.D. has been truly a life-changing experience for me and would not have been possible to do without continuous support and guidance that I received from my supervisor Prof. Daniele Riboni. Pursuing Ph.D. studies under his supervision will always shine in my academic career's trace. The friendly atmosphere between us even during the COVID-19 lockdowns paved the way for me to be motivated and enjoy doing research.

During this journey, the collaborations with the $CoMSA^2T$ and $MMIS$ group at the University of Rostock impeccably culminated in the depth of my engagement in data analysis tasks including the annotation process and impact of goal and intention while facing multistage activities. My sincere thanks go to Prof. Kristina Yordanova and Prof. Thomas Kirste who provided me with an opportunity to join their teams as a visiting scholar, and who gave me access to the laboratory and research facilities. I took delight in collaborations with them and Sumaiya Suravee, and Teodor Stoev, as their Ph.D. students. The companionship of Mana, Salman, Moh'd, and Tomasz during my time in Rostock is all appreciated for the fun times we had working and socializing together.

I would like to offer my special thanks to Prof.Annica Kristofersson and Prof.Petteri Nurmi for their insightful comments and suggestions which improved the coherency of this thesis.

My accomplishments during my Ph.D. years might not be yielded if I have not been blessed by the unconditional love, unwavering support, and encouragement of my parents. Moreover, I am at a loss for words to express my gratitude to my beloved Mohsen who has stood by me through all ups and downs, my absences, my travails, and my impatience. This milestone belongs to both of us.

I would like to express my heartfelt gratitude to my friends Pegah, Elham, Alireza, Mojtaba, Naeime, Moonisa, Rabia, and Nadege for their emotional and intellectual support and the sweet time I spent with them.

My gratitude extends to the Department of Mathematics and Computer Science at the University of Cagliari for their constant help regarding university matters, and for providing me with the resources and financial support throughout my Ph.D. studies. This endeavor would not have been possible without their generous support.

Abstract

The rapid increase in the senior population is posing serious challenges to national healthcare systems. Hence, innovative tools are needed to early detect health issues, including cognitive decline. Several clinical studies show that it is possible to identify cognitive impairment based on the locomotion patterns of older people. Thus, this thesis at first focused on providing a systematic literature review of locomotion data mining systems for supporting *Neuro-Degenerative Diseases (NDD)* diagnosis, identifying locomotion anomaly indicators and movement patterns for discovering low-level locomotion indicators, sensor data acquisition, and processing methods, as well as NDD detection algorithms considering their pros and cons. Then, we investigated the use of sensor data and *Deep Learning (DL)* to recognize abnormal movement patterns in instrumented smart-homes. In order to get rid of the noise introduced by indoor constraints and activity execution, we introduced novel visual feature extraction methods for locomotion data. Our solutions rely on locomotion traces segmentation, image-based extraction of salient features from locomotion segments, and vision-based DL. Furthermore, we proposed a data augmentation strategy to increase the volume of collected data and generalize the solution to different smart-homes with different layouts. We carried out extensive experiments with a large real-world dataset acquired in a smart-home test-bed from older people, including people with cognitive diseases. Experimental comparisons show that our system outperforms state-of-the-art methods.

Keywords — *Abnormal Locomotion Detection*, *Trajectory Mining*, *Deep Learning*, *Cognitive Decline*, *Pervasive Healthcare*

Contents

List of Figures

List of Tables

Chapter 1

Introduction

With the demographic change towards older adult population, the proportion of seniors is increasing and it is projected that the old-age dependency ratio alone in the European Union will increase from 27.5% in 2013 to 49.4% in 2050. Aging is associated with declines in cognitive function and mobility and it has a significant impact on society [4]. For example, in 2013, the number of *People with Dementia (PwD)* was over 35 million people worldwide, and it is expected this number to double by 2030, reaching 115 million by 2050 [5]. With the shift from the young to the older people population, it is also expected that the shortage of professional caregivers will increase, especially for people with chronic diseases such as dementia and cognitive impairment who are at risk of declining levels of independence, and safety issues. Furthermore, it will increase the cost and financial burden on healthcare systems. Therefore, the early detection of cognitive impairments in the elderly population could potentially help them to find timely therapies and to stay longer independent and socially active.

A promising way to address this societal change is to switch from formal care in hospitals and other traditional healthcare settings to in-home care. Studies have shown that many people who need care prefer to stay in their own homes [6, 7]. Meanwhile, with the advancement of sensor-based technologies and *Artificial Intelligence (AI)* techniques, novel home-based e-health solutions are introduced, which include remote health systems in smart-homes. In this context, those systems target the prevention of chronic diseases and the monitoring of residents' behaviors for elderly or disabled people.

1.1 Motivation

The main purpose of *Remote Care (RC)* technologies is to support frail people to reduce the cost of living and care as well as improve the quality of life for people who need care while providing them with the opportunity to live independently [6]. Automated intelligent technologies could provide easier and more accessible ways of early diagnosis of cognitive impairments and enable time-dependent and location-based monitoring to manage *Activities of Daily Living (ADL)* by a variety of assistive technologies. Moreover, patients and caregivers have access to web-based applications that provide information on activity levels, movement processes, to-do lists, social interactions, as well as exercise and medication [7]. They can enable automated systems for the caregivers to monitor and track residents' behaviors and progression of NDD symptoms, and control health status continuously without continuous intervention.

1.2 Research Goals and Contributions

A promising direction in this regard consists in tracking the movements of frail people through positioning technologies and analyzing location traces according to well-established clinical models of wandering behavior. To this aim, several methods have been recently proposed that exploit *Internet of Things (IoT)* data and AI techniques to recognize abnormal behaviors [8–12]. In particular, the analysis of position traces may enable early detection of cognitive decline. However, several research challenges are still open in this area, including the effectiveness of the tools for supporting the diagnosis, privacy, and obtrusiveness concerns, and adaptation of the reasoning modules to different environments. Experiments with a real-world dataset acquired from 99 seniors showed that the integration of heterogeneous features increases recognition accuracy. Furthermore, due to the abundance of Spatio-temporal information encoded by movement traces, and the presence of noise introduced by positioning technologies, there is a need for specific feature engineering methods.

The goal of this thesis is the investigation of the above-mentioned research issues, with the objective of designing indoor locomotion traces data mining framework to effectively detect cognitive decline symptoms. The framework should be generalizable to different smart environments with different layouts, without compromising the inhabitant's privacy or being obtrusive.

For the sake of privacy, the position data processing in the above-mentioned works is executed on the edge, within the inhabitant smart-home system. Only model training is executed on the cloud using anonymized data. In addition, in order to avoid the use of obtrusive wearable sensors or privacy-invasive cameras, in all works, we relied on the acquisition of location data from environmental sensors.

Furthermore, for the sake of simplicity, we consider the case of a person living alone in the home which is a common situation for elderly people. However, in order to support seniors living with other people or pets, the proposed approaches could be easily extended by adopting an identity-aware positioning system, or by applying a data association algorithm in charge of associating each location reading to the individual that triggered the corresponding sensor [13].

1.2.1 Systematic Literature Review

The thesis starts with a systematic literature review of locomotion data mining systems for supporting NDD diagnosis. Since locomotion characteristics and movement patterns are reliable indicators of NDD, the review discusses techniques for discovering low-level locomotion indicators, sensor data acquisition and processing methods, and NDD detection algorithms. It presents a comprehensive discussion of the main challenges for this active research area, including the addressed diseases, locomotion data types, duration of monitoring, employed algorithms, and experimental validation strategies. It also identifies prominent open challenges and future research directions regarding ethics and privacy issues, technological and usability aspects, and the availability of public benchmarks.

1.2.2 Towards Vision-based Analysis of Indoor Trajectories

Recent researches consist in encoding the trajectories walked by the inhabitant into images based on the smart-home floor plan as well as speed and other specific locomotion indicators, and utilizing *Deep neural network (DNN)* for image classification for supporting NDD diagnosis. The rationale of this approach is that trajectory images may effectively capture discriminative features without the need for sophisticated feature engineering efforts. This approach will let us get rid of the noise introduced by indoor constraints and activity execution. Therefore, we proposed a system [14] to identify abnormal indoor movement patterns that may indicate cognitive decline according to clinical models of spatial disorientation [15]. Our solution relies on locomotion trace segmentation, image-based extraction of salient features from locomotion segments by retaining the spatial information in trajectory images, enriching them with additional visual features, and vision-based DL. Preliminary experimental results with a real-world dataset gathered from cognitively healthy persons and PwD show that this research direction is promising.

1.2.3 The TraMiner Framework

In the next step, we extended and refined the above-mentioned work, proposing the TraMiner system [16], which exploits Trajectory Mining for continuous cognitive assessment in smart-homes. The system relies on specific techniques for locomotion data cleaning and segmentation. Each locomotion segment is transformed into two images that capture different aspects related to the clinical indicators of locomotion anomalies, represent the walked trajectory in a 2-dimensional space, and highlight different visual features, such as speed and intersection points. They allow us to visually capture locomotion anomalies corresponding to the pacing and lapping patterns defined by the Martino-Saltzman model [17], naturally encode low-level motion indicators such as sharp angles, straightness, turning angle, and path efficiency, and also enable us to capture low-level motion indicators. Results show that TraMiner can accurately recognize the cognitive status of the senior, reaching a macro F_1 score of 0.873 for the three categories that we target: cognitive health, MCI, and dementia. Moreover, an experimental comparison shows that our system outperforms state-of-the-art methods.

1.2.4 Augmented and Generalized TraMiner

In TraMiner, it is assumed that smart-homes have a fixed layout. However, since using movement patterns from a single smart-home can restrict the generalization of the learned model to other homes with different layouts, in a later work we introduced a data augmentation approach based on random image rotation to increase the generalization of the trained model. We proposed an approach combining *Spatio-Temporal Fea-*

tures (STF) with features extracted from images depicting the trajectories walked within a smart-home [18]. Experimental results with a real-world dataset collected from both cognitively healthy seniors and PwD show that the proposed approach achieves promising results in terms of macro and weighted F_1 with a small subset of features and long-term analysis of the predictions can support a reliable assessment of the cognitive status over time. Using a high number of features in such applications may lead to collinearity and increase the number of features that potentially have no predictive power. Moreover, the computation, storage, and transmission of unnecessary information is a waste of resources [19]. Therefore, we tried to keep the number of features as small as possible.

1.2.5 List of Publications

The publications listed below constitute the majority of the content of this thesis. The first author of them, i.e., the author of this thesis defined their problem statements, developed their methods, performed experiments to assess their underlying strategies, and wrote the manuscripts.

- Samaneh Zolfaghari, Sumaiya Suravee, Daniele Riboni, and Kristina Yordanova. “Sensor-based Locomotion Data Mining for Supporting the Diagnosis of Neurodegenerative Disorders: a Survey”.
- Samaneh Zolfaghari, Andrea Loddo, Barbara Pes, and Daniele Riboni. “A combination of visual and temporal trajectory features for cognitive assessment in smart-home”. In: 2022 23rd IEEE International Conference on Mobile Data Management (MDM). IEEE. 2022, pp. 343–348.
- Samaneh Zolfaghari, Elham Khodabandehloo, and Daniele Riboni. “TraMiner: Vision-based analysis of locomotion traces for cognitive assessment in smart-homes”. In: Cognitive Computation 14.5 (2022), pp. 1549–1570.
- Samaneh Zolfaghari, Elham Khodabandehloo, and Daniele Riboni. “Towards vision-based analysis of indoor trajectories for cognitive assessment”. In: 2020 IEEE International Conference on Smart Computing (SMARTCOMP). IEEE. 2020, pp. 290–295

1.3 Organization

The dissertation is structured as follows. Chapter 2 provides a systematic literature review, and thoroughly discusses different clinical and non-clinical NDD indicators, tools, and technologies. Moreover, it considers algorithms and applications, and open issues regarding sensor-based locomotion analysis in order to detect gait anomaly in NDD at an early stage that has been proposed in the literature. Chapter 3 provides an introduction to a novel framework on locomotion traces segmentation based on a given length and is depicted by images and additional gait features utilizing Martino-Saltzman model [17]. Chapter 4 extends the previous framework in terms of having two different kinds of trajectory images which are segmented temporally and encoded into two images based on movement and acceleration. In Chapter 5 we try to propose a general framework by introducing a new data augmentation methodology, utilizing the extended version of the previously mentioned framework for feature extraction and using additional sensory and trajectory features. Chapter 6 concludes the dissertation by summarizing the technical contributions of the thesis and discussing open problems.

Chapter 2

Systematic literature review

To evaluate the potential of automated technologies to detect cognitive decline, we first need to analyze the indicators of locomotion anomalies associated with cognitive decline, different methods, and sensor-based technologies for detection of cognitive impairments based on locomotion data. Therefore in this chapter, we concentrate on techniques for discovering low-level locomotion indicators, sensor data acquisition and processing methods, and NDD detection algorithms. We present a comprehensive discussion on the main challenges for this active research area, including the addressed diseases, locomotion data types, duration of monitoring, employed algorithms, and experimental validation strategies. Three widespread types of cognitive decline are considered: *Alzheimer's disease (AD)*, *Huntington's Disease (HD)*, and *Parkinson's Disease (PD)*.

2.1 Introduction

Since the average age of the population is projected to increase significantly in the near future, the early diagnosis of cognitive decline among elderly people is becoming a key objective of healthcare systems worldwide [20]. This chapter explored different technologies and methods that have been demonstrated to be successful in detecting symptoms of NDD based on locomotion sensor data and AI algorithms.

The structure of this chapter is illustrated in Fig. 2.1. We divided the core of our study into three different parts, which correspond to the main building blocks of AI-based systems for NDD assessment. The lowest level is related to primary or complex gait indicators, which are used for the diagnosis of NDD according to clinical theory and practice. Those indicators provide the clinical ground for designing NDD detection system since they identify which raw data are necessary for the assessment. Consequently, the middle-level regards existing tools and technologies to acquire locomotion data at coarse- and fine-grained levels in different environments, including wearable and infrastructure-based systems. Finally, the highest level reports and discusses algorithms and applications that process locomotion data for supporting the diagnosis of NDD and for recognizing challenging behaviors that may put the safety of cognitively impaired subjects at risk. Each level is addressed in a specific section of our chapter.

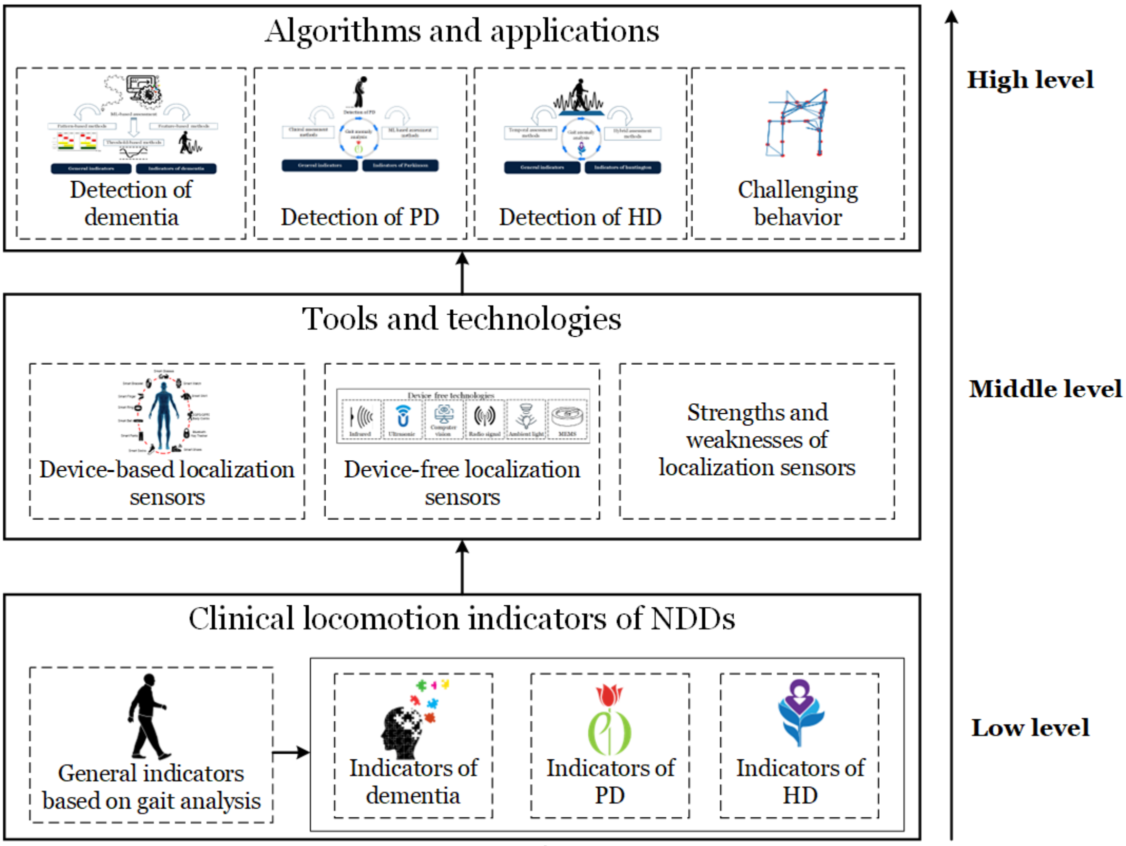


Figure 2.1: Chapter scenario.

2.2 Summary of Methodology and Main Findings

We queried the most prominent scientific search engines with a handcrafted query to retrieve the literature review candidates. From a pool of 1277 retrieved articles, we selected and surveyed 128 papers that matched our criteria regarding types of clinical indicators, sensor technologies, experimental setup, and algorithm types. The chapter indicates that the number of scientific works exploiting AI and locomotion sensor data for the diagnosis of NDD is strongly growing, especially from 2010 on. Most papers address the detection of dementia and Parkinson's disease, which are the most common NDD, while few of them address HD. Most works are based on indoor locomotion monitoring, while few ones consider more complex outdoor movement patterns. Several different *Machine Learning (ML)* algorithms are used for NDD detection. The most common approach is to use classical ML algorithms such as *Random Forest (RF)* or *Support Vector Machine (SVM)*, while few works adopt DL methods. Some works relying on fine-grained motion indicators rely on statistical measures and thresholds to produce a prediction. The duration of monitoring ranges from a few minutes for gait analysis, to hours, days, or weeks for more complex patterns. The majority of the experiments were held in controlled laboratory environments, but a large percentage were conducted in naturalistic real-world environments such as the individual's home.

The results show that this kind of technology may effectively support the diagnosis of NDD and help simplify patient management. However, the review showed that most existing techniques fall short in addressing different challenging issues. The release of location data may reveal several private pieces of information regarding the patient; however, problems related to cyber-security and privacy protection are mostly neglected by existing systems. Of equal importance are aspects regarding trust and legal issues, which seem overlooked in the current literature. Other challenging issues which merit further research regard users' acceptance and usability. From a technological viewpoint, the power capabilities of existing solutions are challenged by the need for long-term evaluation and execution of ML algorithms on wearable devices. Finally, the lack of public datasets acquired in real-world conditions makes it difficult to experimentally compare the different solutions.

The remainder of this chapter is structured as follows. Section 2.3 introduces the three types of NDD, their clinical symptoms, and locomotion indicators. In Section 2.4 we describe the procedure used in this study and the types of papers included. Section 2.5 analyses the clinical locomotion indicators of NDD, while Section 2.6 presents the technologies and tools used for the detection of locomotion indicators. Section 2.7 discusses the existing algorithms for detecting NDD based on sensing technologies. The chapter concludes with a discussion of the shortcomings of existing technologies and methods and the potential future directions in detecting cognitive impairments in the elderly based on locomotion data.

2.3 Clinical Background

In what follows we shortly introduce the three types of NDD and their clinical symptoms and locomotion indicators.

2.3.1 Alzheimer's Disease

AD is the most familiar type of dementia and it is considered a syndrome that has chronic or progressive nature. It is defined as a declination in cognitive function beyond what might be expected from normal aging. PwD suffers from a lack of memory and thinking capability, learning ability, and inability to communicate. The impairment in cognitive function is generally accompanied and periodically preceded by weakening in emotional control and social manners. It is regarded as a predominantly cognitive disorder. Gait abnormalities can also be noticed in the disease's early stages, including decreased walking speed, step length, step frequency, and increased gait variability. Dementia is considered one of the main reasons for disability and dependency among older adults worldwide. It can be troublesome for PwD, caregivers, and family members. A lack of awareness and understanding of dementia is being observed that causes stigmatization and hindrances to diagnosis and care. The effect of dementia on caregivers, families, and the community is very diverse. It can be biological, psychological, social, and economic. It might be challenging to detect dementia early since each individual gets affected by that disease differently, relying on the effect of the disease and the individual's personality before becoming sick. According to the World Health Organization (WHO)[1], around 50 million people are diagnosed with dementia, and the most common symptoms of dementia can be classified into three stages: *early*, *middle*, and *late*.

Some common symptoms for these stages are listed in Table 2.1. It can be noticed that the severity of the symptoms advances with the progression of the disease.

Table 2.1: Symptoms of AD

Early stage	**Middle stage**	**Advanced stage**
Forgetfulness	Having difficulty remembering about recent events and people's names	Having difficulty in walking
Losing track of time	Getting lost at home, having difficulty in communication	Experiencing behavior changes that may escalate aggression
Getting lost in familiar places	Needing help with personal care	Having an increasing need for assisted self-care
-	Experiencing behavior changes, including wandering and repeated questioning	-

2.3.2 Parkinson's Disease

PD is regarded as the most familiar movement disorder, involving over 6 million individuals worldwide. PD can have an early onset, though it primarily affects people over the age of 55, and the progression of the disease slowly increases after the age of 65 [21, 22]. The WHO ranks PD as the second most familiar NDD. It hampers the nerve cells in the brain that generate dopamine. Dopamine is necessary for transmitting messages to control and coordinate movement.

Around $0.1\breve{}0.2$% of the dopaminergic neurons are lost per year during normal aging. This speed is significantly accelerated in *People with PD (PwPD)*, and signs become apparent when $\simeq 70\breve{}80$% of these neurons have been lost.

The PwPD experience both motor and non-motor symptoms. The most common motor symptoms during the early stages of PD are resting tremors, rigidity, and bradykinesia which are explained below.

1. **Tremor / Shaking** - it starts in a limb, often the patient's hand. Patients might experience rubbing their thumb and forefinger back and forth; this is known as a pill-rolling tremor. The patient's hand may shake when it is at rest [23].
2. **Bradykinesia** - PD may slow the patient's action over time, assembling simple tasks complicated and time-consuming. For instance, it may be challenging for PwPD to get out of a chair [23].
3. **Rigid muscle** - Muscle stiffness may appear in any portion of the body. As a result, the stiff muscles cause pain and restrict the range of movement [23].
4. **Impaired posture and balance** - Posture may become stooped. PwPD might suffer from imbalance movement as a consequence of PD [23].
5. **Loss of automatic movement** - PwPD might experience an inability to conduct unconscious movements, including blinking, laughing, or turning their arms when

[1]https://www.who.int/

walking [23].

The difficulty to control movement caused by PD harms the social and psychological situation of the patient, who feels secluded and ineffective in accomplishing simple tasks. PwPD in the middle stage experience cramping (dystonia), dyskinesia, loss of postural reflexes, and *Freezing of Gait (FoG)*. FoG is one of the most common motor signs of PD and appears during the advanced stages of the disease. It is defined by a brief episode of involuntary lack of locomotion, a feeling of being stuck in place when attempting to have a step or navigating through or turning around barriers [24].

2.3.3 Huntington's Disease

HD is defined as a progressive inherited NDD, inducing involuntary movement and cognitive problems, harshly impacting the quality of life. It is caused by a Cytosine-adenine guanine repeat mutation in the HTT gene [25]. It has a comprehensive effect on a person's functional capabilities, resulting in movement, cognitive, and psychiatric disorders. The signs of HD can form at any age, but they usually arise in people aged 30 to 40 years old and the beginning of the disease is diagnosed clinically when motor abnormalities form. Impairment in motor control is regarded as the most familiar sign of HD, ordered by chorea and dystonia. This, merged with cognitive and behavioral symptoms, can impact day-to-day tasks. Nevertheless, cognitive and behavioral symptoms [25] can be noticed many years (even decades) before motor symptoms, which progressively affects the quality of life of *People with HD (PwHD)*.

When HD forms at an early age, signs are identical to those of PD, and the disease may advance faster. Drugs are available to aid the symptoms of HD, but remedies cannot prevent the physical, cognitive, and behavioral deterioration associated with the condition [26]. Therefore, most of the current research in this area is based on detecting HD at an early stage, in order to benefit from prospective medical interventions that may assist in slowing the advances of the disease. The most common symptoms of HD are mentioned in Table 2.2.

Table 2.2: Symtoms of HD.

Movement disorder	**Cognitive disorder**	**Psychiatric disorders**
Involuntary jerking or writhing movements (chorea)	Difficulty in organizing or focusing on tasks	Irritability
Rigidity or muscle contracture (dystonia)	Lack of flexibility to get stuck on a behavior/action	Social withdrawal
Abnormal eye movements	Lack of impulse control that can result in outbursts, acting without thinking	Insomnia
Impaired gait, posture	Difficulty in learning new information	Fatigue and loss of energy
Difficulty with talking / Swallowing	Slowness in processing thoughts or in finding words	Frequent thoughts of death or suicide

2.4 Materials and Methods

We conducted a systematic review to select the relevant studies on locomotion abnormality detection for supporting the diagnosis of NDD. We focused on locomotion-based data mining techniques which are experimented on a significant number of patients, including both healthy control subjects and people with NDD. In the following, we report our search strategy, including inclusion and exclusion criteria, as well as statistics about the selected research works.

2.4.1 Search and Selection Strategy

Fig. 2.2 illustrates the flowchart of our literature search and selection method. We queried different scientific search engines, namely, Web of Science, Science Direct, PubMed, and SCOPUS, considering academic studies published in peer-reviewed journals and in proceedings of international conferences. We handcrafted a search query to identify relevant articles published between 1975 to October 2020, considering terms appearing in the title, abstract, or keywords of the papers. Our search query is reported in Table 2.3. Its syntax is slightly different depending on the functionality of the considered database, without impacting the semantics of the query.

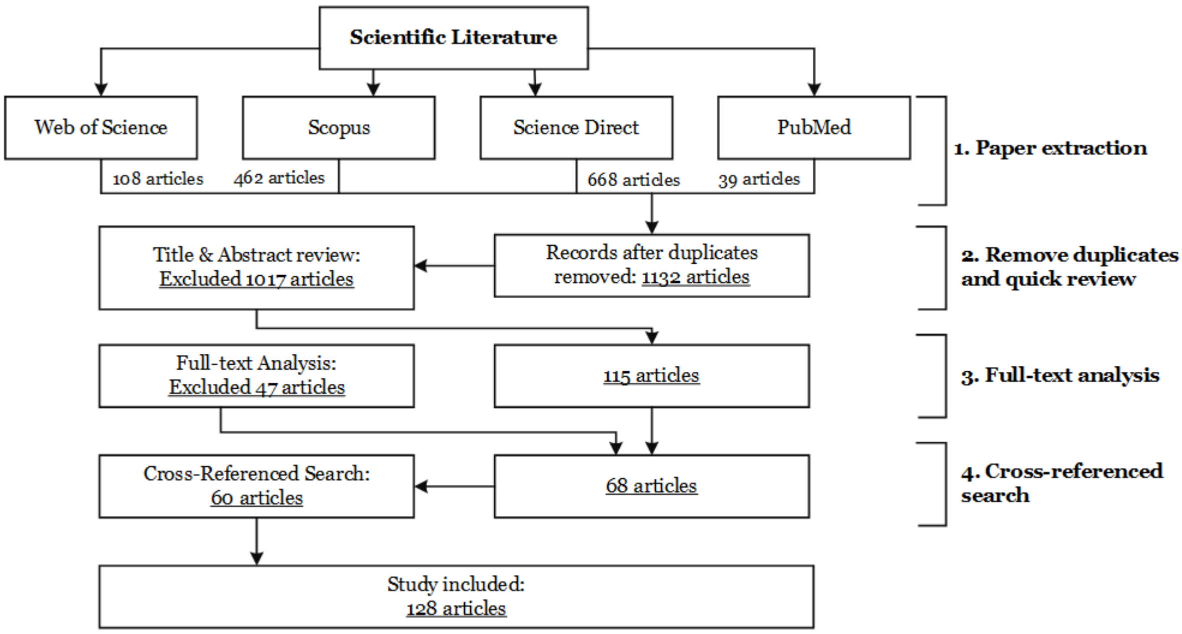


Figure 2.2: Flowchart of our literature search and selection method.

Our literature search and selection method is divided into four phases.

Paper extraction. The whole query is divided into six parts connected by the "AND" operator. The first part of the search query includes different terms to identify "neurodegenerative disorders". Since the target group of our study is elderly people, in the second part of the query we retrieve only publications specifically related to that age group. In the third part, we select only papers related to the use of sensor devices and pervasive computing technologies. The fourth part retrieves only papers related to locomotion data mining. The fifth part selects only papers related to different monitoring methods. The last part retrieves only papers published in conference proceedings or scientific journals and published after 1974. The query retrieved 1277 papers in total.

Table 2.3: Literature search query.

TITLE-ABSTRACT-KEYWORDS((“cognitive impairment" OR “cognitive problem" OR “cognitive issue" OR “cognitive decline" OR “cognitive assessment" OR “dementia" OR “mci" OR “mild cognitive impairment" OR “alzheimer’s disease" OR “neurodegenerative")
AND (“elderly" OR “senior" OR “Aging Adults" OR “aging" OR “older adult" OR “adult")
AND (“internet of things" OR “indoor" OR “outdoor" OR “wearable" OR “ambient intelligence (AmI)" OR “ambient assisted living" OR “aal" OR “healthcare application" OR “positioning technology" OR “ambient sensors" OR “Global Positioning System" OR “accelerometer" OR “gyroscope" OR “environmental sensors" OR “inertial sensor" OR “mobile" OR “Intelligent Assistive" OR “assistive Device" OR “device free" OR “intelligent systems" OR “smartphone" OR “non-invasive" OR “human computer interaction" OR “hci" OR “mobile health" OR “smart homes")
AND (“locomotion anomaly" OR “locomotion pattern" OR “locomotion" OR “abnormal movement pattern" OR “trajectory" OR “wandering" OR “disorientation " OR “movement traces " OR “ambulatory gait analysis" OR “abnormal locomotion" OR “abnormality" OR “gait" OR “mobility" OR “motor impairments" OR “motor assessment" OR “motor function" OR “acceleration" OR “spatial" OR “gait variability" OR “gait-cycle" OR “functional assessment" OR “motor dysfunction")
AND (“monitoring" OR “detection" OR “analysis" OR “non-intrusive" OR “unobtrusive" OR “reconstruction" OR “gait monitoring" OR "gait detection" OR “remote monitoring" OR “trajectory mining"))
AND (LIMIT-TO (DOCUMENT TYPE,“(PEER REVIEWED JOURNAL) ARTICLE") OR LIMIT-TO (DOCUMENT TYPE,“CONFERENCE PAPER") OR LIMIT-TO (DOCUMENT TYPE,“REVIEW")) **AND** PUBYEAR $>$ 1974

Duplicates removal and quick review. In the second phase, initially, we performed duplicate removal, keeping 1132 papers. Then, we applied a quick review procedure to those papers, to ensure that they met our inclusion criteria. The title, abstract, and keywords of each paper were evaluated to ensure that they actually met the inclusion criteria specified in the query string. As expected, the search query provided a relatively large number of false positives. Most papers were excluded because they did not rely on sensor devices or pervasive computing technologies, or considered diseases not related to neurocognitive disorders. After this operation, we retained 128 papers.

Full-text analysis. In the third phase, the full text of each remaining paper was assessed to exclude those papers that were preliminary versions of extended papers already included in our search and to keep only those papers that met our inclusion criteria. In this regard, we excluded those works which lacked a significant experimental evaluation with both cognitively impaired seniors and healthy control subjects. After this phase, we retained 68 papers.

Cross-referenced search. In the fourth phase, we checked the references of the remaining publications to look for further relevant publications matching our search criteria to be included. We also looked for additional relevant papers published by the same authors as the included papers. Thanks to this search, we added 60 for further papers. The full list of the reviewed papers can be found in the Appendix.

2.4.2 Comprehensive Science Mapping Analysis

Recently bibliometric measurements have been increasingly expanding across various fields [27–29]. This technique is particularly suited for implementing the comprehensive science mapping analysis of published studies of fragmented and controversial streams of research. As mentioned previously, the articles in this chapter can be divided into three main categories regarding the NDD, and locomotion anomaly as follows: PD, HD, and dementia. The total number of published and selected articles considering different databases are mentioned in Fig. 2.2.

From another point of view, Fig. 2.3 shows the percentage of selected articles by each category compared to the total number of papers from the same category considering their search engines. As could be seen the selected papers in the Web of Science search engine represent the highest percentage of total articles among the others.

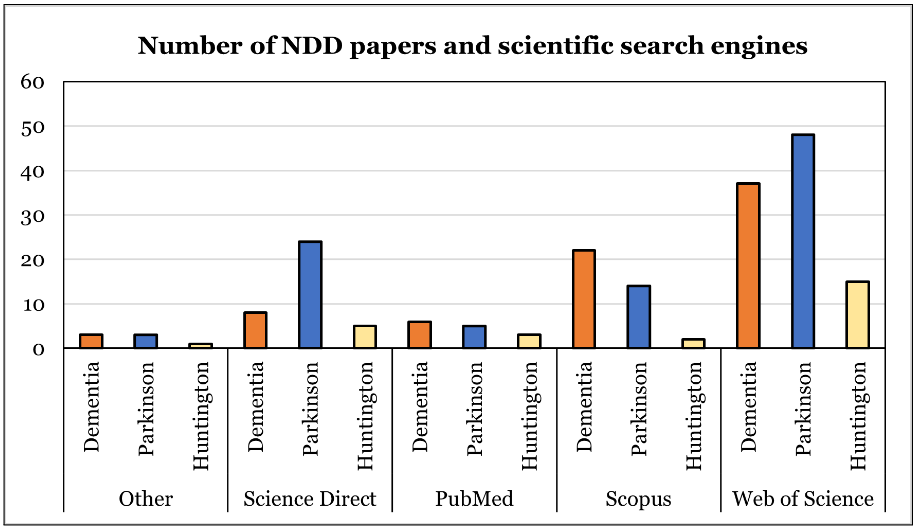


Figure 2.3: Percentage of articles based on considered NDD categories and scientific search engines.

Annual Scientific Production

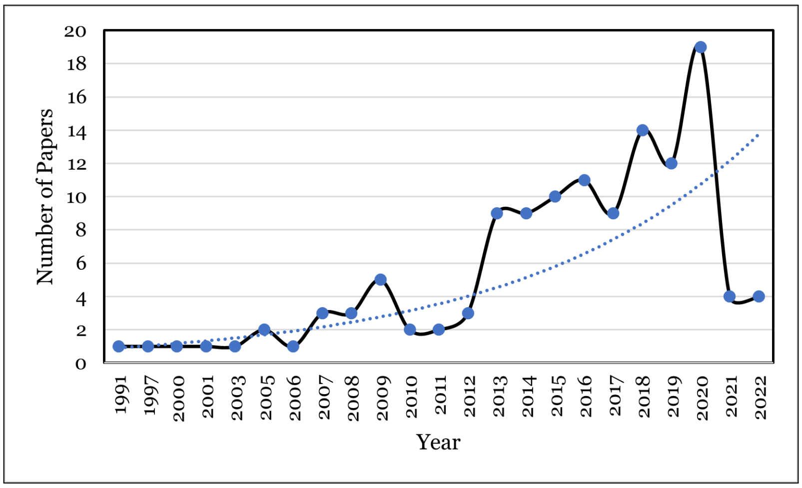
Among the 128 included papers, 33 were survey or reviews papers. Fig. 2.4a represents the temporal trend of papers included and it shows an exponential increase in the number of papers related to sensor-based locomotion data mining for NDD diagnosis.

Word Cloud

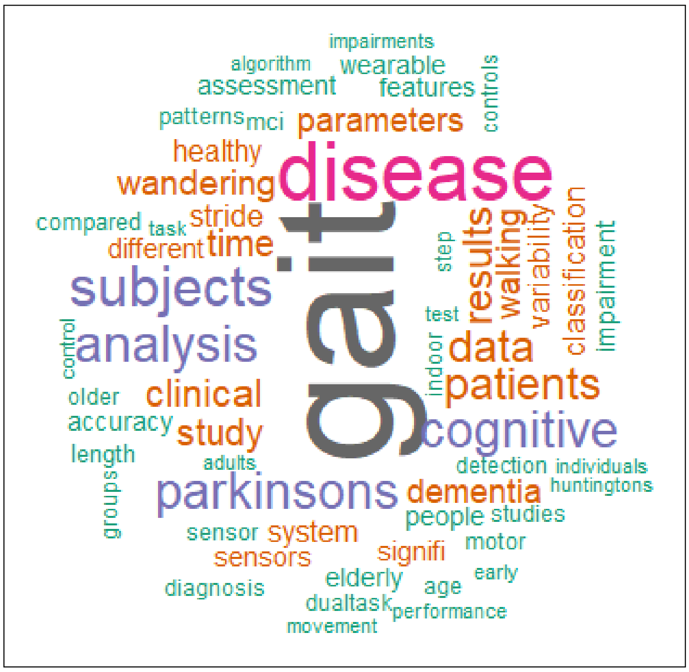
Word clouds are introduced as a tool to identify the most essential topics dealing with a particular subject [27, 29]. Fig. 2.4b presents the most frequent words adopted by previous studies extracted by our search and selection strategy explained in section 2.4.1. These keywords, which are repeated more than 30 times considering all selected papers, demonstrate that most of them are focused on the gait aspect of cognitive disease.

Country-Specific Production

Fig. 2.5 represents that the included research papers came from 38 countries which include case studies conducted in these countries. As demonstrated in the figure, the countries that produced the most papers considering locomotion anomaly detection and NDD in a sensory environment are the USA, Italy, Germany, and the UK. In terms of country-specific production, the highest percentage was achieved by the USA (22.75%), followed by Italy (10.17%), and then Germany(6.58%) and the UK (6.58%).



(a) Number of published papers according to the different years.



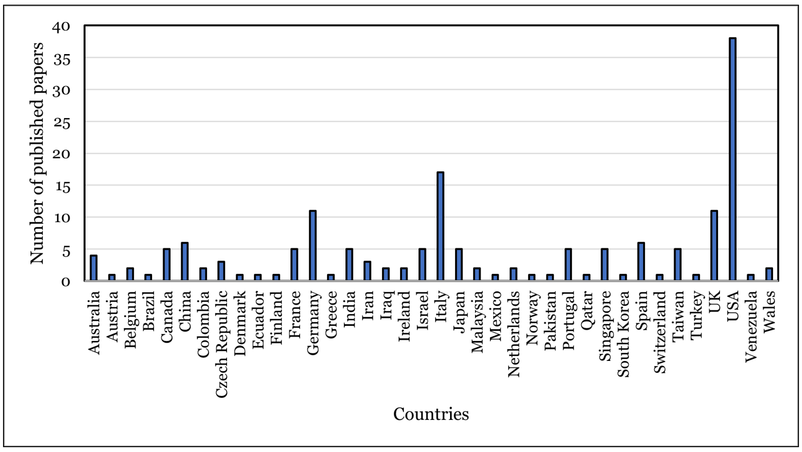
(b) Most frequent words.

Figure 2.4: Selected papers.

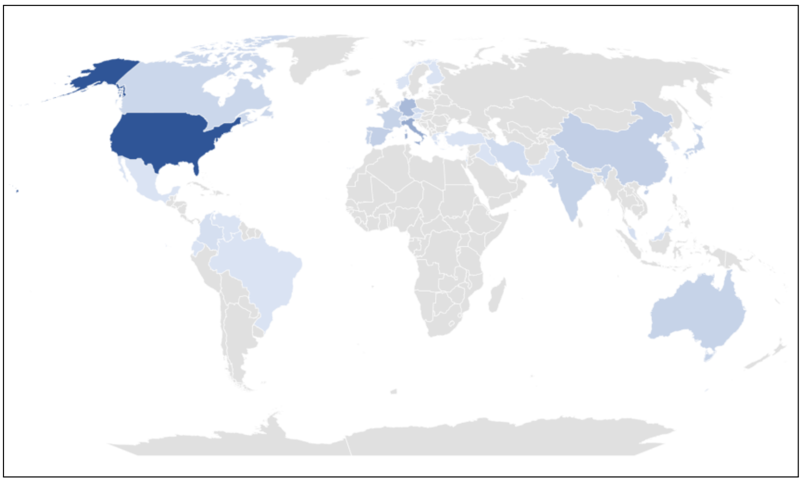
Scientific Production based on Disorders and Observation Location

Considering the kind of disease, Fig. 2.6a shows that PD gained essentially more attention among the researchers compared to dementia, while fewer works are related to HD. Considering that some papers address more than one disease, around 52% of papers address PD, about 41% of papers address dementia, and 15% address HD.

We further analyzed the scenario in which the individual's locomotion is observed to provide the diagnosis. We considered two observation scenarios: *indoor* and *outdoor*. Among the selected papers, as illustrated in Fig. 2.6b, statistics show there are 68.18% of



(a) Country-specific production.



(b) Country distribution production.

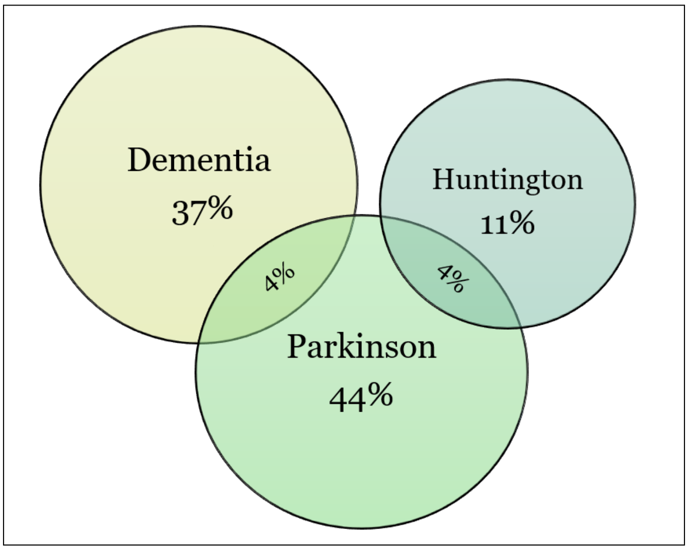
Figure 2.5: Selected papers.

papers that rely on locomotion observation indoors; in particular, in private residences, retirement/nursing homes, or hospitals. Most methods relying on indoor observation assume that the individual performs predefined instructions in the presence of one or more observers. A few other papers rely on the observation of unsupervised locomotion during everyday activities in real-world environments.

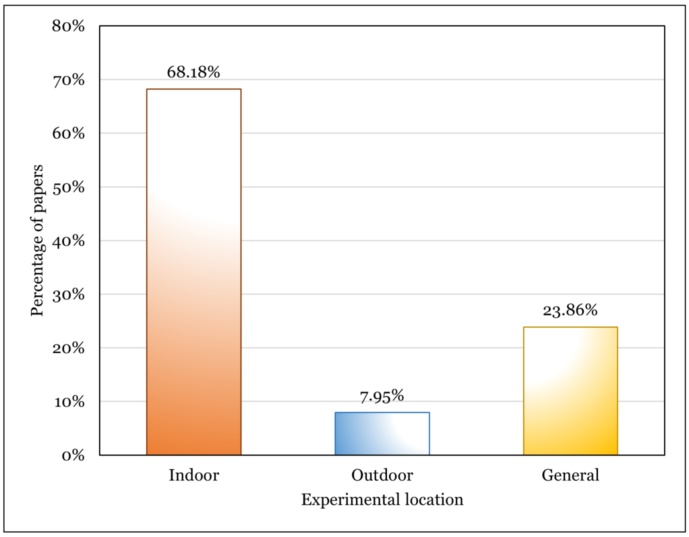
Papers that rely on the observation of outdoor locomotion are fewer in number; i.e, around 7.95% of the papers. Those works assume the use of sensors embedded in wearable/portable devices (mainly smartphones, watches, or shoes), or outdoor localization technologies such as GPS readers. In addition, around 23.86% of the selected papers do not strictly rely on the assumption that the locomotion is observed either indoors or outdoors. The category of those papers is named *general* in Fig. 2.6b.

Scientific Production based on Experiments Scenarios and Monitoring Duration

Fig.2.7a shows the distribution of papers according to the duration of locomotion monitoring used in the respective experimental evaluation. We found out that, among those



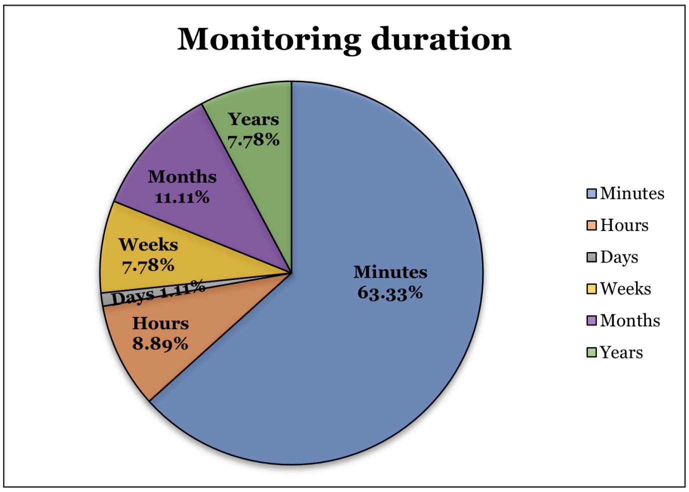
(a) Percentage of papers according to the considered diseases.



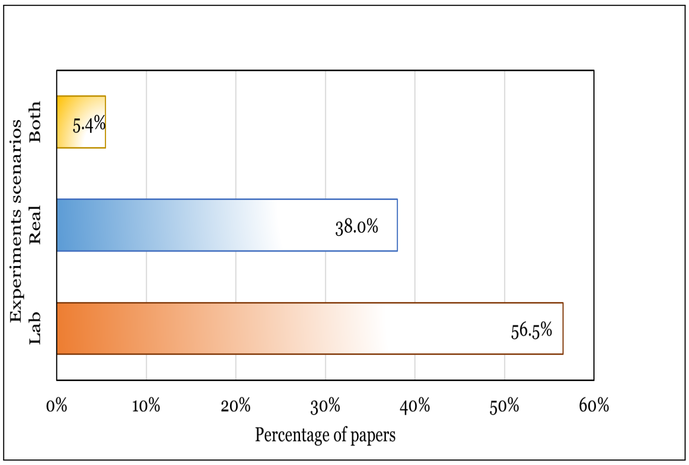
(b) Percentage of papers according to observation locations.

Figure 2.6: Selected papers.

works which explicitly mentioned their observation duration (around 90 papers), many of them (around 63.3% papers) monitored locomotion for less than one hour; around 8.9% of them monitored locomotion for less than 24 hours; around 1% for less than a week; around 7.8% for weeks; around 11.1% for months; and around 7.8% for one year or more. Furthermore, as shown in Fig.2.7b, 56.5% of research works carried out their experiments in a laboratory environment, 38% in a naturalistic environment such as the individual's home, and 5.4% in both a laboratory and naturalistic environments.



(a) Percentage of papers according to monitoring duration.



(b) Percentage of papers based on different experiments scenarios.

Figure 2.7: Selected papers.

2.5 Clinical Locomotion Indicators of NDD

We concentrate on clinical indicators of NDD related to locomotion. Indeed, several works identified variations of gait patterns and locomotion anomalies typically observed in cognitively impaired subjects [30–32]. Different researches consider 'wandering', a concept defined by Algase et al. [33] as a *"syndrome of dementia-related locomotion behavior having a frequent, repetitive, temporally disordered, and/or spatially disoriented nature that is manifested in lapping, random, and/or pacing patterns"*. Moreover, recent sensor technologies provide the possibility to develop methods for gait analysis to characterize NDD based on the observation of subtle anomalies in gait patterns. In a normal gait cycle, each stride contains eight phases with functional patterns and objectives defined as follows:

1. **Heel strike**: initial contact of the foot touching the floor with the heel.

2. **Loading**: loading response when the knee flexes and the body weight is moved onto the limb, while the other foot is lifted.
3. **Mid-stance**: when the opposite leg is lifted and advanced.
4. **Terminal stance**: when the limb advances and the phase ends with the heel striking the ground.
5. **Pre-swing phase**: weight transfer phase, when the opposite foot starts touching the ground and the other one is lifted.
6. **Toe-off**: initial swing when the foot is lifted from the floor.
7. **Mid-swing**: when the anterior limb advances.
8. **Terminal swing**: when the leg moves ahead of the thigh, the foot strikes the floor, and the advancement is completed with the flexion of the knee.

Gait disorders can be related to two main categories: neurological, and non-neurological disorders [32]. For the sake of this thesis, we concentrate on the former category. The instruments used to analyze human gait can be classified into two major categories: ambient/portable wireless sensors such as [31, 34, 35], and wearable sensors like those used in [36]. For example, smart shoe wearable sensor systems can measure the change in gait over time and have been used in neurological exams to diagnose dementia and other neurological disorders. The Center of mass movement during walking can be easily tracked using a small *Inertial Measurement Unit (IMU)* attached to the lower back and was used for neurological assessment considering the sinusoidal waveform produced by trunk movements during the gait cycle [37].

2.5.1 General Indicators based on Gait Analysis

Different low-level motion indicators have been proposed in the literature to detect NDD [16, 34]. We classify these motion indicators into three categories: low-level gait parameters, complex gait parameters, and *Non-Linear Dynamics (NLD)* theory-based features, presented below.

- **Low-level gait parameters**: These indicators regard fine-grained characteristics of gait, mostly considered in isolation, such as stride-to-stride fluctuations in walking (both in terms of magnitude and dynamics), stride time, stride velocity, stride length [38]. In this regard, gait abnormalities mostly include decreased walking speed, step frequency, step length, and increased gait variability [39]. In Table 2.4, we extend and refine the classification proposed by Hollman et al. [40] to define the low-level indicators that we use in the rest of the chapter.
- **Complex gait parameters**: These parameters consider different temporal aspects of locomotion, and structural or geometrical complexity of walked trajectories. We classify them into three categories: variability, postural control, and frequential parameters. Parameters related to variability are based on temporal characteristics of the movement pattern, acceleration, speed, duration, and distance. Postural control parameters such as *Timed Up & Go (TUG)* test, *Berg Balance Scale (BBS)*, *Romberg Balance (RB)*), and *Short Physical Performance Battery (SPPB)* tests, etc. are including different kinds of postural and balance assessments such as regularity

Table 2.4: Low-level gait parameters.

Parameters classification	Parameters	Definition	Ref.
Spatial	Stride length	Distance traveled by the same foot by two consecutive heel contacts.	[37, 38, 41–46, 46, 47]
	Step length	Traveled distance from one heel footprint to the heel of the opposite footprint.	[38, 45, 47–51]
	Step width	Distance between the line of progression of the left heel footprint and the line of progression of the right heel footprint.	[40]
	Distance	The cumulative traveled distance.	[36, 42, 52]
Temporal	Stance/Swing time	Duration of the stance/swing phase.	[31, 48, 53, 54]
	Stride time interval	Time interval starts when one foot makes contact with the ground and ends when that same foot contacts the ground again. It displays fractal dynamics and reflects the rhythm of the locomotion.	[39, 42–44, 49, 50, 53, 54]
	Stride time variability	It is related to the control of the rhythmic stepping mechanism and calculated by the mean and standard deviation of stride time.	[42]
	Step time	The time between two consecutive heel strikes.	[37, 38, 45, 48, 50, 51, 54–56]
	Step rate	The rate of steps per minute also called *cadence*.	[37, 40, 44–46, 46, 47, 50, 56]
	Single support time	'Single support' happens when only one foot is in contact with the ground. Single support time is the duration of single support.	[40, 46, 56]
	Double support time	'Double support' happens when both feet are in contact with the ground. Double support time is the duration of double support.	[43, 46, 47, 49, 56–58]
Spatial-Temporal	Stride velocity	The stride length divided by the stride time.	[38, 49, 50, 55, 59, 60]
	Stride/Step frequency	Number of foot contacts per second.	[41, 44, 60]
	Stride/Step symmetry	Duration amplitude similarity of the shape of acceleration curves comparing right and left strides/steps.	[41, 44, 45, 55, 61]
	Step time asymmetry	Defined as the difference between the mean step time of each leg and the combined mean step time of both legs.	[45]
	Stride/Step regularity	A measure of stride/step to stride/step consistency.	[39, 41, 44, 45, 55, 61]
	Gait speed	The distance walked divided by the ambulation time.	[16, 37–39, 41–44, 44–46, 48, 49, 54]

of movements, angles of movement, trajectory consistency. Frequential parameters consider gait symmetry and are usually derived from the Fourier analysis of trunk accelerations.

In Table 2.5, we provide a classification and description of complex gait parameters.

- **NLD theory based features**: Gait assessment is considered a beneficial tool to help the diagnosis process and to assess the neurological state of people with NDD. It is the assessment of a subject's walking pattern. Walking is a compounded process that can be evaluated through the application of nonlinear analysis of Human Gait Signals. NLD theory has been introduced to the analysis of biological data. There

Table 2.5: Complex gait parameters.

Parameters classification	**Parameters**	**Definition**	**Ref.**
Variability	Approximate Entropy	Measure regularity of a trajectory under the assumption that a sequence is regular when it contains repetitive patterns and how its' structural complexity varies over time.	[55]
	Jerk	The rate at which a subject acceleration changes with respect to time. Jerk is the first-time derivative of acceleration. It quantifies the smoothness of a trajectory.	[16, 44]
	Ambulation fraction	The ratio between the total time of ambulation and trajectory duration.	[62]
	Straightness	The ratio of the distance between two consecutive trajectory segments and the distance between the start and endpoint of these segments.	[1, 16]
	Path-efficiency	The ratio between the distance from the start to the end of a trajectory and the trajectory length.	[16, 62]
Postural control	Turning angle	The sum of the absolute angles between any two subsequent lines in a trajectory.	[16, 44, 62]
	Sharp angles	Vector angles in a trajectory being equal to or more than 90 degrees.	[1, 16, 52, 63]
	Foot clearance	Toe and heel height during the swing phase.	[64]
	TUG test	Time taken for a transition from sitting to standing, walking, turning, and transitioning from standing to sitting.	[44, 57, 58, 61, 65]
	Fall	Any unintentional event that leads to the landing of individuals on a horizontal plane	[42, 57]
	BBS/ RB/SPPB tests	Balance and postural control assessment to diagnose gait disturbance caused by abnormal perception or awareness of the position and movement of the body during predetermined tasks. (i.e. Eyes Open Feet Together, Eyes Closed Feet Together, Eyes Open Feet Apart, Eyes Closed Feet Apart)	[45, 57, 61, 66, 67]
Frequential	*Harmonic Ratio (HR)*	Step-to-step (a)symmetry within a stride.	[55, 60]
	Total Harmonic Distortion (THD)	Evaluate the complexity of human motion by calculating the ratio between the fundamental waves and the harmonic waves.	[55]
	Z-method/ S-method/ M-method	Gait events based on Antero-posterior acceleration, Acceleration norm, and Vertical acceleration. Both the Z-method and M-method define the gait cycle from the initial contact timing. Also, M-method provides final foot contact timing estimates, swing, and stance duration. Conversely, the S-method considers the zero-crossing instants of the acceleration norm.	[54]

are also NLD features [68, 69] available such as the *Correlation Dimension (CD)*, the *Largest Lyapunov Exponent (LLE)*, the *Lempel Ziv Complexity (LZC)*, the *Hurst Exponent (HE)*, the *Detrended Fluctuation Analysis (DFA)* and many others to assess the gait impairments of NDD patients. These features are used to discriminate between NDD patients and healthy subjects and to classify patients in several stages of the disease. In [53, 70, 71], DFA is used for the gait assessments of PwPD and PwHD. In [72], Sejdić et al. performed a combined analysis of spectral and NLD features to assess gait signals of 14 healthy persons, 10 PwPD, and 11 patients with peripheral neuropathy. These features were compared using the Kruskal-Wallis and Mann-Whitney tests. There are notable differences observed in features such as the LZC and the cross entropy, which allow for discrimination between healthy persons and PwPD. In [73] the authors classified 13 PwPD, 13 Amyotrophic lateral sclerosis patients, 13 PwHD and 13 healthy subjects using data obtained from force-sensitive resistors. Prabhu et al. computed NLD features such as Shannon entropy, CD, recurrence rate, and *Recurrence Quantification Analysis (RQA)*. The classification was performed with the SVM and a *Probabilistic Neural Network (PNN)* to distinguish between patients with different NDD. and healthy persons. In Table 2.6, we provide the general NLD theory-based features that are used to assess the neurological state of the patients.

Table 2.6: Non-Linear Dynamic features.

NLD features	Definition	Ref.
DFA	Observes the degree of correlation of one stride interval with previous and subsequent ones.	[53, 70, 71]
LLE	Provides information about the stability properties of the time series as it calculates the sensitivity to initial conditions of the signal according to the rate at which the nearby trajectories of the phase space converge.	[68, 69]
HE	Assesses the long-term dependency of the time series.	[68, 69]
LZC	Relates to the number of different patterns that lie along a sequence which reflects the order that is retained in a one-dimensional temporal pattern.	[68, 69, 72, 74]

2.5.2 Indicators of Dementia

As mentioned in Subsection 2.3.1, dementia causes a decline in thinking skills, severe enough to impair daily life and independent living. In particular, it affects behavior, locomotion, feelings, and relationships. Different high-level indicators have been presented in the literature to characterize the locomotion behavior of people suffering from dementia [30].

We classify those indicators into four categories: trajectory-based, permission-based, purpose-based, and performance-based indicators. In Table 2.7, we define the specific indicators according to our categorization, and the most relevant research works in which they are considered. In the following, we briefly discuss the three classes.

1. **Trajectory-based indicators** They are well-known indicators for categorizing the patterns of abnormal locomotion behaviors by PwD. A popular model in this regard was proposed by Martino-Saltzman [17]. That model categorizes the trajectories into one of four distinct patterns of movement: direct, random, lapping, or pacing, illustrated in Fig. 2.8.
    - **Direct**: a simple or uncomplicated trajectory from one location to another one.
    - **Pacing**: at least three consecutive back-and-forth movements between two locations along very similar paths.
    - **Lapping**: at least two circular movements between at least three distinct locations.

Table 2.7: Dementia locomotion indicators.

Indicators classification	Indicators	Definition	Ref.
Trajectory-based indicators	Direct	Defined as moving straight from one location to another one without relevant diversion.	[75, 76]
	Pacing	At least three consecutive back-and-forth movements between two locations.	[34, 52, 75–77]
	Lapping	Repeated circular movements around a small area.	[34, 52, 75–77]
	Random	Inefficient or aimlessly movement across different locations, generally passing through more than four locations.	[75–77]
	FractalD	A statistical value extracted from a trajectory, which measures the geometric complexity and tortuosity; it ranges from a value of 1 when the movement path is entirely straight to a value of 2 when the movement path is random.	[36]
Permission-based indicators	Abscond (or Elopement)	This situation is referred to when a patient leaves the hospital or the ward with intent, leaving the safe environment's boundaries, or forays into the community without caregiver's consent, causing severe concerns.	[33, 78, 79]
	Exit seeking	In this situation the patient attempts to leave a safe environment, pressing panic bars or trying to open locked exit doors and sometimes includes pulling, pushing, kicking and knocking, or pounding on the door.	[33, 76]
	Invasion and trespassing	This situation occurs when the patient enters other people's rooms without permission, or when the patient walks into unauthorized spaces.	[33]
Performance-based indicators	MMSE	Widely used set of question answering test for screening cognitive function. It indicates the presence of cognitive impairment in PwD. It has the measures of orientation, registration (immediate memory), short-term memory as well as language functioning.	[61]
	MoCA	Considered a clinician-reported measure that takes about 10 minutes to analyze cognitive impairment. It measures cognition in various domains such as visuo-spatial skills, executive functions, attention, concentration, calculation, language, abstraction, memory, and orientation.	[49, 50, 80]
	CCNA	Considered as a protocol on how to assess gait in elderly including preferred and fast pace gait and dual-task gait	[81]
Purpose-based indicators	Inappropriate to circumstance	This term is used when the patient constantly searches for something that is unattainable, shows aggression, repetitive behaviors, and inappropriate behavior by social standards.	[33]
	Aimless and disoriented	This type of wandering behavior is characterized by a lack of focus or no apparent direction for reasons such as fear, memory loss, and feelings of discomfort (e.g., hungriness, boredom, pain). In this situation, the patient has difficulties finding the way and he/she is getting lost in familiar and unfamiliar places.	[33, 79, 82]
	Escapist	In this situation, the patient attempts to get somewhere beyond the view and control of the caregiver.	[33]
	Persistent	This situation occurs when the patient searches for 'missing' people or places without rest for a long time.	[33]
	Modeling (or Shadowing/ Tagging/Trailing)	In this condition the patient follows other people around.	[33]
	Nocturnal	This situation occurs when the patient walks around inappropriately at night.	[33]
	Pottering	Pottering refers to partial attempts to carry out household tasks that, with the progress of cognitive decline, become less and less meaningful.	[33]
	Repetitive	This situation occurs when the patient walks towards a purpose or carries out tasks, inappropriately often, repeatedly, and with abnormal frequency	[33]

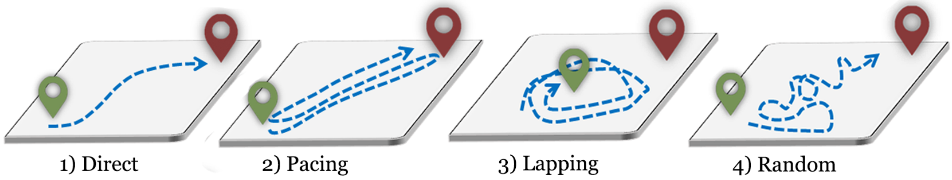


Figure 2.8: Travel patterns according to the Martino-Saltzman model [1].

- **Random**: a continuous and aimless movement across numerous locations with multiple directional changes, that generally passes through more than four locations.

The direct path is walked by cognitively healthy people, while random, pacing, and lapping patterns are typical indicators of dementia. In particular, scientific studies demonstrated that severely demented individuals perform trajectory-based anomalies all day long, while in moderately demented, the percentage of those anomalies increases in the evening and mostly in the night [17].
In a different research conducted by Kearns et al. [36], it was shown that the tortuosity of a walked trajectory is significantly correlated with the cognitive status. A high value of the *fractal* mathematical index of path tortuosity (Fractal D) indicates abnormal trajectories that are typically observed in wandering behaviors [36]. Fractal D is a compact and effective measure to characterize wandering behaviors.

2. **Permission-based indicators** Another class of indicators considers anomalous locomotion patterns of people living in constrained environments, which violate the permissions of the caregivers. We name this class of dementia-related locomotion anomalies *permission-based indicators*. As shown in Table 2.7, these indicators are further classified as abscond/elopement (leaving a safe environment without caregiver's consent), exit seeking (trying to open locked doors without consent), and invasion/trespassing (invading the private environment of other people without consent) [33].
3. **Purpose-based indicators** Most of the studies about wandering behavior consider it as an aimless, directionless movement. As mentioned in Tabel 2.7, only a few research support the theory of wandering as a goal-seeking behavior. According to the latter theory, some wandering behaviors have a specific purpose; e.g., to satisfy a need or to communicate a need. Accordingly, we classify those behaviors as purpose-based clinical indicators. Most of these indicators have been identified by Algase et al. [33], and are described in Table 2.7.
4. **Performance-based indicators** These are based on the performance of certain tasks that evaluate cognitive dysfunction and memory impairment. The *Mini-Mental State Examination (MMSE)*, *Montreal Cognitive Assessment (MoCA)*, and *Canadian Consortium on Neurodegeneration in Aging (CCNA)* are the widely used measures and protocols to evaluate cognitive dysfunction based on gait analysis [50, 61, 80, 81]. The score range of MMSE and MoCA is from 0 to 30. In these tests, if the final score is lower than 24 in MMSE, or less than 20 in MoCA, the sub-

ject will be regarded as cognitively impaired. However, the CCNA classifies the gait disturbance into different categories such as normal gait, ataxic gait, antalgic gait, cautious gait, frontal gait, hemiparetic gait, and many others.

While trajectory-based indicators are mostly used for diagnosis only, permission-based indicators, purpose-based indicators, and performance-based indicators are also used for ensuring the safety of the elderly suffering from NDD by monitoring his/her locomotion behavior and prompting caregivers accordingly.

2.5.3 Indicators of Parkinson's Disease

As anticipated, PD severely affects the human motor system. Gait impairment such as bradykinesia is one of the most common disabling symptoms of PwPD. It refers to the slowness of movement observed in patients. Locomotor dysfunction, shortened stride length, increased variability of stride, and shuffling gait are cardinal features of PD. Therefore, different indicators were proposed to characterize pathological gait in PD. Gait analysis on the walking behavior of PwPD is usually performed by monitoring several low-level parameters, mentioned in Table 2.4, over extended periods, including stride length, step length, stride velocity, swing time. There are also a few common complex gait parameters and NLD features that are used to detect gait abnormality in PD, mentioned in Table 2.5 and 2.6.

Generally, gait disorders in PwPD are evaluated by observing the gait in a lab with the help of one or more other clinical assessment scales. Several clinical indicators have been introduced in the literature and hence we categorized them as multi-task assessment indicators, which are illustrated in Table 2.8. The *Unified PD Rating Scale (UPDRS)*, the updated version of UPDRS, and the *Movement Disorder Society-sponsored version of the UPDRS (MDS-UPDRS)* are the most common assessment scales to evaluate the severity of PD. They are focused on estimating the intensity of PD. UPDRS was formed in 1987 as a gold standard for observing the reaction to medications employed to reduce the signs of PD [83]. These tools are scored on a 0-4 rating scale, where higher scores denote risen severity. Traditionally these scales include three sections used to estimate critical areas of disability. These sections are based on motor function, including getting up from the chair and postural stability. The Hoehn and Yahr Scale, formed in 1967 Melvin Yahr and Margaret Hoehn [84] is another most commonly used tool to evaluate Parkinson's symptoms and the level of disability established on motor function. It is ranked in stages from 1 to 5 and describes complex patterns of advanced motor impairment.

Advancement in Hoehn and Yahr stages is connected to motor decline, the decline in quality of life, and neuroimaging studies of dopaminergic loss. Table 2.8 summarizes the leading clinical indicators for PD related to locomotion analysis.

2.5.4 Indicators of Huntington's Disease

The PwHD experience locomotion impairments that can lead to falls, reduce the quality of ADL, and increase hospital admission and mortality. There are two main approaches

Table 2.8: PD movement indicators.

Indicators classification	Indicators	Definition	Ref.
Single-task assessment	Functional Reach Test (FRT)	Evaluates the stability of individuals by measuring the maximum distance they can reach forward while standing in a fixed position. This test evaluates the stability of individuals by measuring the maximum distance they can reach forward while standing in a fixed position.	[57]
Multi-task assessment	UPDRS	Employed as a tool to calculate the intensity of PD, formed as a gold standard to observe the response of medications for Parkinson's patients. It is scored on a $0-4$ rating scale and is established on a few segments such as motor impairment, behavior, and daily life activities.	[24, 85, 86]
	UDRS	Used to estimate involuntary movements in PwPD due to medication assumption. The scale has measurements for 'on-dyskinsesias' (jerking or turning movements) and 'off-dyskinesias' (cramps).	[87]
	MDS-UPDRS	Revised version of UPDRS, formed in 2007, utilized to measure different aspects of PD, including non-motor and motor functions in ADL and motor complications.	[88]
	Hoehn and Yahr	Used to assess the progress of Parkinson's advancement and the level of disability, formed in 1967.	[51]
	FoG-Questionnaire (FoG-Q)	Employed to measure FoG advancement for PwPD, FoG frequency, disorders in gait, and connection to clinical features associated with gait and motor aspects	[89]
	New FoG-Questionnaire (NFoG-Q)	Renowned tool to estimate the progression of FoG. It is a self-reported questionnaire with nine items to assess FoG	[89]

to assessing mobility and balance impairments for HD diagnosis: semi-quantitative clinical observational tests, and laboratory-based assessment. The former approach is based on observation by a clinical expert, and regards the assessment of locomotion impairments such as bradykinesia and decreased velocity, dynamic balance loss, and increased base of support [57]. The latter approach is expensive, since there is a need for extensive training, and it is not available in most clinical settings. Hence, there is increasing interest in innovative tools for supporting the diagnosis of HD by utilizing sensor instruments. Different clinical indicators have been proposed in the literature. We classify them into two categories: single-task assessment, and multi-task assessment indicators, which are illustrated in Table 2.9. Most of the gait indicators used for HD diagnosis are general gait indicators (presented in Section 2.5.1). Here, we classified the locomotion indicators which are combined and presented as clinical tests for recognizing anomalous gait related to PwHD. Aside from those indicators, other research studies investigated the use of general gait indicators (including swing and stance intervals, stride interval time series, Gait velocity, TUG test, BBS, and RB tests) for HD diagnosis [31, 46, 53, 54].

1. **Single-task assessment** Single-task assessment indicators rely on the examination of gait or stability during the execution of a given locomotion task. FRT evaluates stability by measuring the maximum distance that an individual can reach forward while standing. This measure proved to be highly correlated with HD severity [57]. This indicator is performed during a single session and led by a therapist.

Table 2.9: HD clinical indicators.

Indicators classification	Indicators	Definition	Ref.
Single-task assessment	FRT	This test evaluates the stability of individuals by measuring the maximum distance they can reach forward while standing in a fixed position.	[57]
Performance -oriented assessment	Unified HD rating scale (UHDRS)	It includes four components: Total Motor Score, Functional Assessment Scale, Total Functional Capacity scale, and IS. It evaluates motor impairment considering a range of voluntary and involuntary movements, including retropulsion pull test for postural stability, bradykinesia, coordination, balance, and gait.	[45, 47, 56, 57, 90–92]
	HD Activities of Daily Living (HD-ADL)	A scoring-based scale which is including adaptive functioning assessment based on ADL and family relationships and it is validated for PwHD.	[57]

2. **Performance-oriented assessment** Performance-oriented indicators evaluate different abilities, including stability and locomotion, during the execution of complex tasks. The UHDRS considers motor impairment due to different voluntary and involuntary movements, together with the ability to independently execute ADL [47,56]. The HD-ADL assesses balance, postural control, and adaptive functioning during certain tasks, which may be impaired by the abnormal perception of the body's position and movement in PwHD [45, 57].

2.6 Tools and Technologies

It is possible to use a wide range of low-cost sensors to track the position of users and their movements, detect cognitive problems, and ensure their safety. Therefore, all locomotion analysis methods have as a first step the collecting of movement data by utilizing sensory instruments. In this section, we will explain the most common sensors, either wearable/unwearable, for healthcare solutions, and discuss their pros and cons regarding locomotion anomalies and NDD. Moreover, we refer to *device-based technologies* for those tools that require the user to wear a device/tag, or even a device needs to be carried, while *device-free technologies* do not require users intervention and mostly they are embedded in objects/environment [93, 94]. However, most of these devices could be invasive and obtrusive, especially the ones that need to be worn all the time by the user. Most importantly, indoor localization technologies raise some serious privacy risks, since the position of the user is always known and that is not very desirable for the user [95].

2.6.1 Device-based Localization Sensor Technologies

Device-based location identification consists of wearable/mobile devices, such as watches, bands, pendants, earphones, collars, and so on, that help to locate the user. The magnetic-based technology utilizes a mobile magnetic sensor, usually a mobile phone, to measure the magnetic fields in different positions of an indoor environment. These measurements are used to construct a map of the location, which represents a reference for the user localization [96]. In mechanical-based devices, the user's location is estimated with IMU. IMU uses a combination of accelerometers, gyroscopes, and even magnetometers to calculate a target's current position from a known starting point, with previously determined speed and direction [35, 77].

Location-based *Radio-Frequency Identification (RFID)* utilizes electromagnetic fields to specify tags connected to things. An RFID system has a radio transponder, receiver, and transmitter. It transmits data to a reader device when triggered by an electromagnetic interrogation pulse from the reader device [97]. *Ultra-Wide Band (UWB)* systems [36,62] transmit information over a large bandwidth and use measures such as *Time of Arrival (ToA)* and *Time Difference of Arrival (TDoA)* to locate the distance between two entities. The UWB systems provide high accuracy. The UWB signal can penetrate walls and many other additional materials. Force sensing technologies are those sensors used to detect physical pressure, squeezing, and weight. They could be simple resistors that are embedded in the shoes and change their resistive value based on how much they are pressed, which are low cost [98] or mat-shaped step sensors to detect contact of the feet on the floor where a footswitch is installed next to the patient's bed [30].

A wristband, watch, or smartphone is incorporated with IMU technologies or different types of sensors which are used as a combination of accelerometers, gyroscopes, touch screens, and even magnetometers. Smartphone, as an example of IMU, makes remote patient monitoring possible and give faster access to providers and care, and are widely adopted for NDD monitoring [24, 35, 95, 99–102]. It also leads to improved communication, fewer hospital visits, and reduced patient costs. Furthermore, these wearable wristbands and watches can be used in healthcare solutions because of their simple design, common on-body placement, and connectivity with mobile phones [71, 77, 103].

2.6.2 Device-free Localization Sensor Technologies

Device-free technologies allow gathering the user's position without needing him or her to carry any device. They are mainly based on motion detection and provide data in real-time [95, 104]. There are different sensor technologies that can be used for this purpose, which are illustrated in Fig. 2.9 and briefly explained in the following.

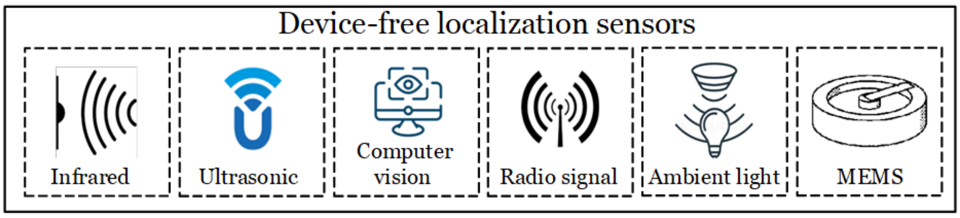


Figure 2.9: Well-known device-free sensor technologies.

- Infrared-based technologies are utilized in *Passive InfraRed (PIR)* sensors, and *Active InfraRed (AIR)* sensors [34, 50, 75, 105]. The former measures infrared light radiations from people since they emit heat energy in the form of radiation. The latter requires a transmitter to continuously send beams of infrared light, and a receiver to detect when the beam stream gets interrupted by a mobile object moving across the scan area.

- *MicroElectro Mechanical Systems (MEMS)* pressure sensors have a central role in controlling the environment to detect falls and wandering patterns based on the number and pattern of activation on a gait mat or on the floor and measure foot strike [106, 107].
- Ultrasonic transmitters emit an ultrasonic wave that gets reflected by objects in the scan area, and detect doppler shift at low audio frequencies, similarly to microwave devices [108].
- Computer vision-based sensors such as utilizing cameras or Visual Sensor Networks are promising in ambient sensing approaches for pervasive healthcare delivery. By utilizing these kinds of technologies it is possible to compare sequential images from captured video streams, monitor 3D spaces, and detect movements when there are enough changes between the frames by scene analysis and proximity techniques even by compact on-node image processing and computer vision algorithms [17, 50, 109, 110].
- Radio signals and their reflections can be used to detect individuals' movement and position over time. Furthermore, by utilizing microwave signals, the movement of an object causes a phase shift in the emitted radiation, creating a signal at a low frequency. Thanks to this technology, ultra-low-power radio signals in tomographic motion detectors [94], and wall-mounted sensors [36] can sense radio waves at frequencies that penetrate most obstacles and walls, detecting the user's position over large areas.
- Ambient light communication technologies are based on light sensors that receive the signals of *Light-Emitting Diode (LED)* emitters with different flicker encoding so that they can be compared in order to measure direction, position and provide localization [94].

2.6.3 Strengths and Weaknesses of Localization Technologies

All device-free and device-based sensor technologies, as shown in Table 2.10, have their own strengths and weaknesses.

Mechanical-based systems are cheap and effective. They have a high Mean Time Between Failures and consume less power, but they are vulnerable to cumulative error.

Acoustic systems can provide high accuracy even between rooms, but the signal detection should be low power not to be heard by a human ear and not to cause sound pollution. They are also sensitive to temperature changes and noise. Magnetic-based systems offer high accuracy, but they are sensitive to conductive and ferromagnetic materials.

Optical-based systems provide high accuracy and they are not affected by the multipath effect, but they require line of sight, consume higher power, and range is affected by obstacles [94, 95]. WiFi-based systems are relatively cheap and are widely available without needing complex hardware. Bluetooth is supported by most modern devices, such as smartphones and smartwatches. It is low cost and has very low power consumption, but the signal is very attenuated from obstacles.

Table 2.10: Comparison of tools and technologies related to movement detection.

Tools	Sensors	Accuracy	Installation Cost	Complexity	Scalability	Power Consumption	Advantages	Disadvantages
Device-based	Magnetic	High	Low	Moderate	Moderate	Low	Real-time - Easier to assess physical activity	Unethical as it decreases a person's autonomy
	Mechanical	High	High	Moderate	Moderate	Relatively high	Real-time - Easier to assess physical activity	-
	UWB-IR sensors	Low	Low	Moderate	Low	Relatively high	Cheap - Non intrusive	-
	RFID	High	High	Moderate	Moderate	Low	Real-time - Easier to transmit information over a large bandwidth - A variety of activities can be detected - High accuracy	Initial cost - The array of tags is needed - Adjustment is needed in different environments - Computationally complex - Feature extraction needed - Reduced performance in complex environments
	Force sensing	Moderate	Low	Moderate	Low	-	Cheap - Non-intrusive - Easy to extract data - Detection computationally simple	Arrangement of sensors is important for higher accuracy - Impractical for some activities due to vibration
	IMU	High	Low	Moderate	Low	Moderate	High sampling rate - TriAxial data measurement enables 3D analysis- Sensors are small, lightweight, and cost-effective - Monitoring of gait properties during daily activities - Active role of a patient can be monitored.	Suffer from drift - Uncomfortable since sometimes need to attach with the body - Interruption in actual data measurement due to skin movement artifacts - Different positions of sensor attachments show variations in acceleration sensing - Limited battery duration - Complex strategy to estimate gait parameters.
Device-free	Infrared	Moderate	High	Low-Moderate	Moderate	Low	Cheap for the end user - Easy to use - Detection in darkness - Preserves privacy (Low resolution)	Sunlight inference - Needs more receivers - Noise sensitive - Low range of detection
	MEMS pressure sensors	Moderate	Moderate	Low	High	Low	Extremely high sensitivity and consistency - Non-intrusive - Low power consumption - Extremely scalable - Can be readily integrated with microelectronics	Expensive - Fabrication, assembly unit costs, testing equipment to characterize the quality and performance can be very high for low quantities
	Ultrasonic/ Ultrasound	Moderate	High	Moderate	Moderate	Low-Moderate	Good precision - Non intrusive	Cost - Multipath effects and line of sight.
	Computer vision	High	High	High	Low	Moderate	Real-time - Good accuracy	Sensitive to light conditions - Privacy concerns Unable to detect subtle changes in motion patterns and deduce details
	Radio Signal	Low-Moderate	Low-Moderate	Moderate	Moderate	Low	Cheap - Penetrate most obstacles and walls and cover a large area - Non intrusive - Cost efficiency - High accuracy - Acceptable performance in complex environment	Require proximity - Computationally complex - Feature extraction needed - Sensitive to the noise interference - Adjustment is needed in different environments
	Ambient light	Low	Low	Moderate	Low	Relatively high	Cheap - Non intrusive	Sensitive to light conditions - Could be annoying for the user

UWB systems provide high accuracy. They are less sensitive to multipath effects and are immune to interference, but they are shorter range and their cost is high. RFID systems consume low power, have a wide range, and are low cost, but require proximity and localization accuracy is low. The MEMS pressure sensors are small in size, have lower cost and power consumption, and provide high consistency.

In terms of accuracy, both mechanical-based systems and ultrasound systems offer higher accuracy. The latter can reach accuracy from 0.01 to 1 meter. Magnetic-based systems provide a high accuracy on the order of a few centimeters. WiFi has an accuracy between 1 and 5 meters; Bluetooth, instead, from 2 to 5 meters. A beacon can determine three ranges of proximity: immediate (less than 50 cm); near (between 50 cm and 2 to 5 meters); far (between 5 meters and 30 meters). The accuracy depends on interference from physical obstacles. UWB offers an accuracy of up to 10 cm, while RFID accuracy is relatively low and it is from 1 to 5 meters.

In terms of obtrusiveness and privacy, ambient light systems, such as audible sound, could be annoying for the user, but they could be resolved to reuse an already available light infrastructure in order to be not intrusive or, in audible systems cases, using digital watermarking of audio signals. In computer vision sensors, although, they can do real-time monitoring there are still privacy concerns and scalability problems. Also, there is a difficulty for detail deduction or subtle changes in movement patterns and they are unable to detect physiological parameters which may lead to hindering their application for ambient sensing frameworks [95].

Infrared sensors offer 1 to 2 meters accuracy, while LED implementation using fixed lamps reports an accuracy below 20 cm. Utilizing infrared technology has also some limitations such as moderate accuracy, it needs for more receivers to improve accuracy, and interference of infrared waves in presence of fluorescent light and sunlight, leading to the reduction of system usability. They also are invisible to the human eyes, instead, ultrasound is undetectable to the human ear, so they are not intrusive at all [95]. Although, they are useful for movement detection still there is a general limitation which is low accuracy due to multipath effects and line of sight.

In conclusion, in practical applications, both device-based and device-free technologies provide complementary information and successful systems are only feasible by integrating the two sensing modalities.

2.7 Algorithms and Applications

In this section, we classified sensor-based algorithms and applications for recognizing NDD according to the locomotion indicators reported in Section 2.5. This classification is presented in Fig. 2.10. We also illustrate ambient intelligence techniques to recognize challenging behaviors.

2.7.1 Detection of Dementia

In order to categorize the existing solutions for recognizing symptoms of dementia, we propose the classification shown in Fig. 2.10. In the following, we present the most promi-

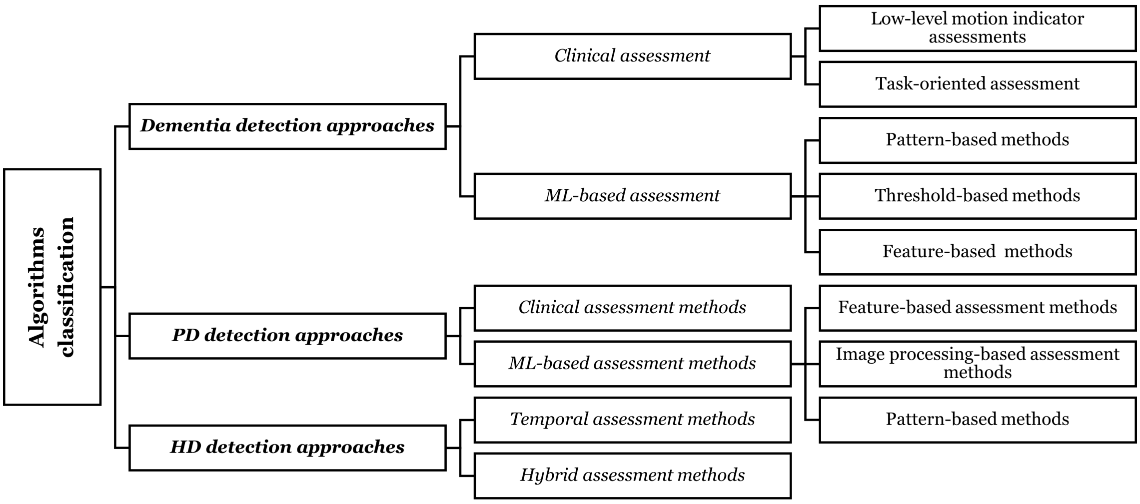


Figure 2.10: The proposed framework for dementia detection approaches.

nent methods according to our classification, namely Clinical assessment and ML-based assessment. Those methods are summarized in Table 2.11.

Clinical Assessment

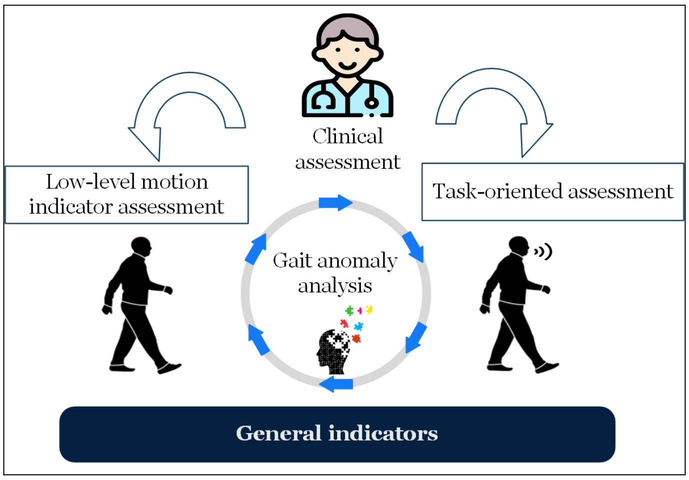
In this group of approaches, detection is based on prior knowledge, results of clinical tests, and statistical analysis of locomotion data by the supervision of operators and medical experts. Therefore, these kinds of approaches strongly rely on human resources and experts to evaluate the cognitive status of an individual. We further classify the clinical assessment methods into *low-level motion indicator assessment* and *task-oriented assessment* methods, both of which rely on general gait indicators. The former methods consider specific low-level motion indicators, that in some cases allow distinguishing among the different dementia disease sub-types, such as AD and dementia with Lewy bodies [38, 48]. Hence, the choice of specific indicators has an important impact on the diagnosis. In addition to motion indicators, the latter methods also consider executive and memory functions, adopting an approach named *dual tasking*.

In both approaches, the patient evaluation is supervised by clinicians and executed during predefined, short, structured testing sessions. The fact that tests are not performed in naturalistic conditions can obviously have an impact on the effectiveness of the evaluation [44, 48].

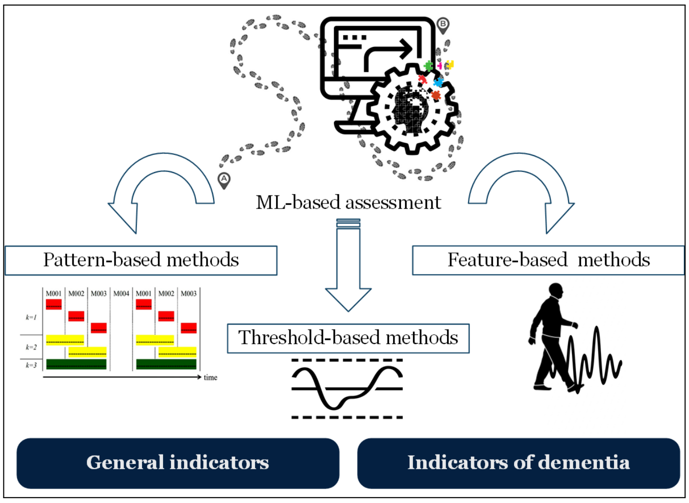
1. **Low-level motion indicator assessment**
   The evaluation of different gait features, including simple and complex gait parameters, is commonly considered an important part of dementia assessment, and their locomotion patterns are considered good predictors of diverse adverse health outcomes and mobility "bio-markers" [54]. Different studies have shown that by sensor-based gait cycle analysis of PwD vs cognitively healthy seniors, it is possible to find a correlation between variability in different gait parameters and cognitive decline progression [44, 48]. As an example, the experiments conducted by Kearns

Table 2.11: Classification of dementia detection methods.

Locomotion anomaly detection approaches		Main idea	Characteristics	Challenges	Algorithms
Clinical assessments	*Low-level motion indicator assessment*	These methods rely solely on different low-level gait indicators including simple and complex gait parameters.	-Possibility to find the correlation between gait parameters and cognitive status -Detecting early and longitudinal cognitive changes -Possibility of real-time assessment -Useful to help differentiate between PwD and cognitively healthy seniors	-Relevant clinicians' effort for the evaluation of the cognitive status -Clinical indicators and assessment algorithms must be carefully chosen -Experiments are supervised and they are based on predefined, short, structured testing sessions	Statistical analysis [36, 44, 48, 58]
	Task-oriented assessment	Based on single or dual-task assessment; the latter consists in evaluating gait parameters together with executive and memory functions	-Ability to assess the concurrent performance of a motor-cognitive or motor-motor task independently -More naturalistic gait assessment -Useful to support the diagnosis of cognitive impairment symptoms in the early stage	-Need for clinical experts for evaluating the test outcomes -Algorithms, tests, and indicators must be carefully chosen -Complex execution and evaluation of tests	Statistical analysis [38, 39, 41, 42, 49, 55, 59]
ML-based assessment	*Pattern-based methods*	Consider locomotion data as a temporal sequence of locations (trajectories)	-They rely on unobtrusive environmental positioning infrastructures -Based on wandering models such as the Martino-Saltzman model [17] -Location data represented by sequences or images -Possible to add extra features and data sources -Suitable for long-term analysis	-Need large volume of data -Trajectory segmentation is challenging -Execution of ADL may interfere with the walked trajectories	Shallow ML algorithms [1, 34], Multi-layer deep neural network [16], K-repeating substrings features [75]
	Threshold-based methods	They rely on data-driven thresholds to recognize gait and locomotion phases	-Adaptive thresholds for the different classes of individuals -Low computational complexity and latency	-Thresholds definition is challenging and subject to contextual factors They need model calibration for the different subjects	Gait phase detection method [111], Proposed algorithm based on degree of movement and orientation [76], low-pass filtering and threshold-based peaks and valleys identification [65]
	Feature-based methods	Based on supervised ML and feature extraction methods to capture multi-domain characteristics of dementia.	-Inclusion of multiple factors for the recognition of dementia -Integrated analysis of locomotion, gait, and postural features -Use of feature selection to improve performance and reduce execution time	-Classification performance depends heavily on feature engineering -Need large volumes of data	Shallow ML algorithms [60, 80, 112],Convolutional Neural Networks (CNN) [50], Trend analysis [62], Multiple logistic regression [43], PNN [61]



(a) Clinical assessment approaches overview.



(b) ML-based assessment overview.

Figure 2.11: Detection of Dementia approaches.

et.al revealed that there is a correlation between higher tortuosity of the path with lower MMSE scores which is assessed by clinicians [36].

2. **Task-oriented assessment**
   Task-oriented methods are based on single-task and dual-task (sometimes called Talking While Walking [61]) walking assessment, which considers the concurrent performance of a motor-motor or motor-cognitive task. The evaluation relies on measuring the interference of the different tasks with each other. Indeed, while the individuals divide their attention to multiple tasks, they have difficulty regulating the stride-to-stride variations of locomotion, and this difficulty is stronger for cognitively impaired people [43, 49]. Impairment in executive functions (e.g., verbal fluency [55], visual-spatial skills [42], counting aloud backward from 100 to zero [55]) is one of the earliest indicators of cognitive decline. Different experiments have proved that PwD has a more variable within-bout and irregular trunk

acceleration pattern, higher step duration and gait complexity, and less variable across-bout walking patterns on single and dual-task walking (e.g., words enumeration) compared to healthy persons [38, 39, 42]. The execution and evaluation of task-oriented assessment methods are more complex than the one of low-level motion indicator methods but allow the recognition of early-stage cognitive decline.

ML-based Assessment

Another group of approaches relies on ML algorithms to distinguish between cognitively healthy subjects and PwD based on the observation of movement and behavior. Compared to the clinical assessment approach, ML-based assessment enables the evaluation of the cognitive status in more naturalistic settings. Indeed, the observation is usually carried out in the inhabitant's smart-home or in instrumented retirement homes. Moreover, ML-based assessment can be carried out unobtrusively for long time periods, and in general requires less clinical effort compared to clinical assessment methods, enabling both long-term and short-term monitoring [34].

As can be seen in Fig. 2.10, we classified the different ML-based methods into three categories: *pattern-based methods*, *threshold-based methods*, and *feature-based methods*. Pattern-based methods consider movement as a temporal sequence of locations, which describe the trajectories walked by an individual, and directly process that sequence to provide a hypothesis of diagnosis. Threshold-based methods use thresholds inferred from the data to detect dementia based on locomotion signals collected by ambient or wearable sensors. Finally, feature-based methods apply ML algorithms to feature vectors extracted from locomotion data for recognizing dementia.

The three classes are depicted in Fig. 2.11b. The underlying clinical indicators used by these methods are reported in Section 2.5.

1. **Pattern-based methods** These methods process trajectory data to recognize abnormal patterns that may indicate dementia according to specific indicators, such as the Martino-Saltzman model [17]. Since ambulation episodes are composed of locomotion and non-locomotion phases, a key step of these methods is to segment locomotion traces to recognize significant trajectories.
   A wrong segmentation of trajectories may disrupt the effectiveness of the pattern recognition algorithms. Moreover, the execution of ADL, especially in indoor environments, may impact the individual's movements, increasing the complexity of trajectories and incorrect detection [34].
   Some pattern-based methods are non-supervised. For example, in [34], Khodabandehloo and Riboni detect loops (i.e., pacing and lapping episodes) building a buffer on the trajectory segments and considering the percentage of intersection among the buffered segments composing the same trajectory. Other works represent the trajectory as a string of locations and detect abnormal patterns using the longest repeated sub-string algorithm [75]. Other authors propose the use of supervised ML algorithms to recognize abnormal trajectories. Zolfaghari et al. [16] represent trajectories as colored pictures in order to encode features such as speed

and sharp points and use a DMLP for determining whether the trajectory is walked by a PwD, by a person with MCI, or by a cognitively healthy senior. Since pattern-based methods rely on data acquired in naturalistic environments, they are prone to misclassification errors due to noise in sensor data acquisition and interference of external factors (e.g., activities, interaction with other people, obstacles in the home). Hence, these approaches tend to be effective mostly for long-term monitoring [34].

Other methods for increasing the effectiveness of pattern-based methods include the application of low-pass filters to location data for noise reduction especially for data collected from inertial sensors, or the addition of extra features such as statistics extracted from trajectory data [34, 75], activities and abnormal behaviors [1]. Furthermore, Chaudhary et al. in [113] tried to implement an early dementia detection system in an indoor environment using travel patterns of the inhabitant and *Recurrent Neural Network (RNN)*, which automatically extracts the high-level features.

2. **Threshold-based methods**
   This category of methods detects gait phases by mining thresholds from the data for segmenting events, recognizing gait cycles, and locomotion phases. Meng et al. used accelerometer data and adaptive thresholds to recognize the gait phases of PwD and cognitively healthy seniors [111]. In [76] the authors presented a solution for detecting locomotion anomalies in dementia patients using a wearable Opal monitor which is including an accelerometer, gyroscope, and magnetometer. In order to recognize direct, pacing, lapping, and random movement patterns, they considered translational acceleration threshold to detect walk events, then they tracked the movement orientation until the algorithm detects the subject had made a complete stop. The classification is done by considering the different ranges of orientation degrees for different locomotion patterns. Wang et al. [65] proposed a threshold-based method to automatize the TUG test. In that work, event segmentation is based on thresholds to identify peaks and valleys during forward motion, swing points, and stance-point. Experimental results showed that PwD need more time for TUG test tasks such as sitting and standing up, with respect to cognitively healthy subjects. Of course, in such methods, a key factor is the definition of the thresholds. Since different subjects may walk with high variation in cadence and step length, those works need adaptive thresholds for different classes of subjects, and specific model calibration for the different individuals. An advantage of threshold-based approaches is the low computational complexity and feasibility for real-time applications at the edge.
3. **Feature-based methods** As explained before, dementia is a complex impairment that impacts several domains. Hence, it is natural to consider different features for its detection. Feature-based methods rely on feature extraction techniques to represent the different characteristics of locomotion data, and on supervised ML algorithms to classify the feature vectors according to the cognitive status of the subject. In feature-based methods, locomotion features used for recognizing de-

mentia include kinematics characteristics of postural control such as displacement on the transverse plane and dispersion radius [80], accelerometer-based gait parameters (e.g., walking speed, step frequency, compensation movements, acceleration variance) [60], gait symmetry and regularity [61], and other gait variables including step counts, step duration, speed, accelerometer and gyroscope statistical measures [112].

Toosizadeh et al. [43] extracted different features from accelerometers worn by patients on the upper arm, on the wrist, and on the shins, during the execution of dual-tasking. Those features considered both upper-extremity function parameters (e.g., elbow angular velocity, acceleration) and gait parameters (e.g., speed, time interval, distance). Analysis of variance tests showed a significant correlation between upper-extremity features acquired during the dual task and the MoCA cognitive assessment result of the patient. Kumar et al. used trend analysis on different navigational features, including speed, path-efficiency, angle-turn, and ambulation-fraction, to distinguish PwD from cognitively healthy seniors considering UWB location data acquired in an assisted living facility [62]. Together with feature extraction, some of these methods apply feature selection techniques to increase recognition rates, reduce computational effort, and avoid overfitting [60, 61, 112].

Kondragunta and Hirtz in [50] used data acquired from depth cameras during single and dual-tasking, and extracted several features including step length, step time, stride time, and cadence, by applying 3D human pose estimation techniques. They proposed to use dynamic time warping on those features to recognize PwD, MCI individuals, and cognitively healthy seniors. Compared to wearable sensor systems, techniques based on cameras are less obtrusive, but are prone to detection errors in low-light conditions, and are generally more computationally expensive. Moreover, the use of cameras poses serious privacy issues, especially when they are deployed in private homes [114]. A shortcoming of feature-based methods is that the accuracy of recognition strongly depends on feature engineering. Moreover, being based on supervised learning, those methods need large volumes of training data that are expensive to capture in real-world settings.

2.7.2 Detection of Parkinson's Disease

As explained in Section 2.5.3, our human motor system is affected by PD. The most significant indicators of PD are locomotor dysfunction, shortened stride length, increased variability of stride, and shuffling gait. Therefore, it is essential to identify these parameters for diagnosing PD. Generally, gait disorders of PD are assessed by UPDRS. Gait freezing deteriorates the quality of life by reducing mobility and increasing falls. Patients with freezing episodes also have problems with a lack of steady gait. Researchers have recognized the gait disorders of PD based on wearable sensors [66, 107] placed in the patient's back or wearable devices such as smart watches [103]. Several studies were also conducted to measure Spatio-temporal gait parameters using pressure-sensitive mats such

Table 2.12: Classification of PD detection methods.

Approaches		Main Idea	Characteristics	Challenges	Algorithms
Clinical assessment		- These methods are based on prior knowledge, results of clinical tests, and statistical analysis of locomotion data by the supervision of medical experts. - Based on single or dual-task assessment such as free walking, opening, and closing doors, climbing stairs	- Detecting long-term changes in stride length - Demonstrate the effectiveness of gait in natural environment - Provides clinical validity of the algorithm derived from the sensor to detect dyskinesias in PwPD - Possibility of real-time assessment	-Challenging to monitor accurately stride length over an extended period to characterize pathological gait	Statistical analysis [64,87,106, 107,109,115–119]
ML-based assessment	***Feature-based assessment methods***	- These methods rely on various feature extraction methods , data collected from wearable sensors and use ML based algorithms to distinguish between PwPD and healthy control subjects	-Investigate the effect of gait and tremor features for early detection of PD - Based on postural analysis such as step distance, walking speed, stance, and swing phase - Apply in real-life conditions	-Difficult to determine significant features - Need extensive data for the feature classification task	Linear Linear Discriminant Analysis (LDA) [120], SVM [51, 120–122], Naive Bayes (NB) classifier [51, 121, 123], RF [121, 123], Multi-Layer Perceptron (MLP) [123], Decision Tree (DT) [51], K-Nearest Neighbour (kNN) [123], Deep 1D-Convnet [124], Deep MLP (DMLP) [100], CNN [125]
	Image processing-based assessment methods	- These methods rely on the camera that is used for gait analysis to classify normal or PD's gaits. Based on processing images and videos from walking sessions of the PwPD and a classifier, it can detect abnormal gait patterns using a computer vision-based algorithm	- Process images and videos from the patient's activity, identify every stride of the patients' - Employ ML based classifier - Identify PwPD in the early stage and diagnose Parkinson's ailment with the support of a clustering method that detects abnormal gait patterns	-Difficult to determine significant features from the image - Need extensive data for the classification task	Principal Component Analysis (PCA) [126], LDA [126], Regional-CNN (R-CNN) [127], Canny operator and gaussian filter [99], SVM [127,128].
	Pattern-based methods	- Processed data to recognize abnormal patterns that may identify Parkinson - Based on shifted one-dimensional local binary patterns (Shifted 1D-LBP), abnormal gait patterns and ML methods using the dataset on gait signals	- Considers 1D-LBP from the LBP for extracting features from sensor signals - Employ in a real-time application by detecting local changes in gait signal	-Difficult to determine significant patterns - Need extensive data for the classification task	NB [129], Logistic Regression (LR) [129], RF [129, 130], SVM [130], DT [130], ZUPT algorithm and Kalman filter [131], Bayes classifier [110], Bag-of-words method [130]

as GAITRite [117]. Emerging wristbands or smartwatches integrated with IMU are pledging into wearable healthcare solutions. Experiments also showed that *Upper Body (UB)* variables need to be computed together with the consideration of Spatio-temporal characteristics to gain a more holistic inspection of PD for use in a clinical or in the nonclinical environment [103, 117]. Wearable inertial sensors were used to monitor and measure the head and pelvis accelerations. Pearson's product-moment correlations were computed from UB accelerations, including magnitude, smoothness, regularity, symmetry, attenuation, and spatiotemporal characteristics such as postural control [117]. In order to categorize the existing solutions for recognizing symptoms of PD, we propose the classification shown in Fig. 2.12. Table 2.12 summarizes the characteristics of existing techniques.

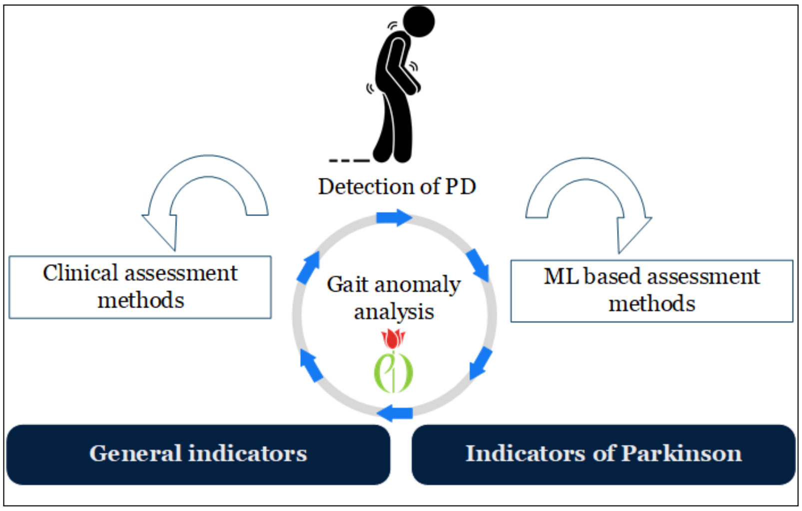


Figure 2.12: PD assessment methods classification.

Clinical Assessment Methods

In the clinical assessment method, PD is detected based on prior knowledge, results of clinical tests, and statistical analysis of locomotion data by the supervision of medical experts. Hence, these approaches intensely depend on expert evaluation to assess an individual's cognitive status. Patient evaluation is supervised by clinicians and executed during predefined, short, structured testing sessions. Generally, the severity of PD is measured with UPDRS [132] score and the Hoehn and Yahr stage [133], NFoG-Q [134]. Clinical evaluation can be done based on the performance of a simple motor task such as walking a short distance and standing up out of the chair and the standing or walking turns [118]. The short stride length characteristic of Parkinsonian gait can be noticed from long-term changes in stride length. Locomotor impairment is one of the leading characteristics of PD. On the other hand, many other symptoms of PD such as rigidity, difficulty swallowing, upper-body tremor, and dyskinesias, cannot be noticed with the stride monitor [115]. Clinical evaluation was conducted employing the leg dyskinesia item of the UPDRS [87]. Generally, dyskinesias in PwPD are associated with motor dysfunctions, including gait and balance deficits.

ML-based Assessment Methods

Currently, PD is not curable. Early detection of PD symptoms is necessary to enhance the patient's treatment. Gait analysis is an essential step for the PD diagnosis, as gait abnormalities have been reported to appear at the earlier stages. Since changes in gait are among the foremost symptoms of this disease, a gait classifier would be beneficial for physicians. Therefore, ML assessment methods can classify abnormal and normal gait. There are different approaches available to detect PD using ML, here we divided ML assessment methods into three categories: *Feature-based assessment methods*, *Image processing-based assessment methods*, and *Pattern-based assessment methods*.

1. **Feature-based assessment methods** The diagnosis of PD can be challenging in its earlier; Parkinsonian gait is characterized by small steps, a slower gait cycle, a smaller swing phase, and a lengthier stance phase. Physicians evaluate these features in their diagnosis process to confirm the presence of PD. Gait evaluation can be difficult since it can be influenced by several aspects such as age and health condition. Despite the considerable interest in Parkinsonian gait analysis, there is no accurate tool to help physicians with gait evaluation. To detect the characteristics of gait, feature extraction methods, and ML have been used. However, gait is a physiological characteristic that differs for each person according to age, health, and other intrinsic factors. Therefore, manual preprocessing and feature extraction will always be limited in their capacity. Generally, a feature-based assessment method is used to extract significant features that will help to diagnose PD. Various features such as step distance, stride length, stride velocity, stance and swing phases, heel and normalized heel forces, swing time of Parkinsonian patients, and walking speed were extracted from the data collected from the wearable sensors and after that examined using ML-based algorithm to select the most influential features that would help to differentiate between the two groups: PwPD and healthy people. Generally, supervised learning methods such as LDA [120], SVM [51, 120–122], NB classifier [51, 121, 123], RF [121, 123], MLP [123], DT [51], kNN [123], Deep 1D-Convnet [124] are used for distinguishing between PwPD and healthy cognitive subjects. Furthermore, recently novel machine and DL-based multi-modal technologies are used to identify the severity of PwPD actions by analyzing speech, and movement patterns and evaluation of motor capabilities [100, 125]. The rationale of this approach is that they may effectively capture discriminative features from time-series data or other IMU sensors collected data without the need for sophisticated feature engineering efforts.
2. **Image processing-based assessment methods** Image processing technologies have been employed widely for PD diagnosis. PwPD show large gait variability and slower walking speeds than normal people. Cho et al. [126] introduced a gait analysis system based on a computer vision-based technique for the detection of gait patterns of PD. They captured a few videos of both normal subjects and PwPD. They processed the images from the videos to characterize the subjects. PCA and LDA were employed to extract features and the minimum distance classifier was

used as the classifier. Seven PwPD and seven healthy people from Buddhist Tzu Chi General Hospital in Taiwan participated in this study. It used the image sequences of human silhouettes during walking and extracted the intrinsic features by LDA. It can identify healthy people and PwPD by their gaits with high reliability and it is considered a promising aid in the diagnosis of PD. Khan et al. [128] also presented a computer-vision-based marker-free method to detect abnormal gait in PwPD. In this study, subjects are videotaped with several gait cycles for the gait analysis of the PwPD. To develop a silhouette, the subject's body is segmented through a color segmentation process. The skeleton is formed by computing the medial points of each body segment. The motion cues such as the cyclic motion of legs and the posture lean of the subject during the gait are extracted from the skeleton. Then the comparison study compared these two cues with the probable perfect gait pattern to assess the gait impairment. Generally, a computer vision-based technique is introduced for gait analysis to classify normal or PD's gaits using a camera. In [127], a masked R-CNN is applied for extracting human silhouettes from video frames based on recorded videos of normal gaits. After that, the gait energy images are constructed based on extracted human silhouettes as features, which are applied to develop an SVM model for classifying healthy and PD gaits in video clips.

3. **Pattern-based assessment methods** These approaches process trajectory data to recognize abnormal patterns identifying PD. Walking is a part of human movement monitored by the human brain. Gait deficits and abnormal walking patterns may appear if the brain fails to control this movement. Walking patterns can be monitored continuously and remotely over time by wearable sensors. The bag-of-words approach [130] was introduced where each individual's walking time series is defined as a bag of words. The ratio of the words together with ML techniques such as linear SVM, DT, RF, and kNN were employed to distinguish between patients with PD and healthy individuals. Although the bag-of-words method is used to distinguish between PD and healthy age-matched individuals, this method is also applicable to other health conditions. Each individual's walking time series is converted into signal subsequences using an overlapping sliding window. Then, each subsequence is characterized using a few statistical descriptors and similar subsequences are assigned the same word. Therefore, each person's data is converted into a bag of words and then evaluated using accelerometers' data collected from the ankles. The proposed approach illustrates a vital step towards providing healthcare through continuous monitoring and advanced analysis of movement patterns [130]. Another method was introduced to diagnose PD based on Shifted 1D-LBP using ML algorithm [129]. The *gaitpdb* dataset was used for the evaluation task, consisting of three gait datasets based on gait signals from different circumstances. Statistical features were extracted from histograms of gait signals changed by Shifted 1D-LBP. ML methods such as NB, LR, and MLP, were employed to extract and classify features that can be successfully used in PD detection from gait [129]. This approach may also be utilized to detect other symptoms. It can also be applied in any real-time application by detecting local changes in a signal.

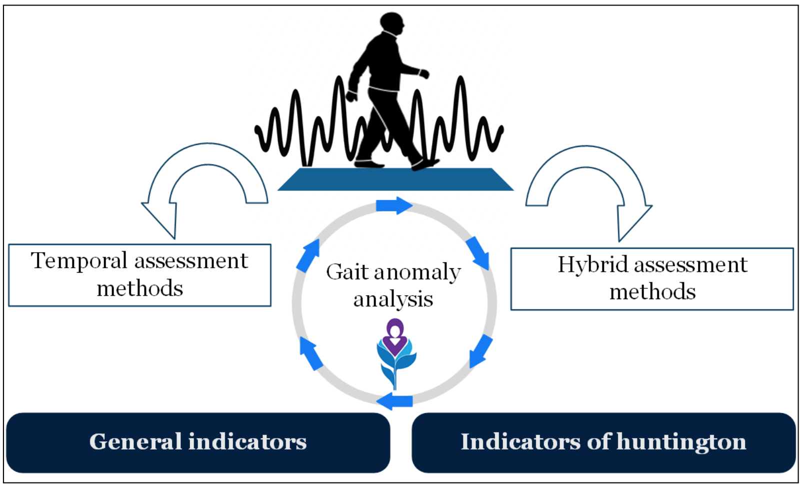


Figure 2.13: HD assessment methods classification.

Nevertheless, it is hard to define significant features or patterns that can help to diagnose PD. Moreover, ML-based assessment methods require large volumes of training data to employ in the classification task.

2.7.3 Detection of Huntington's Disease

As explained in Section 2.5.4, HD determines impairment in motor control characterized by chorea and dystonia. Several studies have shown that HD symptoms based on locomotion are observable in pre-manifest individuals well before the actual diagnosis [45, 56]. Therefore, recognizing temporal changes in gait parameters is important for early diagnosis and to help delay the disease progression. Different studies used pressure-sensitive walkway instruments capable of recording Spatio-temporal gait data with high precision [45,46,56,57,91]. Other works are based on wearable sensors, such as force-sensitive switches embedded in shoes [53,71], accelerometer and gyroscope positioned in a waist-belt [54], or IMU attached to the shank [92]. Experimental results have shown that PwHD experience a decrease in velocity, stride length, and cadence, and an increase in parameters related to dynamic balance impairment, including increased time in double support and gait asymmetry [91]. Furthermore, the ability to preserve steady locomotion, i.e., low stride-to-stride variability of gait cycle interval and its' sub-phases, would be reduced in persons with NDD [31]. Therefore abnormal timing of steps in NDD leads to a distraction in gait and locomotor activity generation and fortunately these categories of clinical tests are highly correlated with functional limitation and quantitative gait measures related to gait speed [31, 57]

Since there are different approaches to detecting HD locomotion anomalies, we classified the techniques into two categories: *temporal assessment methods*, and *hybrid assessment methods*, which are illustrated in Fig. 2.13. The main characteristics of these approaches are summarized in Table 2.13.

Table 2.13: Classification of HD detection methods.

Approaches	Main Idea	Characteristics	Challenges	Algorithms
Temporal assessment methods	Use IMU mounted on the waist or embedded in shoes to monitor temporal gait parameters such as stride interval	-Applicable indoors and outdoors -Data can be acquired in naturalistic conditions -Minimally obtrusive	-Limited to certain locomotion data -External events and noise can impact the recognition performance -Need for extensive training datasets acquired in different conditions	Statistical analysis [71], Gait event detection methods [54], Threshold dependent symbolic entropy [53]
Hybrid assessment methods	Use wearable sensors or sensorized pressure-sensitive walkways to investigate a different aspect of mobility and balance by considering different types of clinical gait indicators.	-Accurate acquisition of motor data alongside clinical walking measures. -The use of different types of indicators increases accuracy. -Good correlation with fluctuation limitation and quantitative gait measures and gait patterns, dynamic balance, and fall risk.	-Results may reflect general gait deterioration rather than HD specifically. -Some of them need specific laboratory equipment	Intraclass Correlation Coefficient and Coefficient of Variation [46], Hidden Markov Models (HMM) [92], Statistical analysis [45, 47, 56, 57, 91], Radial Basis Function neural networks [31], Long short-term memory network [135]

Temporal Assessment Methods

These methods use different strategies in order to examine gait cycles and their correlations with HD by the analysis of complexity and uncertainty measures. In particular, the stride interval in human locomotion reflects the rhythm of the locomotor system and its analysis provides a non-invasive approach for quantifying gait dynamics [53]. Since there is a correlation between fluctuation in stride interval and HD, stride analysis allows the detection of locomotion impairment in PwHD at an early stage. Furthermore, the correlation degree in this indicator is inversely associated with the degree of functional impairments in PwHD [71]. Different research studies were able to differentiate PwHD from cognitively healthy subjects relying on accelerometer-based gait event detection [54] and Shannon entropy [53]. However, these temporal assessment methods need large volumes of training data acquired in different conditions, and noise or data perturbation due to external events can affect their accuracy and reliability.

Hybrid Assessment Methods

In order to detect locomotion changes and quantify motor symptoms of HD in premanifest and early stages, it is useful to consider further markers in addition to temporal indicators. Hybrid assessment methods investigate the progression of gait disorders through the different HD stages according to a heterogeneous set of locomotion indicators. In particular, the estimation of gait events related to stance and swing [92], as well as gait cycle variability, proved to be effective in recognizing early and longitudinal gait changes in PwHD [45]. Other works consider gait indicators to measure balance and symmetry in locomotion, which are correlated to walking impairment progression in PwD [45,57]. Those methods apply quantitative phase plot analysis on the sinusoidal consecutive waveforms produced by trunk movement, and statistical assessment methods. However, those systems are subject to possible recognition errors due to gait deterioration not specifically related to HD. The use of particular instruments such as sensorized pressure-based pathways in controlled environments is useful to reduce noise in locomotion data acquisition and to reduce the impact of external factors. Those methods do not support the data acquisition in fully naturalistic conditions, and their cost makes them unsuitable for continuous and large-scale deployments [57].

2.7.4 Challenging Behavior Recognition

In people who suffer from NDD, disorientation, and wandering behaviors can cause potential harm such as accidents, injuries, and sometimes death, which can occur during either the day or night [136]. Therefore, these kinds of behaviors are the main concern for care personnel, as patients require continuous surveillance. Continuous monitoring of patients with NDD is a stressful task, which leads to confinement feelings and immense stress for caregivers. However, it is possible to use AmI and assistive technologies to recognize that *challenging behaviors* which may lead to accidents and injuries in patients with neurocognitive diseases [30, 136]. Generally, when a challenging behavior is recognized, those systems promptly inform the caregiver by issuing an alert or automatically triggering procedures to avoid the occurrence of accidents. For instance, the system may automatically lock doors or use wireless technologies to activate an alarm through the emission of sound or light.

In order to perform accurate motion analysis, those systems use techniques similar to the ones used to recognize symptoms of neurocognitive diseases [105, 136]. Human locomotion data in an indoor environment can be collected by using both device-free and device-based sensing modalities, while systems use in outdoor environments rely on mobile devices. Advanced systems use sensor data fusion methods to improve the accuracy and significance of acquired data. While *Single-modality* methods consist of one or multiple sensors of the same technology, *Multi-modality* methods use different kinds of sensors to acquire multi-modal data. In the following, we present existing challenging behavior detection approaches according to the above-mentioned categories. The main methods are summarized in Table 2.14.

1. **Single-modality methods:** In different works, including [52, 136], the authors use GPS data to detect wandering behaviors, while other works, including [137], use accelerometers for the same objective. Regarding data analysis, the techniques proposed in [52, 136] rely on clustering, while in [52] Lin et al. detect loop-like locomotion traces based on the Martino-Saltzman model [17]. In particular, the work presented in [136] is specifically based on detecting wandering by means of iterative clustering followed by ML. Other approaches monitor patients with cognitive impairment to alert caregivers when they leave the bed or exit the door. In [78] the authors use cameras and background subtraction technologies to model the scene background, together with HMM to automatically detect elopements and alert caregivers. A tool, named AssisT-In, for indoor wayfinding and wandering detection is presented in [82]. It is based on tagging the environment with QR codes, that need to be scanned by the user through a smartphone so that he/she can be located and can receive indications to get to the destination. That method is

Table 2.14: Challenging behavior recognition.

Approaches classification	Diseases	Behaviors	Applications environment	Experiments environment	Sensor technologies	Algorithms
Single-modality	Dementia (+ Parkinson)	Gait disturbance, Wandering, Ambulatory gait behavior	Indoor/ Outdoor	Lab / real-world	Computer vision [78], GPS [52, 136], accelerometer [137], QR codes [82]	Statistical analysis [82], Density-Based Spatial Clustering of Applications with Noise [136], Loop detection method called Θ_WD [52], Analytical algorithm for analyzing acceleration data + K-means clustering to classify the gait variables [137], HMM [78]
Multi-modality	Dementia (+ Parkinson)	Wandering, Disorientation, Limping, Fall detection, Agitation, Localization	Indoor/ Outdoor/ General	Lab / real-world/ Both	GPS [17, 63, 138], accelerometer [63, 105, 138], Computer vision [17], accelerometer, metal plate, Infrared [105], electronic patch, RFID [17], Actillume, StepWatch, Step Sensor, and TriTrac-R3D [77], Optical and video cameras [139]	Proposed algorithm [63], Different ML methods [138], Markov chain model [105], Pedestrian Dead Reckoning, Statistical analysis [17, 77], Multistage spatial-temporal graph convolutional network [139]

simple, inexpensive, and easily deployable. However, the used data localization technology is not well suited for people with cognitive impairment, since QR codes must be frequently scanned. An obvious advantage of single-modality approaches is simplicity; however, noise and heterogeneous environmental conditions can affect the robustness, feasibility, and stability of those approaches.

2. **Multi-modality methods:** With respect to wandering detection, the recognition of more complex challenging behaviors such as persistent, shadowing, pottering, or repetitive behaviors, poses additional issues. Those behaviors are not based only on the patient's trajectory, but also consider environmental conditions, such as the presence or movement of other people. For this reason, some systems, including [17], integrate different technologies such as RFID and GPS. In [105] Homdee et al. use door sensors and wearable devices to detect doorway crossing events and location tracking errors with walking directions by a Markov model method, and provide correct location information using the most likelihood method. In another work [63] the authors use a smartwatch provided with GPS and an accelerometer to detect wandering and to alert the patient's relatives when needed. Moreover, the development of novel treatments for objectively assessing FoG, which is a debilitating gait impairment in PD, is severely limited by its difficulty. Therefore Filtjens et al. [139] used a Vicon 3D motion analysis system, which is a combination of optical and video cameras for FoG assessment. They have formulated it as an

action segmentation problem where temporal models are tasked to recognize and temporally localize the FoG segments. It applies spatial graph convolutions on the human skeleton graph at each time step that connects the same markers across consecutive time steps.

2.8 Conclusion

This chapter introduced a detailed overview of different technologies and AI methods for detecting symptoms of NDD based on locomotion sensor data. We investigated 128 peer-reviewed articles discussing the detection of dementia (37%), HD (11%), and PD (44%) as well as some discussing both dementia and PD (4%) and PD and HD (4%). The experimental results presented in these articles have shown that these new technologies may provide adequate support for practitioners and caregivers to improve diagnosis and simplify patient management, making the detection of NDD symptoms more accessible and beneficial for the research community and for the practice. In the following chapters, we will analyze locomotion traces acquired from a real-world dataset by proposing a novel methodology to detect cognitive impairment symptoms employing thorough experiments.

Chapter 3

Towards Vision-based Analysis of Indoor Trajectories

In the previous chapter, we thoroughly investigated the most prominent methods which have been proposed to exploit IoT data and AI techniques employing locomotion data to support the diagnosis of cognitive decline [12, 140, 141]. In that case, the analysis of position traces can enable us to detect the symptoms of cognitive decline earlier. In this chapter, we present a preliminary investigation of the challenging issue of recognizing symptoms of cognitive decline based solely on the analysis of indoor movement patterns which relies on trajectory segmentation, visual feature extraction from trajectory segments, and vision-based DL on the edge [14]. In order to avoid privacy issues, we rely on indoor localization technologies without the use of cameras. We have carried out experiments with a dataset of real-world trajectories acquired in a smart-home from both cognitively healthy persons and PwD. Initial results show that our approach is promising, and may enable effective cognitive assessment in the long term.

3.1 Introduction

A promising direction in tracking the movements of the elderly through unobtrusive positioning technologies is based on analyzing location traces according to clinical models of wandering behaviors [17, 142]. Indoor wandering recognition is challenging because movements are constrained by the ambient shape, and are impacted by the execution of ADL. Lin et al. proposed a method to identify repetitive locomotion episodes in the home according to well-known models of wandering [143]. Khodabandehloo and Riboni proposed a collaborative mining approach to assess the cognitive status of smart-home inhabitants based on statistical features extracted from their trajectories [144]. Kearns et al. proposed the use of accurate localization technologies deployed in a common indoor living space of a retirement home and measured the tortuosity of trajectories to recognize wandering episodes [145]. As mentioned before, in several studies on the same setup, the authors found out that other features, including speed, path-efficiency, and angle-turn, were predictive of dementia [62]. Other studies such as Dodge et al. work [146] showed that the relation between walking velocity and activity patterns was significantly correlated to the cognitive status of the inhabitant.

Indeed, due to the abundance of Spatio-temporal information encoded by movement traces, and the presence of noise introduced by positioning technologies, feature engineering from trajectory data is not a trivial task. For this reason, a recent research direction consists of encoding trajectories into images and using DNNs for image classification. The rationale of this approach is that trajectory images may effectively capture discriminative features without the need for sophisticated feature engineering efforts.

Kieu et al. used trajectories in the form of 3D images containing geographical features and driving behavior features to predict the identity of drivers [147]. They applied unsupervised auto-encoder neural networks to avoid over-fitting and supervised neural networks to identify drivers. Endo et al. used DNNs as an automatic feature extraction method, along with handcrafted features, for estimating users' transportation modes from images of their travel trajectories [148]. Transportation modes were recognized using supervised learning methods. In this chapter, we investigate the application of image-based trajectory classification to the domain of cognitive assessment. To the best of our knowledge, only one previous work adopted a similar work in the same domain. Gochoo et al. in [3] represent trajectories in a 2-dimensional grid, in which one dimension is time, and the other is (mono-dimensional) space. They map each 3-dimensional Spatio-temporal trajectory point into the 2-dimensional grid. The corresponding binary image is then classified using convolutional DNNs to recognize different patterns of wandering behavior. However, as a consequence of the mapping, the spatial information is disrupted, since metric operations and topological relationships are not preserved.

In our work, we pursue a different direction, retaining the spatial information in trajectory images, and enriching them with additional visual features that may indicate cognitive decline according to clinical models of spatial disorientation [15]. Our method relies on specific techniques for trajectory segmentation, visual feature extraction, and DNN-based trajectory image classification. For the sake of privacy, all these operations are executed on the edge, within the inhabitant smart-home system. However, it is not the best approach to assure privacy, and the images themselves reveal details about the layout of homes and potentially violate privacy. Therefore, it will be discussed in detail in Chapter 6. The DNN is trained on the cloud by a trusted third party based on anonymous data, and the trained model is fed to individual smart-homes.

3.2 System Overview

In this chapter, we assume a smart-home infrastructure capable of continuously monitoring the inhabitant's position at a fine-grained level. Regarding the use of single-resident smart-home infrastructure, our system may extract position information not only from localization infrastructures but also based on the inhabitant's interaction with sensorized objects and appliances.

Fig. 3.1 illustrates our system architecture. A sensor-based infrastructure is in charge of gathering data about the inhabitant's position (e.g., through PIR sensors), and about

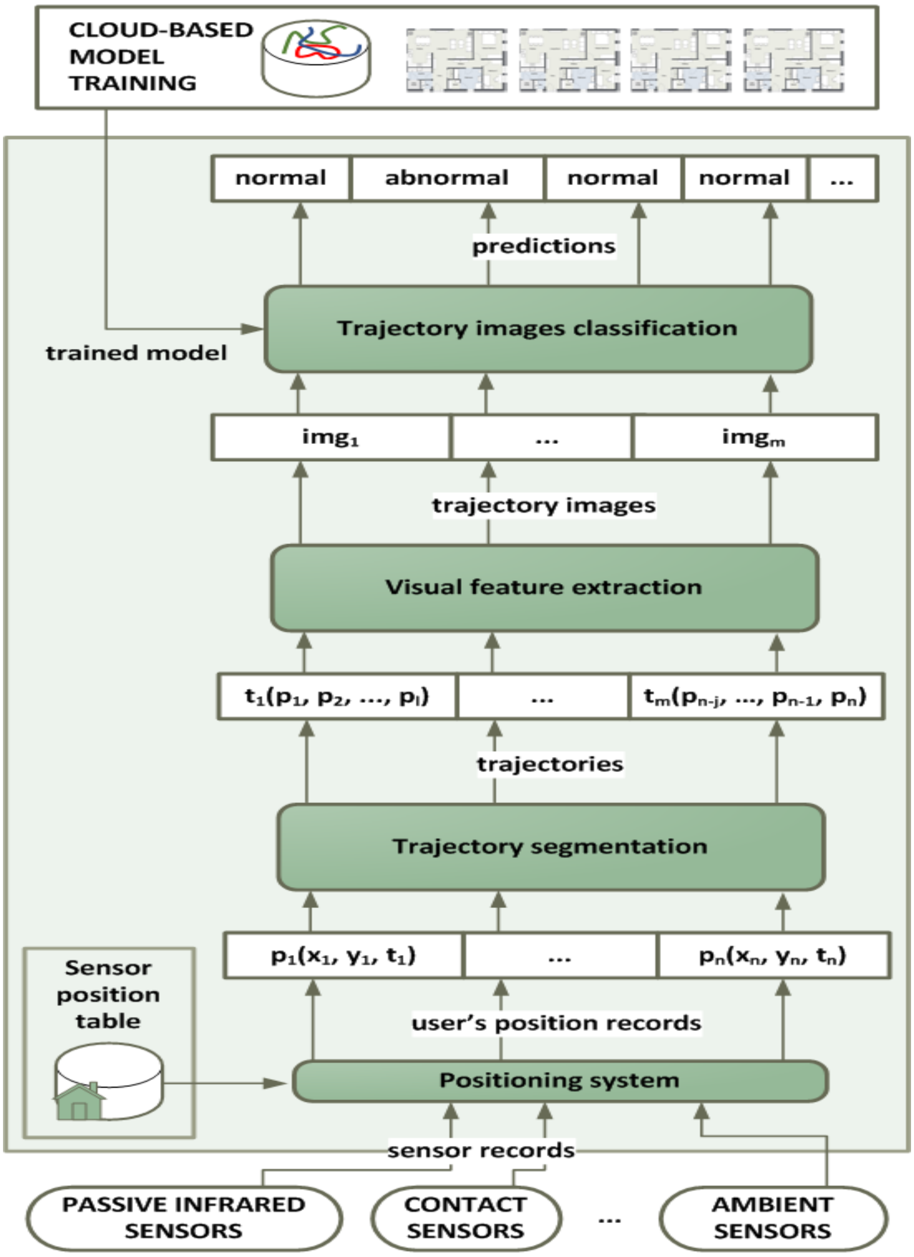


Figure 3.1: The proposed system overview.

his/her interaction with the environment. At each firing of a sensor, the infrastructure sends a **sensor record** r to the positioning system of the home:

$$r = \langle t, s\_id, v \rangle,$$

where t is the timestamp of sensor firing, s_id is the sensor's unique identifier, and v is the sensor value. For instance, the sensor record:

$$r = \langle \mathit{2020\text{-}04\text{-}05\ 16{:}46{:}18.323,\ sens5371,\ open} \rangle,$$

states that the sensor identified as ‘sens5371’ (which is a sensor attached to the fridge door) fired a value ‘open’ at timestamp ‘2020-04-05 16:46:18.323’. A sensor position table stores the relative position of each sensor in the home. A record of sensor position is a triple:

$$\langle s\_id, (x, y)\rangle,$$

where s_id is the sensor’s identifier, and (x, y) are the relative coordinates of that sensor in the home. When the positioning system receives a sensor record, it joins the record with the position table and projects the coordinates and timestamp values, to obtain a **position record** p:

$$p = \langle x, y, t\rangle,$$

The trajectory segmentation module is in charge of partitioning the temporal stream of position records into trajectory segments, named **trajectories** for short in the following. Trajectories are temporally contiguous sequences of positions of a given length l_s; for instance, l_s may be set to $50m$. Each trajectory t_i is passed to the visual feature extraction module, which outputs an image *img*$_i$ representing the walked trajectory and highlighting additional visual features, such as the points of trajectory intersection.

The trajectory images classification module is in charge of classifying each trajectory as either normal or abnormal. To this aim, it uses a DL classifier trained on the cloud using a set of anonymous trajectories labeled according to the cognitive health status of the individual: PwD are assumed to walk abnormal trajectories, while cognitively healthy persons are assumed to walk normal ones.

3.3 Trajectory Feature Extraction

In this section, we explain how we segmented the history $P = \langle p_1, \ldots, p_n\rangle$ of the person’s position records and how we extracted visual features.

In real-world conditions, noise reduction is an inevitable step in preparing the data. For this reason, we applied two noise reduction methods to the position history P:

- We set a threshold T_v for the maximum possible velocity v of a person moving into the home. If the speed between any two consecutive position records $\langle p_i, p_{i+1}\rangle \in P$ is higher than T_v, the record p_{i+1} is considered a noisy reading; hence, it is deleted from P. For the sake of this work, we set T_v to $15\, m/s$.

- By considering the arrangement of sensors in the test-bed of our experiments, the maximum distance between any two adjacent sensors is below $3\, m$. By carefully analyzing the person’s trajectories, we observed that some paths spatially deviated from the expected trajectory due to abrupt movements between non-contiguous sensors. In this regard, if the distance between the positions of two consecutive records $\langle p_i, p_{i+1}\rangle \in P$ exceeds a threshold T_d (which is set to $5\, m$), we remove p_{i+1} from P.

After noise removal, the trajectory segmentation module is in charge of identifying trajectories by considering spatial information. To this aim, the position history P is partitioned into a set T of non-overlapping trajectories:

$$T = \{t_1, t_2, \ldots, t_m\},$$

where each trajectory $t \in T$ is a temporal sequence of consecutive position records:

$$t = \langle p_j, p_{j+1}, \ldots, p_k \rangle.$$

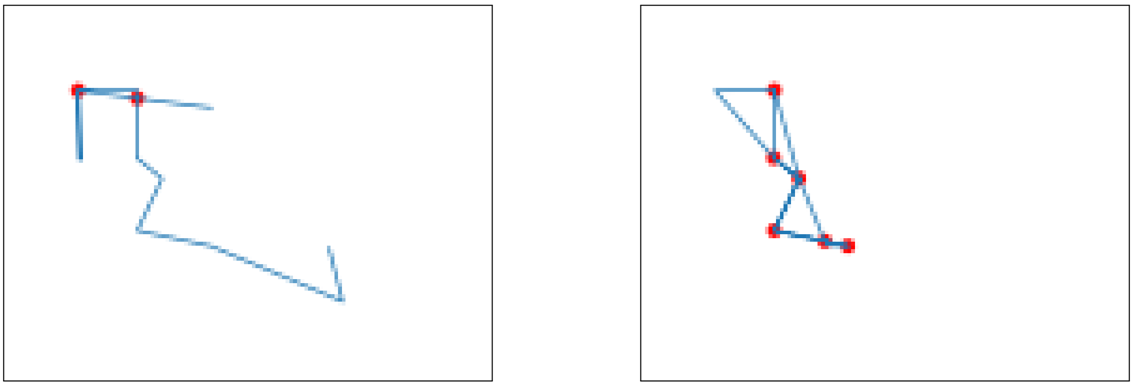
The segmentation algorithm partitions P into trajectories whose length is approximately equal to a given value l. In our experiments, we evaluated different values of l, ranging from 25m to 150m. The first trajectory is initialized with the first entry of P, and continues until the overall distance (computed as the summation of the distance between each of two consecutive position records) exceeds l. The next trajectory is initialized with the last entry of the previous one, and continues until its length exceeds l; and so on, until the end of P.

The next step is visual feature extraction, which consists in representing each trajectory through an image that visually encodes its salient features. Since visual feature extraction from trajectories is a challenging task, to exploit DNN's performance, there is a need to have sufficient informative data. Unfortunately, as we increase the resolution of trajectory images, the sparsity of non-zero pixels also increases. The latter effect may decrease the generalization capability of a DNN [148]. Images with low resolution reduce the sparsity problem, but low resolution may determine the loss of multiple information corresponding to the same pixel. Moreover, the accuracy of such classification models highly depends on the number of samples and on the architecture of the neural network [3]. After considering different resolutions, we set the images to 100×130 pixels resolution. Hence, based on the smart-home area, each pixel represented one square decimeter of the area. As explained below, the images have three colors. The image color is encoded in the third dimension of each pixel.

As mentioned before, wandering is a complex behavior, and there is still no complete agreement on its definition. However, one common component in the different definitions of wandering is disorderliness in the individual's movements [33]. In this regard, the visual extraction module plots the whole trajectory in its corresponding image in blue color, in order to visually represent the trajectory's complexity. Moreover, in order to emphasize the intricacy of the trajectory, the module computes the intersection points between each line in the trajectory and depicts it in the image by a red circle. Considering image resolution and test-bed size, the circle radius measures $0.25m$. Fig. 3.2 shows the images obtained through visual feature extraction of two sample trajectories, walked by a cognitively healthy person and by one person with dementia, respectively.

3.4 Vision-based Trajectory Classification

Fig. 3.3 illustrates our framework for cloud-based model training. Anonymous trajectory images are collaboratively collected from a set of inhabitants. As mentioned in Section 3.2, images are annotated as either normal or abnormal according to the cognitive status of the inhabitant that walked the corresponding trajectory. As shown in Fig. 3.1,



(a) Trajectory image of a cognitively healthy senior.

(b) Trajectory image of a PwD.

Figure 3.2: Trajectory images example.

after applying supervised learning with a DNN, the trained model is released to the individual systems to classify novel trajectories walked by the local inhabitant.

The pre-processing component image conversion is in charge of converting each trajectory image to a flat feature vector based on its width, height, and color value of each pixel. Then, labels are added to the feature vectors in order to train the network. The architecture of the used model for this binary classification task is depicted in the trajectory image-based DNN architecture of Fig. 3.3. We have used MLP DNN to distinguish normal from abnormal trajectories based on their images. In order to fine-tune the DNN, we tested the different number of neurons (from 32 to 128), hidden layers (from 1 to 4), batch sizes (from 32 to 256), activation functions, and also hyper-parameters for regularization and learning rate reduction. In the rest of the chapter, we referred to the configuration that achieved the highest recognition rates. The presented MLP is composed of three fully connected (dense) layers: one input layer, one hidden layer, and one output layer, with 32 neurons for the input and hidden layers, and 1 neuron for the output layer. The layers used the *Rectified Linear Units (ReLU)* function as the activation function. Since we faced a binary classification problem, we chose the Sigmoid function as the activation function on the output layer. Furthermore, all layers are followed by Batch Normalization and Dropout layers in order to speed up learning, increase the stability of the neural network, and significantly reduce over-fitting. Therefore, we have used a low learning rate, set to 0.0001, with Adam optimizer. This solution allows for major improvements over other regularization methods [149, 150]. The fraction to drop units has been set at 0.5. As a loss function, we have used binary cross-entropy.

The neural network needs to start with some weights and refine them iteratively. To this aim, we used the He_uniform distribution Kernel Initializer for obtaining the initial weights. Furthermore, we used Mini-batch gradient descent (Batch Size) that divides the training dataset into small batches to calculate model error and update model coefficients. Mini-batch gradient descent achieves robust convergence avoiding local minima, and performs a computationally efficient process, without the need of keeping all training

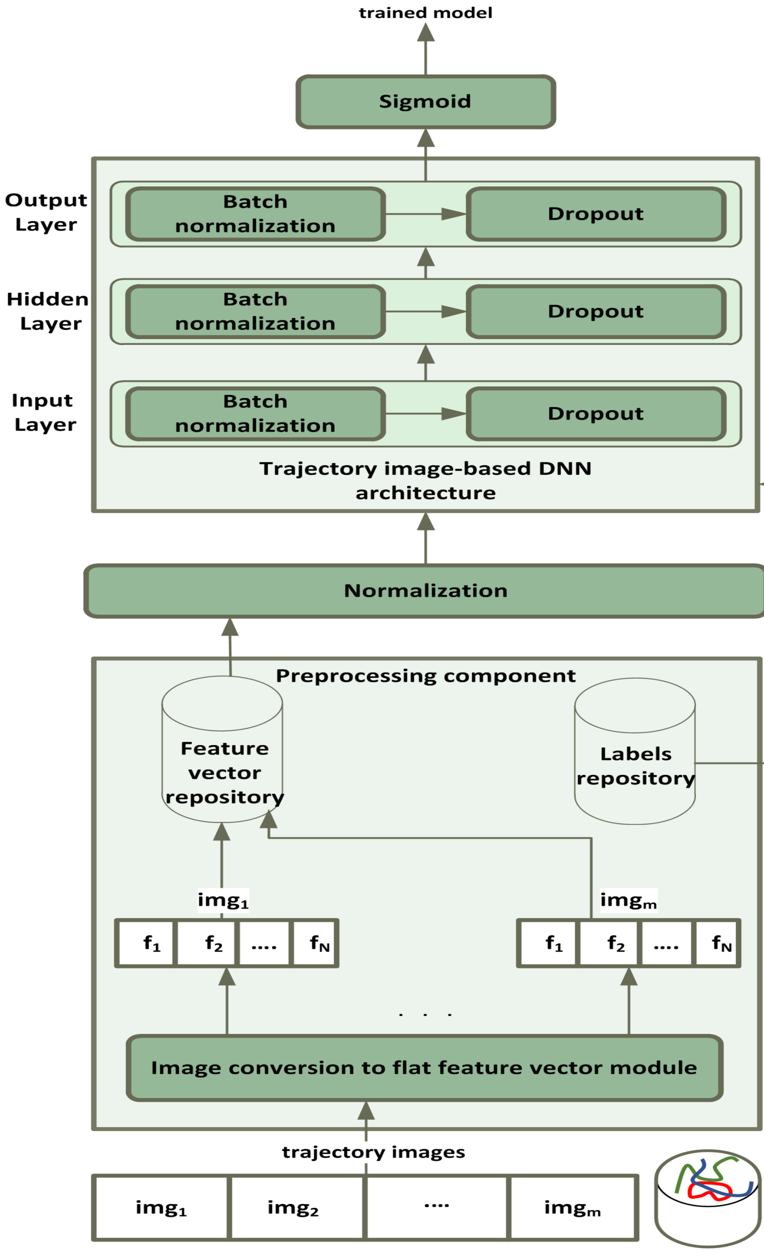


Figure 3.3: Cloud-based model training architecture.

data in main memory [151]. The Batch Size is set to 128.

In order to have an adaptive learning rate, we also used the ReduceLROnPlateau callback to reduce the learning rate [151]. This callback is used to fine-tune model weights when there is no change for a 'patience' (set to 5) number of epochs and monitors a metric that is specified by the 'monitor' argument (set to 'val_loss'). In this regard, by considering 10% of trajectories for the validation set and monitoring the validation loss, the learning rate will be reduced by an order of magnitude if the validation loss does not improve. The new learning rate is the result of multiplying the recent learning rate by a ‘factor’ argument, which is set to 0.1. To focus on significant changes, the ‘min_delta’ argument, which is a threshold for measuring the new optimum, is set to $1E-7$.

3.5 Experimental Evaluation

We conclude this chapter by briefly evaluating our proposed architecture in terms of the considered dataset, setup and requirements, the experimental results, and future directions.

3.5.1 Dataset

The experiments are based on real-world trajectories acquired in a smart-home of the CASAS test-bed [152]. That dataset was acquired from a total of 400 individuals and annotated by the researchers of the *Center for Advanced Studies in Adaptive Systems (CASAS)* at Washington State University (WSU) [140]. The smart-home layout is represented in Fig. 3.4.

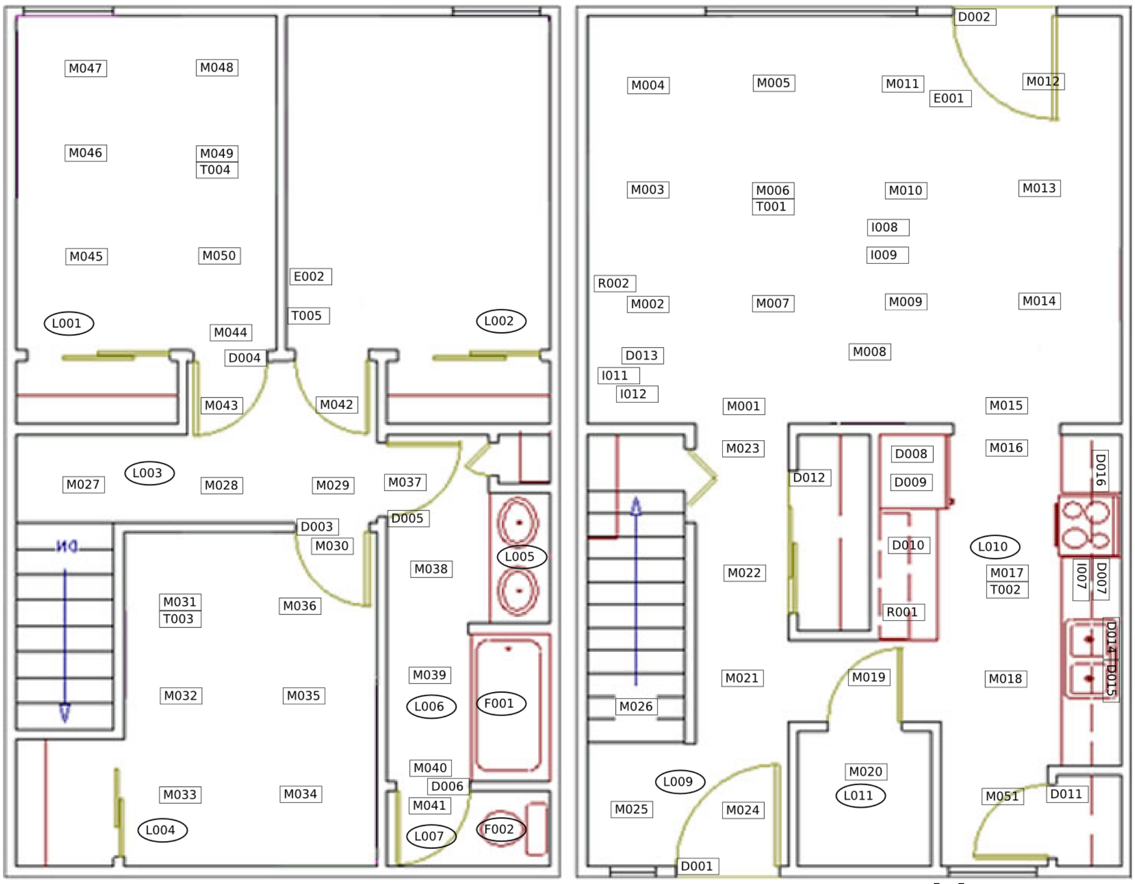


Figure 3.4: The smart-home layout used in our experiments [2].

The smart-home is a two-story apartment equipped with different kinds of sensors, and its floor plan includes a living/dining room, three bedrooms, a kitchen, and a bathroom. During the data acquisition phase, the researchers asked the participants to perform a set of scripted activities in the home, such as preparing a meal and cleaning. The smart-home included a living/dining room, three bedrooms, a kitchen, and a bathroom, and was equipped with different kinds of sensors. For the sake of our experiments, we relied on PIR motion sensors and door sensors to track the movements of the individuals in the home. PIR sensors are mounted on the ceiling and their accuracy is about one meter. In total, the apartment included 51 motion sensors and 16 door sensors.

Participants were recruited by advertisement and physician referrals. After obtaining informed consent, participants underwent multidimensional clinical examination by neuropsychologists, in order to assess their cognitive health status. For the sake of anonymity, explicit identifiers of the individuals involved in the study were removed, and quasi-identifier personal data, such as age, were generalized to age ranges. The protocol of recruiting and data collection was approved by the Institutional Review Board of WSU [140]. As a consequence of clinical examination, each participant was classified as either PwD, a person with MCI, or a cognitively healthy person.

MCI is considered an intermediate phase between cognitive healthiness and dementia. Previous studies showed that it is difficult to distinguish MCI from the other two classes based on IoT solutions [140,141]. Hence, for the sake of this work, we simplify the problem by considering only PwD and cognitively healthy seniors.

Participants were asked to individually execute scripted *Day Out Tasks (DOTs)* in the smart-home test-bed. DOTs are naturalistic tasks involving the execution of interleaved activities for reaching a certain goal [153]. Each participant executed the DOTs in a single day for an average of three hours. Data collection occurred in the morning or in the early afternoon. During the execution of DOTs, the sensor infrastructure acquired the sensor data triggered by their actions and movements. The detailed descriptions of DOTs, together with the collected dataset, are available on the Web[1]. The smart-home setup is described in detail in [154]. We considered those PwD who were able to carry out activities in the home (19 individuals), and young-old seniors aged 60 to 74 years old (80 individuals).

Table 3.1 reports the average number of trajectories per person of the considered classes. The average numbers are very close for the two classes. However, there is more variability (larger value of *STandard Deviation (STD)* in PwD. STD in the table is an indicator of different total trajectory lengths for patients. As patients did not have an equal walk in the home, consequently the number of trajectory images per patient varies. By increasing the length of the segment (from $25m$ to $150m$), the number of images for each patient and consequently STD for different segment lengths decreased. The total number of samples in different length trajectories are 7759 in $25m$, 4011 in $50m$, 2715 in $75m$, 2053 in $100m$, 1657 in $125m$ and 1389 in $150m$ trajectories.

3.5.2 Setup

In order to develop our system, we have used Python, using the Keras neural network library[2]. We have run experiments on a departmental Linux server with *Graphics Pro-*

[1] http://casas.wsu.edu/datasets/assessmentdata.zip
[2] https://keras.io/

Table 3.1: Average number of trajectories per person.

Trajectory length	Cognitively healthy	PwD
$25m$	$78.40(\pm 17.09)$	$78.26\ (\pm 27.67)$
$50m$	$40.49\ (\pm 8.82)$	$40.63\ (\pm 14.21)$
$75m$	$27.41\ (\pm 5.95)$	$27.47\ (\pm 9.60)$
$100m$	$20.74\ (\pm 4.42)$	$20.74\ (\pm 7.28)$
$125m$	$16.73\ (\pm 3.60)$	$16.79\ (\pm 5.70)$
$150m$	$14.03\ (\pm 2.95)$	$14.05\ (\pm 4.90)$

Table 3.2: Results of vision-based classification according to different lengths of trajectory segmentation.

Comparison of segmented trajectories by different lengths							
Measures		25m	50m	75m	100m	125m	150m
Micro	Precision	**69.32%**	63.72%	57%	61.97%	63.75%	65.51%
	Recall	83.07%	**85.64%**	83.06%	85.24%	84.71%	83.62%
	F1-score	**75.58%**	73.07%	67.6%	71.76%	72.75%	73.46%
Macro	Precision	54.5%	**59.5%**	54%	58.5%	58%	56%
	Recall	53.5%	**56.5%**	52.5%	55.5%	55%	54%
	F1-score	53%	**54.5%**	49.5%	53.5%	53.5%	52.5
Classification time per image		~ 0.001875s	~ 0.00326s	~ 0.00441625s	~ 0.005726s	~ 0.007s	~ 0.00785s

cessing Unit (GPU) acceleration.

To evaluate the effectiveness of visual feature extraction, we have experimented with different trajectory lengths, ranging from $25m$ to $150m$. We applied a *leave one person out* cross-validation approach to keep one participant's image trajectories as a test set and the remaining ones for the train set and validation set. Since the presented model requires tuning of hyper-parameters, training trajectories are split by a fraction of 10% for validation and 90% for training.

It should be mentioned that the performance measure 'accuracy', which is the total number of correct predictions divided by the total number of predictions, is inappropriate for imbalanced classification problems such as the one we are tackling. Indeed, depending on how severe the class imbalance is, the accuracy value regarding the majority class would overwhelm the accuracy value of the minority class. Hence, for evaluating the overall performance of our technique, we use the metrics of precision, recall, and F_1 score, which are standard metrics in imbalanced classification problems. In particular, the macro-averaged F_1 score is well representative of the classification performance, since gives the same weight to the performance of both classes, despite the distribution of instances in the classes.

3.5.3 Experimental Results

In our experiments, we evaluate the effectiveness of the DNN classifier in correctly recognizing the cognitive status of a person given the observation of a single trajectory walked by him/her. According to the results shown in Table 3.2, among different fixed lengths from $25m$ up to $150m$, the best results are achieved using $50m$ trajectories. Indeed, trajectory images with $50m$ length obtained the best performance in distinguishing between PwD and cognitively healthy seniors in terms of macro-averaged F_1 score.

Considering the confusion matrices illustrated in Tables 3.3b and 3.3d, for trajectories with lengths ranging from 50m to $125m$, the ratio of correct classification is over 50%

classified as →	Normal	Abnormal
Normal	**4348**	1924
Abnormal	**886**	601

(a) $25m$ length

classified as →	Normal	Abnormal
Normal	**2064**	1175
Abnormal	346	**426**

(b) $50m$ length

classified as →	Normal	Abnormal
Normal	**1250**	943
Abnormal	255	**267**

(c) $75m$ length

classified as →	Normal	Abnormal
Normal	**1028**	631
Abnormal	178	**216**

(d) $100m$ length

classified as →	Normal	Abnormal
Normal	**853**	485
Abnormal	154	**165**

(e) $125m$ length

classified as →	Normal	Abnormal
Normal	**735**	387
Abnormal	**144**	123

(f) $150m$ length

Table 3.3: Confusion matrices of vision-based classification according to different lengths of trajectory segmentation.

in both classes. Based on an analysis of the results, we noticed that if the length of the trajectory is too small, the shapes of the trajectories of different patients tend to be similar, and consequently, the model cannot distinguish the different classes. If the length of the trajectory is too large, the shapes of trajectories become very involved and difficult to distinguish from each other. Hence, optimal results are achieved by a compromise between long and short trajectories.

As mentioned before, in this dataset, the ratio of trajectories walked by healthy seniors vs. PwD is highly imbalanced, at about a $5:1$ ratio. As it can be seen in Table 3.2, in all experiments, micro-averaged values are higher than macro-averaged ones. This result is due to the fact that the DNN is biased toward predicting the most frequent class.

Moreover, in order to evaluate the feasibility of executing our methods on the edge, we measured the execution times of trajectory image classification. It should be mentioned that the execution time of trajectories grows with the length of the trajectory. However, as shown in Table 3.2, the classification time of a single trajectory image is in the order of milliseconds.

In general, we can conclude that the classification of a single trajectory does not provide a reliable prediction of the cognitive status of the subject. However, we observe that, with trajectory lengths ranging from $50m$ to $125m$, the most frequently predicted classes are the correct ones. For instance, with the length of $50m$, 426 trajectories of PwD were correct as abnormal, while only 346 of them were classified as normal. Moreover, 2064 trajectories of cognitively healthy seniors were classified as normal, and only 1175 of them were classified as abnormal. Hence, we believe that a long-term analysis of trajectories may support reliable cognitive assessment; however, this hypothesis should be supported by further research and experiments.

3.6 Conclusion

In this chapter, we tackled the challenging issue of recognizing symptoms of cognitive decline based on the analysis of indoor movements. To this aim, we proposed a technique to extract visual features from indoor trajectories, and a deep learning model for classification. Experiments with a real-world dataset collected from both cognitively healthy seniors and PwD suggested that a long-term analysis of the predictions may achieve promising results.

Furthermore, our experiments have shown that trajectory segmentation has a strong impact on the classification results. Hence, we have to investigate more sophisticated methods for segmentation, including not only spatial but also temporal conditions. Visual feature extraction could be improved by adding some other useful characteristics, such as speed, or abrupt changes in direction. The neural network model should also be refined to exploit visual features. Finally, in the next chapter, we will investigate a technique for long-term analysis of predictions in order to support a reliable assessment of the cognitive status over time.

Chapter 4

The TraMiner Framework

In order to get rid of the noise introduced by indoor constraints and activity execution, and employ important clinical indicators for accurate assessment which support MCI subjects as well, we introduce novel visual feature extraction methods from locomotion data collected by sensors embedded in the environment considering both spatial and temporal aspect of movements. This method is in a framework which in general is called *TraMiner*. We carried out extensive experiments with a large dataset acquired in a smart-home test-bed from 153 seniors, including people with cognitive diseases. Results show that our system can accurately recognize the cognitive status of the senior, reaching a macro F_1 score of 0.873 for the three categories that we target: cognitive health, MCI, and dementia. Moreover, an experimental comparison shows that our system outperforms state-of-the-art methods.

4.1 Introduction

In this chapter, we contribute to propose *TraMiner*, a novel system based on Trajectory Mining for continuous cognitive assessment in smart-homes. Our system relies on clinical indicators that characterize cognitive decline in terms of abnormal locomotion patterns of the elderly, as mentioned in the Chapter 2.

We have taken a different approach compared to the preliminary investigation presented in Chapter 3, representing locomotion traces through images and relying on DL for the classification of those images according to the cognitive health status of the inhabitant. Our method relies on specific techniques for locomotion data cleaning and segmentation. Each locomotion segment is transformed into two images that capture different aspects related to the clinical indicators of locomotion anomalies. Each couple of images is fed to a DL classifier in charge of predicting the anomaly level of the corresponding locomotion segment. Since it would be unrealistic to provide a hypothesis of diagnosis based on the observation of a single trajectory, our system includes a long-term analysis module. The latter is in charge of processing the history of DL predictions for computing a hypothesis of diagnosis, which is provided to clinicians for supporting the neuropsychological assessment.

We have developed a prototype of our TraMiner system and carried out extensive experiments with a real-world dataset [2] gathered in a smart-home test-bed with 153 seniors, including cognitively healthy subjects, people with MCI [155], and PwD. This dataset is described thoroughly in Section 3.5.1. Results proved the accuracy of TraMiner in predicting the cognitive health status of the inhabitants. Indeed, based on the observation of the locomotion traces acquired during one day per patient, our system achieved a macro F_1 score of 0.873. Moreover, an experimental comparison showed the superiority of our approach with respect to state-of-the-art techniques. In order to enable the full reproducibility of our experiments, we have released the code of all our system components, and the used dataset is available on the Web [1]. Hence, we extend the preliminary version of locomotion analysis, discussed in Chapter 3 in detail, considering general indicators (i.e., complex gait parameters) and indicators of dementia, explained in Chapter 2, and introduce new framework with:

i. Support for recognition of MCI,
ii. A novel locomotion trace segmentation algorithm,
iii. A new visual feature extraction technique,
iv. A novel two-input DL architecture,
v. An additional algorithm for long-term assessment of the cognitive health status,
vi. Experiments with a larger dataset,
vii. New experiments to evaluate all the components of our system,
viii. An experimental comparison with state-of-the-art techniques, and
ix. A dashboard is accessible on the Web to inspect the visual features and the system predictions.

In fact, the theoretical basis of the proposed TraMiner system is based on complex gait parameters of general indicators' category (including Jerk, Turning angle, Sharp angle, Straightness, and Path-efficiency) and dementia trajectory-based indicators (i.e, direct, random, pacing, and lapping). Several random, pacing and lapping patterns can be observed in the home, which is actually due to the normal execution of ADL by cognitively healthy inhabitants. Hence, in this system, we do not aim at explicitly recognizing those patterns, but we rely on a supervised learning approach for recognizing abnormal locomotion patterns.

4.2 TraMiner System Overview

This system regarding the usage of a single resident smart-home infrastructure is capable of continuously monitoring the inhabitant's position at a fine-grained level. Moreover, seniors living alone may have particular benefits from remote monitoring and assessment of cognitive functions.

Fig. 4.1 illustrates the TraMiner architecture. Since the focus of this chapter is on processing locomotion data, the core methods of our contribution are largely independent of

[1] https://sites.unica.it/domusafe/traminer/

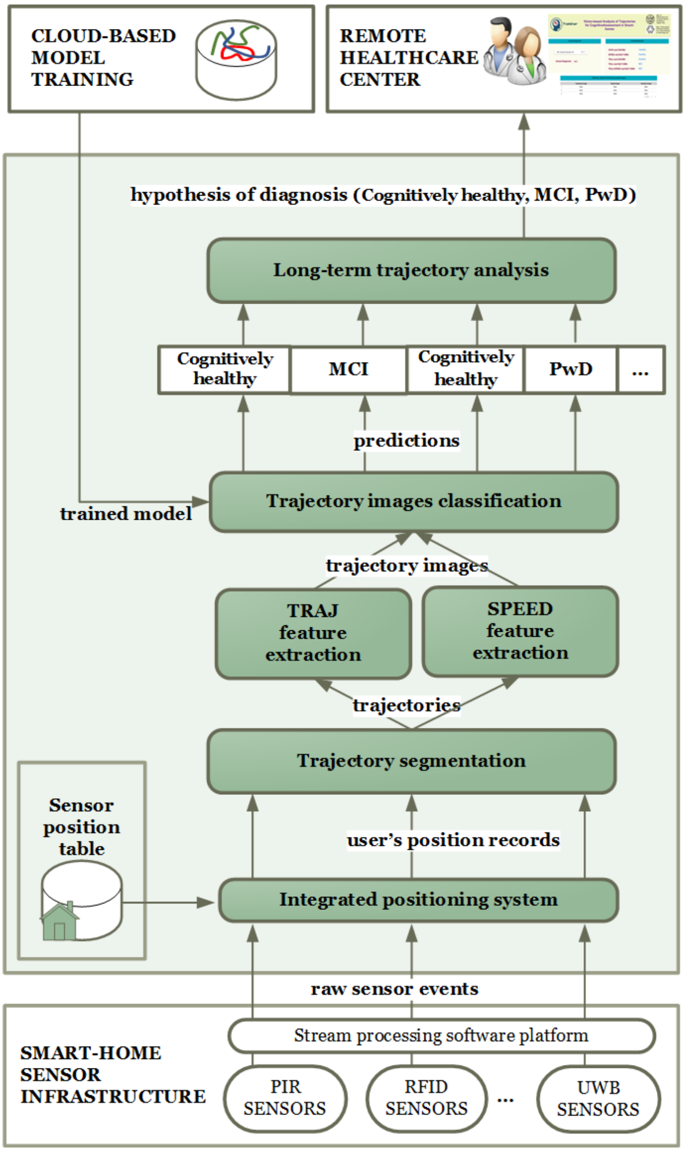


Figure 4.1: Overview of the TraMiner system.

the available sensor infrastructure. We assume that a smart-home sensor infrastructure is in charge of continuously gathering data about the inhabitant's position; e.g., through PIR sensors. The smart-home system communicates raw sensor data to a stream processing software platform (e.g., Apache Kafka) for integration and temporal synchronization.

As mentioned in the Chapter 3, each time a sensor fires, the platform sends a **raw sensor event** to the TraMiner system:

$$rse = \langle t, s\_id, v \rangle,$$

where t is the timestamp of firing, s_id is the sensor's unique identifier, and v is the generated value. Since we assume that the home is inhabited by a single individual, we are not interested in associating the sensor record with the person that triggered it.

Likewise, the integrated positioning system is in charge of deriving Spatio-temporal information from raw sensor events. To this aim, it relies on a **sensor position table** storing the relative position of each sensor in the home. A record of sensor position in that table is a triple:

$$\langle s\_id, (x, y) \rangle,$$

where (x, y) are the relative coordinates of the sensor identified by 's_id' in the home. For the sake of simplicity, we consider only static sensors in the home; hence, we assume that the position of sensors does not change with time. Each time the integrated positioning system receives a raw sensor event, it joins the corresponding record with the sensor position table to obtain the (x, y) coordinates, producing a **user's position record**:

$$r = \langle p, t \rangle,$$

where $p = (x, y)$ are the relative coordinates of the sensor that fired at time t.

The trajectory segmentation module is in charge of reducing noise in the data and partitioning the temporal stream of position records into **trajectories**. A trajectory is a temporally contiguous sequence of positions that corresponds to a locomotion episode.

Each trajectory is passed to the modules for traj and speed feature extraction. Those modules represent the trajectory as an image each. The two images represent the walked trajectory in a 2-dimensional space and highlight different visual features, such as speed and intersection points.

The trajectory images classification module is in charge of classifying each trajectory as either walked by a cognitively healthy person, MCI individual, or PwD. To this aim, it uses a DL classifier processing the two images corresponding to each trajectory. The classifier is trained on the cloud using a set of anonymous trajectories labeled according to the cognitive health status of the individual. According to the history of predictions, the long-term trajectory analysis module computes a hypothesis of diagnosis for the individual. The hypothesis may be *cognitively healthy*, *MCI*, or *PwD*. Finally, the hypothesis of diagnosis is communicated to the remote healthcare center, to support the clinicians in the evaluation of the patient.

4.3 Trajectory Segmentation and Visual Feature Extraction

This section reports the details of modules in charge of trajectory segmentation and visual feature extraction.

4.3.1 Position Data Cleaning and Trajectory Segmentation

As explained before, the integrated positioning system continuously provides TraMiner with the user's position records. These records instantiate the **position history** $H = \langle r_1, r_2, \ldots, r_n \rangle$, which is the temporal sequence of the user's positions records. Inevitably, the position history contains inaccuracies because, in real-world conditions, sensor data are affected by a relevant level of noise. Therefore, in order to noise reduction, like what is done in the preliminary version of TraMiner in Chapter 3, we manually analyzed the Spatio-temporal information of the dataset used in our experiments by plotting movement traces over the home layout. We observed several unfeasible deviations from the expected trajectories, which were due to wrong position detection by the positioning system. Hence, the trajectory segmentation module performs noise reduction by considering the maximum possible velocity v of a person moving in the home (which is set to $15\,m/s$) and the maximum distance between any two adjacent sensors (which is set to $5\,m$).

Likewise, after position data cleaning, the trajectory segmentation module is in charge of partitioning the de-noised H into **trajectories** by considering temporal and spatial information. In this regard, the position history H is partitioned into a set T of non-overlapping trajectories:

$$T = \{t_1, t_2, \dots, t_m\},$$

where each trajectory $t \in T$ is a temporal sequence of consecutive position records:

$$t = \langle p_j, p_{j+1}, \dots, p_k \rangle \in H.$$

A trajectory consists of locomotion and non-locomotion phases. The non-locomotion phases happen during a time interval between any two consecutive sensor activations that do not exceed a given threshold T_s. In our experiments, we evaluate different values of T_s ranging from $30s$ to $180s$. The rationale of our segmentation algorithm is that a phase of non-locomotion may happen in a trajectory if no sensor is triggered for less than T_s. Otherwise, if no user movement is detected for more than T_s, the previous trajectory is completed, and a new one is initialized.

Our segmentation algorithm initializes the first trajectory with the first entry of H, and each trajectory t_i is a temporal sequence of consecutive position records from H such that the time interval between any two consecutive position records does not exceed T_s. The next trajectory is initialized with the last entry of the previous trajectory and continues until the threshold condition is met. The algorithm continues until the end of H.

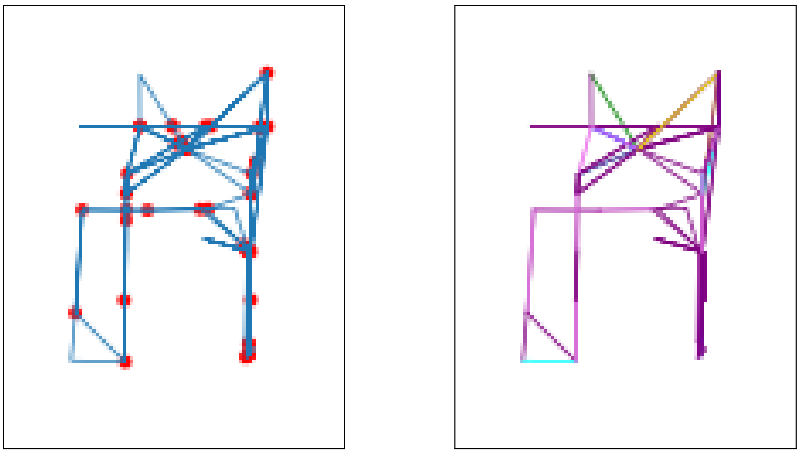
4.3.2 Visual Feature Extraction

In order to prepare input data for the DNN, the modules for traj and speed feature extraction are in charge of visually representing the salient features of each trajectory through images. To prepare the images, we use the RGB color model. Hence, each image has three colors: red, green, and blue. For every pixel, the values related to these colors are represented by a byte each. Hence, each pixel is characterized by three integer values ranging from 0 to 255. In our work, the maximum spatial extent of all the trajectories is the same and corresponds to the home layout.

Choosing the image size is an important aspect of feature extraction. By increasing the resolution of the image, the sparsity of non-zero pixels in the image increases, and may decrease the learning capability of the DNN [148]. Low-resolution images can alleviate this issue; however, important information in the image could be lost, since the values of multiple contiguous pixels could be mixed. After considering different resolutions for the images, for our experimental setup, we chose image length and height of 100 by 130 pixels. By considering the size of our smart-home test-bed, each pixel in the image corresponds to approximately $0.1\,m^2$.

TRAJ Feature Extraction

Fig. 4.2a shows an example of an image obtained using the TRAJ feature extraction method from a person's trajectory in our smart-home test-bed.



(a) TRAJ feature extraction. (b) SPEED feature extraction.

Figure 4.2: Example of visual feature extraction from a trajectory.

The trajectory path is shown through a monochrome line string. The weight of each line is set according to the number of times that the corresponding path has been walked. The line weight is 1 if the path has been walked only once; the weight is 2 if it has been walked twice, and so on. Consequently, lines corresponding to paths walked several times are bolder than those of paths walked sporadically. This feature extraction method allows us to visually capture locomotion anomalies corresponding to the pacing and lapping patterns defined by the Martino-Saltzman model [17].

For emphasizing the intricacy of the trajectory, which may indicate a random walk according to the Martino-Saltzman model [17], the intersection points between the trajectory lines are shown in the image as a red circle. By considering the image size, the radius of that circle corresponds to $0.25m$.

Moreover, the trajectory line string naturally encodes low-level motion indicators such as sharp angles, straightness, turning angle, and path efficiency.

SPEED Feature Extraction

Patterns of locomotion speed are important indicators of cognitive decline. However, speed information is not captured by the TRAJ feature extraction method. Hence, TraMiner produces a second image of the trajectory, using the SPEED feature extraction method. Fig. 4.2b shows an image obtained using the SPEED method from a person's trajectory in our experimental test-bed.

With this method, the trajectory is partitioned into sections, such as the speed of the inhabitant is steady in each section. The color of each section depends on its speed range. When a section is walked multiple times, the most recent speed of that section is considered for drawing the image. For the sake of this work, we consider 7 different speed ranges, with 7 associated colors. In particular, the speed ranges are $0-2$, $2-4$, $4-6$, $6-8$, $8-10$, $10-12$, $12-14$, and more than $15ms$, and the corresponding colors are purple, violet, blue, cyan, green, yellow, orange, and red, respectively. Of course, some of those speed ranges are exaggerated when referring to people moving inside an apartment. The explanation is that the positioning infrastructure used in our experimental test-bed has approximately 1 meter resolution, and (being based on PIR technology) the detection range of sensors partially overlaps. For this reason, the computed speed is inevitably approximated and subject to errors. However, as confirmed by our experimental results, those approximated speed values are useful to improve the recognition performance of our system. The SPEED feature extraction method allows capturing the jerk low-level motion indicator.

4.4 DNN Trajectory Classification and Long-term Analysis

In this section, we present the DNN trajectory image classification method and the long-term analysis module.

4.4.1 Cloud-based Model Training

The goal of the cloud-based model training module is to train a DNN model to classify every trajectory as either walked by a cognitively healthy subject, by a person with MCI, or by PwD. To this aim, we take a collaborative approach. That module periodically receives a training set of trajectory images from the local instances of the TraMiner system, running in the individual homes. Each image is labeled with the cognitive status of the anonymous inhabitant (i.e., either 'cognitively healthy', 'MCI', or 'PwD'). Trajectory images are locally computed on the edge by the different instances of TraMiner, as explained in Section 3.3. Based on that training set, the trusted cloud-based module is in charge of training a DNN model for trajectory classification. The TraMiner local instances receive the model from the cloud and use it for classifying the trajectories of the inhabitant. Note that the TraMiner instances do not receive any trajectory image. Indeed, for the sake of privacy, trajectory images are processed only by the trusted cloud module.

Fig. 4.3 shows the MLP DNN architecture used by the cloud-based infrastructure. For each trajectory, the MLP DNN takes as input two images. The first one is obtained through the TRAJ feature extraction method as shown in Fig. 4.2a, while the second one is obtained through SPEED feature extraction as shown in Fig. 4.2b.

Since we use two images with different features for each trajectory, our model relies on 'mixed data'. Developing systems capable of handling mixed data is still an open area of research, and can be challenging since each input with a different feature representation may require separate preprocessing steps. In order to prepare the trajectory images for training, we convert them to flat feature vectors based on the width, height, and color values of each pixel. Hence, since images have 100 by 130 pixels, and each pixel is represented by three color values, each feature vector has a size $39,000$. So, each fea-

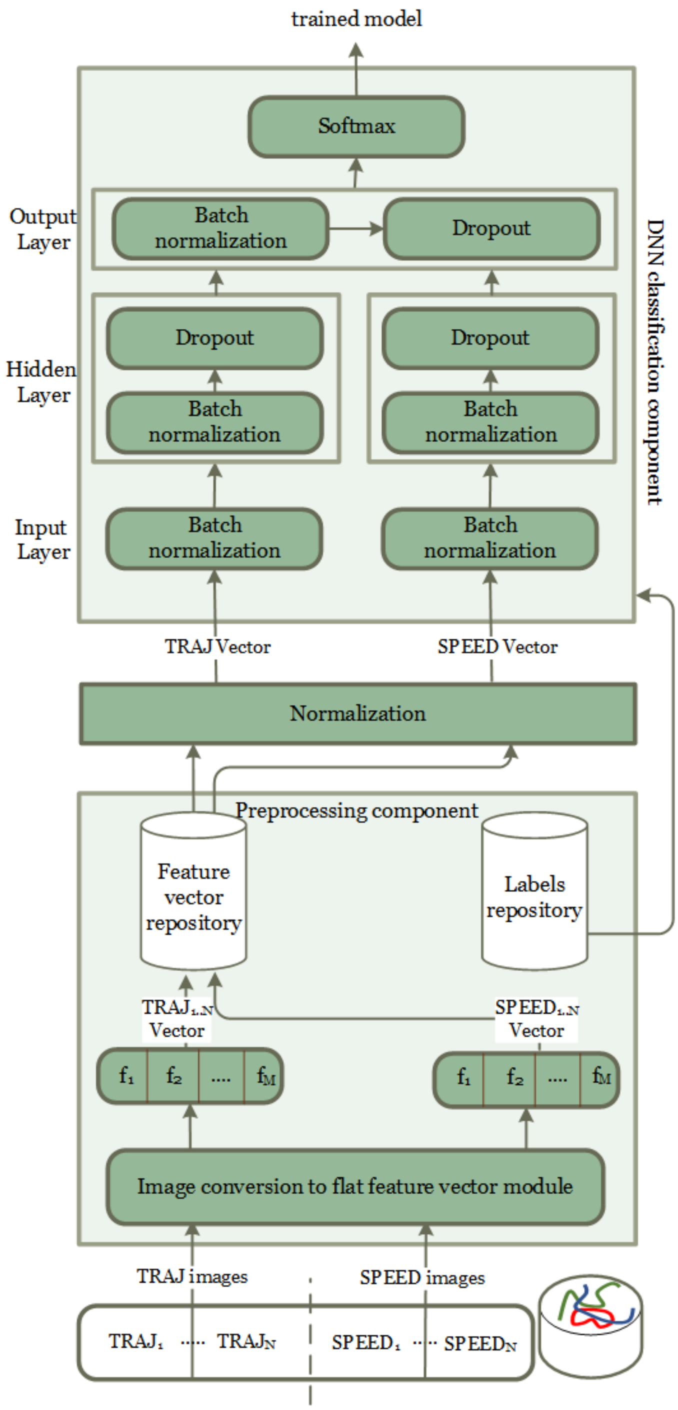


Figure 4.3: Cloud-based model training MLP DNN architecture.

ture corresponds to the color value of a single pixel. Then, we apply binarization to the color values of the image to reduce the computational cost of training. Finally, we add the labels to the feature vectors before feeding them to the DNN for training.

The used MLP DNN for each input is composed of two fully connected (dense) layers:

one input layer and one hidden layer, with 32 neurons for both. The layers used the ReLU as the activation function. Furthermore, for both inputs, each layer is followed by batch normalization to speed up learning and increase the stability of the neural network. In the last layer for each of them, there is also a dropout layer in order to significantly reduce over-fitting. The fraction of drop units has been set to 0.5. Then, we combine the output of both inputs (TRAJ and SPEED) and apply one more fully connected layer with three neurons followed by batch normalization and dropout with the same drop units. Since we are facing a three-class classification problem, we have chosen the softmax function as the activation function on the final output layer. This function is used to find a probability distribution of the mentioned categories as follows:

$$p(k) = \frac{g_s}{\sum_{j=1}^{N_c} g_j}, g_i = max(0, \sum_i f_i.w_{ij} + h_j)$$

where $p(k)$ is the probability of a trajectory belonging to the k-th class, and g_s is a standard exponential function applied to each element of the input vector. This function gives a positive value above zero, which will be very large if the input was large and very small if the input was negative. Furthermore, N_c denotes the number of classes, f_i is a value of i-th neuron in the last fully connected layer, w_{ij} and h_j are coefficients of the softmax function [3].

Furthermore, we have used a low learning rate, set to 0.00001, with adam optimizer. As a loss function, we have used category cross-entropy, which is an effective loss function for classification problems that have softmax activation function in the output layer. This loss function is based on the maximum likelihood estimate approach and it is used for single label categorization [156]. In our case, this ensures that a trajectory belongs to exactly one class.

We have used a batch-size approach to calculate the model error and to update the model coefficients. We divided the training dataset into small batches of 64 samples which are utilized in one epoch. In order to fine-tune the number of epochs, we have used the *early stopping* procedure. We tested different numbers of epochs, ranging from 20 to 100 epochs. According to this procedure, the training is stopped when the generalization error increases. Therefore, we evaluated the model during training on a holdout validation set after each epoch. When the performance of the model starts to degrade (i.e., the loss begins to increase), the training process is stopped. In the represented configuration, the number of epochs was set to 27. With this approach, we improved the computational efficiency of the learning process, without the need of keeping all training data in the main memory. The approach also provides robust convergence, avoiding local minima [151].

4.4.2 Long-term Trajectory Analysis

As shown in Figure 3.1, the trained model is communicated to the trajectory images classification module of the individual smart-home systems, which uses it for trajectory image classification as soon as new trajectories are observed in the home. Finally, the classification predictions are processed by the long-term trajectory analysis module, which is in charge of computing a hypothesis of diagnosis regarding the inhabitant's cognitive health (i.e., cognitively healthy subject, MCI, or PwD).

The aim of that module is to generate a hypothesis of diagnosis based on the long-term predictions of the vision-based trajectory classifier. Of course, in order to produce a reliable hypothesis, the long-term analysis module needs a sufficient quantity of trajectory classifications. Therefore, it is assumed that the module considers the whole data acquired in a given time period; e.g., all the predictions about the trajectories observed in the previous 30 days. The module analyses the whole history of vision-based trajectory classifications produced in that period as VTC:

$$VTC = \{class_1,\ class_2,\ \dots,\ class_m\},$$

where the value of $class_i$ can be either *'cognitively healthy'*, *'MCI'*, or *'PwD'*. Also, there is a need to compute the number of predictions of each class in VTC. Then, the module outputs the hypothesis corresponding to the most frequent class fc as follows:

$$fc = arg\,max_{class \in D} \,|\, \{cl \in VTC : cl = class\} \,|,$$

where $D = \{$'cognitively healthy', 'MCI', 'PwD'$\}$.

4.5 Experimental Evaluation

In this section, we report our experimental evaluation which was carried out with real-world locomotion data acquired in an instrumented smart-home from a large set of seniors, including cognitively healthy seniors, PwD, and persons with MCI. Therefore, in the following subsections, we explain the used dataset, the experimental setup, and the achieved results. We also experimentally compare our technique with existing state-of-the-art methods which will be described in the following sections.

4.5.1 Dataset

The experiments were carried out considering real-world trajectories acquired from 153 individuals in a smart-home of the CASAS test-bed [152] such as the preliminary version. Likewise, for our experiments, we relied on PIR motion sensors and door sensors to track the movements of the individuals in the home.

As mentioned before, in this data set, after clinical examination the participants were classified as either PwD, persons with MCI, or cognitively healthy persons.

While 40 PwD were recruited, only part of them was able to participate in the data collection in the smart-home. Hence, in our experiments, we considered only PwD who were able to carry out activities in the home (19 individuals). Moreover, we considered the data acquired from the 80 seniors aged 60 to 74 years old as cognitively healthy persons, and from the 54 persons with MCI.

4.5.2 Comparison with State-of-the-Art Methods

In order to experimentally compare our method with the state-of-the-art, we implemented both a baseline numeric feature extraction method and the image-based method proposed by Gochoo et al. in [3].

State-of-the-Art Numeric Feature Extraction

As a comparison, we implemented a baseline feature extraction method, in which each feature corresponds to a locomotion-based clinical indicator of cognitive decline proposed in the literature. We call this method *Numeric Feature Eextraction* (NFE). We consider the following indicators:

- *Pacing* [17] travel pattern, defined in the Martino-Saltzman model: this feature counts the number of observations of pacing in the last day.
- *Lapping* [17] travel pattern, defined in the Martino-Saltzman model: this feature counts the number of observations of lapping in the last day.
- *Random* [17] travel pattern, defined in the Martino-Saltzman model: this feature counts the number of observations of random on the last day.
- *Jerk* [157] is computed as the first time derivative of acceleration. This feature represents the average jerk observed in the individual's trajectories on the last day.
- *Straightness* [158] represents the average straightness computed on the individual's trajectories of the last day.
- *Sharp angles* [159] feature counts the number of sharp angles observed in the individual's trajectories during the last day.

In order to compute the above-mentioned indicators, we adopt the algorithms presented in [160].

State-of-the-Art Gochoo Visual Feature Extraction

In the original paper where the method proposed by Gochoo et al. [3], the *Gochoo Visual Feature Extraction (GVFE)* technique was used to recognize those abnormal locomotion patterns that are strong indicators of neurocognitive diseases according to the Martino-Saltzman model [17]; i.e., pacing, lapping, and random patterns. The authors experimented with their GVFE technique in the same smart-home environment used in our experiments, with data acquired from a cognitively healthy senior over 21 months. They obtained very good results, achieving accuracy above 97%. Those results indicate that the GVFE technique is effective in recognizing abnormal travel patterns that indicate cognitive impairment. For this reason, we experimentally compare the GVFE technique with our visual feature extraction method.

In the GVFE technique, images in each trajectory are prepared based on the sequence of activation of the position sensors. Each trajectory is converted to a binary image, where the x axis represents the temporal order of the sensor activation, and the y axis represents the numeric identifier of the fired sensors. For example, suppose that the temporal sequence of activated motion sensors in a trajectory is: M005, M003, M005, M010, M011, and M001. Then, the only non-zero pixels in the image correspond to the following coordinates: $(1,5),(2,3),(3,5),(4,10),(5,11),(6,1)$.

Also for GVFE method, we apply trajectory segmentation using different values of the threshold T_s. The width of the corresponding image is chosen based on the maximum length of trajectories. For example, in our dataset, using $T_s = 60\,s$, the maximum

Figure 4.4: Example of images generated through the GVFE method. The left-hand side image is extracted from a trajectory using $T_s = 90\,s$. The right-hand side image is extracted from a trajectory using $T_s = 150\,s$.

length of trajectory for all considered individuals is 32. Hence, images computed using that threshold value have 32 pixels width.

As mentioned before, the y axis represents the numerical identifier of the fired sensor. Since in our dataset we consider 67 sensors (i.e., 51 PIR sensors and 16 door sensors), the y axis includes 67 different values. Consequently, the images have 67 pixels in height, irrespectively from the value of the threshold T_s. For thresholds T_s set to $30\,s$, $60\,s$, $90\,s$, $120\,s$, and $150\,s$, the image size is (14×67), (32×67), (60×67), (110×67) and (169×67), respectively. Fig. 4.4 shows two samples of images obtained using different threshold values.

State-of-the-Art Deep CNN

In order to compare our DNN architecture with a state-of-the-art one, we consider the *Deep CNN (DCNN)* used by Gochoo et al. in [3]. As illustrated in Fig. 4.5, that network has three zero padding convolution layers and three fully connected layers which are followed by max-pooling layers and feature filters size of 5×5. The pooling window size is set to 2×2 and, since max-pooling creates a smaller version of input maps, the output images become two times smaller than the input. The first convolution layer has 32 kernels, the second one, which receives the output of the first max-pooling layer as inputs, has 128 feature filters, and the last convolutional layer receives the second max-pooling layer output and convolutes them with 256 feature filters.

Finally, in the fully connected part, the layers are flattened, and the output of the third max-pooling layer is converted into a feature vector. In this part, the first, second, and third fully connected layers have 512, 128, and 64 neurons, respectively, and neurons of the last fully connected layer are connected to all three outputs; i.e., cognitively healthy, MCI, PwD. In order to find the probability distribution of the classes, the softmax function is applied.

Since the reference paper [3] does not mention internal details such as the used optimizer and its rate, or the chosen loss function, we used the same parameters chosen for

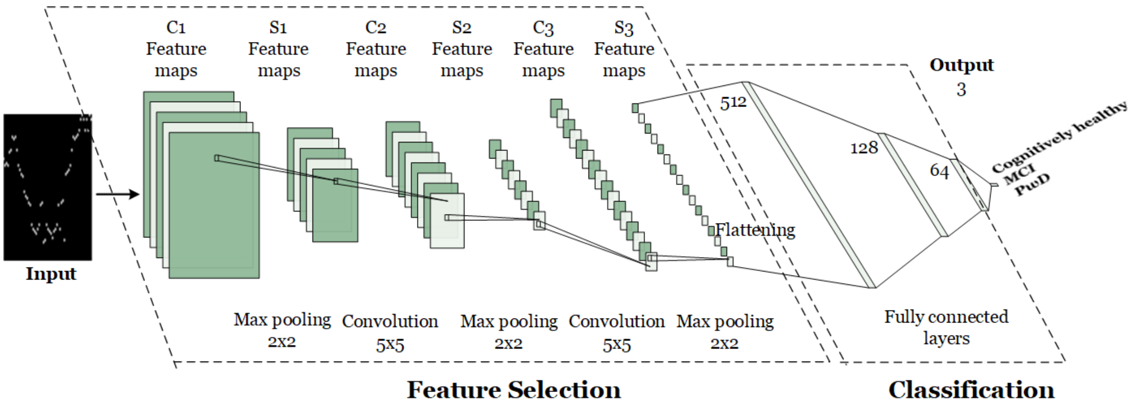


Figure 4.5: The state-of-the-art DCNN used by Gochoo et al. in [3].

our proposed DNN configuration described in Section 4.4.

4.5.3 Experimental Setup

We developed all the algorithms in Python. For experimenting with the NFE method, we used the machine learning algorithms implemented by the Weka toolkit [161]. The code for extracting the NFE features is available online[2]. We have used the Python Keras neural network library[3] to develop the proposed DNN classification systems. In order to support scalability, in the general architecture of our system we envision the use of a cloud-based system for training the DNN model. However, given the relatively small size of the training set used in our experiments, we trained the DNN on a departmental server. We have run experiments on a Linux server with four NVIDIA Tesla p6 graphic boards, a single NVIDIA Pascal GP104 GPU, and 16 GB GDDR5 memory. To evaluate the effectiveness of our TRAJ and SPEED visual feature extraction techniques, we have experimented with different values of the T_s threshold for trajectory segmentation, ranging from 30 seconds up to 180 seconds. We also developed the feature extraction method and the DCNN used by Gochoo et al. [3] to experimentally compare our methods with the state-of-the-art.

In all the experiments, we applied a *leave one person out* cross-validation approach: we used the data of one individual for the test set, and the data of the other persons for training and validation, iterating on each person to execute the tests on the whole considered participants. With this approach, the data of the same person is never used both for training/validation and testing at the same time. For tuning the hyper-parameters of the DNN, training trajectories are split by a fraction of 10% of each category for validation and 90% of them for training.

For the overall performance evaluation, we have used the metrics of macro precision, macro recall, and macro F_1 score. These metrics are standard ones for imbalanced problems. In particular, the macro F_1 score is a reliable metric in imbalanced cases, since it gives equal weights to the different classes, despite their size. Since the 'accuracy' performance measure is inappropriate for imbalanced classification problems like the one

[2]https://sites.unica.it/domusafe/healthxai/
[3]https://keras.io/

we are tackling, we do not consider that measure in our evaluation. Indeed, depending on the degree of imbalance, the majority class's accuracy value would overcome the accuracy value of the minority classes.

4.5.4 Results of NFE Method

At first, we evaluated the NFE method explained in Section 4.5.2. For each participant, we built the feature vector using all the trajectory data collected during the day. Each feature vector was labeled with the cognitive status of the individual; i.e., cognitively healthy, MCI, or PwD. We experimented with several classifiers:

- The well-known *NB* [162] classifier;
- *LR* classifier [163], relying on a multinomial logistic regression model with a ridge estimator;
- *MLP* feed-forward artificial neural network algorithm;
- *SVM* [164]
- *kNN* [165] lazy classifier, with $k = 5$;
- *Ripper* [166] propositional rule learner;
- *C4.5* [167] DT;
- *Random tree* [168] classifier.
- *RF* [169] classifier.

Results are reported in Table 4.1. Overall, the results achieved by the NFE method are poor. Indeed, all classifiers achieved a macro-average F_1 score close to the one of a random classifier. The classifier achieving the best performance in this pool of experiments is the RF algorithm, with F_1 score of 0.37. These results seem to indicate that, in a home context, numerical statistics about locomotion-based indicators of cognitive decline are ineffective for automatic cognitive assessment. This fact is probably due to the high level of noise introduced by two factors that influence the movement patterns; i.e., obstacles in the home, and execution of ADL.

4.5.5 Results of Single Trajectory Image Classification

At first, we experimentally compare the effectiveness of our TRAJ feature extraction method with the one achieved using Gochoo's visual feature extraction (GVFE) method. For this experiment, we used the DCNN used by Gochoo's et al. In this regard, we want to assess the ability to correctly recognize the cognitive status of a person by the observation of a single trajectory walked by him/her.

According to the results shown in Table 4.2, for both techniques, the best results are achieved with the trajectories obtained setting $T_s = 120s$. As it can be observed in Fig. 4.6, the technique using TRAJ and DCNN slightly outperforms the one relying on GVFE and DCNN in terms of macro F_1 score.

However, the results achieved using those methods are rather poor, since the best achieved F_1 scores only slightly outperform the ones that would be obtained using a random classifier. The poor performance of the GVFE technique in the task of recognizing

Table 4.1: Results of NFE method.

Class	Measure	NB	LR	MLP	SVM
Cognitively healthy	F_1 score	0.50	**0.69**	0.65	**0.69**
	Precision	**0.56**	0.55	0.53	0.53
	Recall	0.45	0.91	0.84	**1.00**
MCI	F_1 score	**0.46**	0.32	0.25	0.04
	Precision	0.38	0.57	0.39	**1.00**
	Recall	**0.59**	0.22	0.19	0.02
PwD	F_1 score	0.00	n/a	n/a	n/a
	Precision	0.00	n/a	n/a	n/a
	Recall	0.00	0.00	0.00	0.00
Avg.	F_1 score	0.32	n/a	n/a	n/a
	Precision	0.31	n/a	n/a	n/a
	Recall	0.35	**0.38**	0.34	0.34

Class	Measure	kNN	Ripper	C4.5	Rand. tree	RF
Cognitively healthy	F_1 score	0.61	**0.68**	0.59	0.54	0.64
	Precision	0.55	0.53	0.47	0.55	**0.56**
	Recall	0.68	**0.93**	0.79	0.54	0.74
MCI	F_1 score	**0.43**	0.21	0.00	0.34	0.39
	Precision	0.46	**0.50**	0.00	0.35	0.44
	Recall	**0.41**	0.13	0.00	0.33	0.35
PwD	F_1 score	0.00	n/a	0.00	0.00	**0.08**
	Precision	0.00	n/a	0.00	0.00	**0.20**
	Recall	0.00	0.00	0.00	0.00	**0.05**
Avg.	F_1 score	0.35	n/a	0.20	0.29	**0.37**
	Precision	0.34	n/a	0.16	0.30	**0.40**
	Recall	0.36	0.35	0.26	0.29	**0.38**

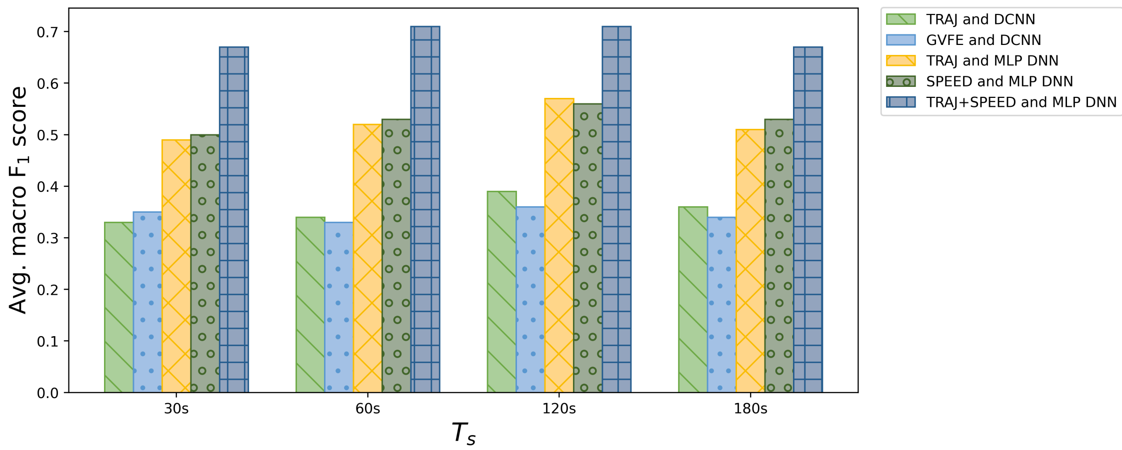


Figure 4.6: Trajectory images classification: macro F_1 score for the different techniques.

the cognitive status of the individual may be explained by the fact that, as we argue in the previous chapters, indoor movements are constrained by the ambient shape, and are impacted by the execution of ADL. Hence, the GVFE technique may classify as abnormal several normal trajectories walked by cognitively healthy individuals.

In the second set of experiments, we compare the performance of the TRAJ vs SPEED

Table 4.2: Trajectory images classification: results obtained using our TRAJ feature extraction method and DCNN vs. GVFE and DCNN.

Class	Measure	TRAJ and DCNN				GVFE and DCNN			
		30s	60s	120s	180	30s	60s	120s	180s
Cognitively healthy	F_1 score	0.54	0.52	**0.57**	**0.57**	**0.57**	**0.57**	0.56	0.55
	Precision	0.57	0.53	**0.62**	0.6	**0.62**	**0.62**	0.6	0.57
	Recall	0.51	0.5	0.52	**0.53**	0.53	0.52	0.53	**0.54**
MCI	F_1 score	0.34	0.36	**0.5**	0.38	0.36	0.36	**0.4**	0.35
	Precision	0.33	0.36	0.4	**0.37**	0.34	0.34	**0.39**	0.35
	Recall	0.35	0.37	**0.41**	0.39	0.38	0.38	**0.41**	0.36
PwD	F_1 score	0.12	**0.13**	0.1	0.12	0.11	0.056	**0.13**	0.11
	Precision	0.1	**0.11**	0.08	0.08	0.09	0.04	**0.1**	0.09
	Recall	0.14	0.15	0.13	**0.18**	0.15	0.081	**0.17**	0.13
Avg.	F_1 score	0.33	0.34	**0.39**	0.36	0.35	0.33	**0.36**	0.34
	Precision	0.33	0.33	**0.37**	0.35	0.35	0.33	**0.36**	0.34
	Recall	0.33	0.34	0.35	**0.37**	0.35	0.33	**0.37**	0.34

feature extraction methods, using our MLP DNN. Table 4.3 shows the achieved results. The two feature extraction methods achieve comparable results. As it can be observed in Fig. 4.6, for both methods, the best results in terms of average macro F_1 score are obtained using $T_s = 120s$. It is evident that the results obtained using the TRAJ feature extraction method with our MLP DNN strongly improved with respect to using the DCNN. Indeed, using the MLP DNN we achieve a macro F_1 score larger than 0.57 with less computation time, while the best macro F_1 score obtained using the more complex DCNN was close to 0.36. We believe that this result may depend on the relatively limited size of the training set. Indeed, using a larger training set, the more complex DCNN could possibly outperform the MLP DNN, at the cost of additional time and resource consumption. Due to these results, in the rest of the experiments, we use our MLP DNN for performing the classification tasks.

Table 4.3: Trajectory images classification: results of our TRAJ vs SPEED feature extraction methods, using our MLP DNN.

Class	Measure	TRAJ and MLP DNN				SPEED and MLP DNN			
		30s	60s	120s	180	30s	60s	120s	180s
Cognitively healthy	F_1 score	0.62	**0.67**	**0.67**	0.64	0.62	0.66	**0.72**	0.67
	Precision	0.56	**0.65**	0.62	0.59	0.56	0.66	**0.7**	0.64
	Recall	0.68	0.69	**0.72**	0.69	0.68	0.65	**0.74**	0.7
MCI	F_1 score	0.5	0.55	**0.58**	0.56	0.53	0.52	**0.59**	0.57
	Precision	0.46	0.5	**0.52**	**0.52**	0.51	0.46	0.55	**0.56**
	Recall	0.56	0.62	**0.65**	0.6	0.56	0.61	**0.64**	0.59
PwD	F_1 score	0.35	0.34	**0.47**	0.33	0.37	**0.42**	0.39	0.35
	Precision	0.58	0.49	**0.75**	0.54	**0.56**	**0.56**	0.51	0.45
	Recall	0.25	0.27	**0.34**	0.24	0.28	**0.34**	0.31	0.28
Avg.	F_1 score	0.49	0.52	**0.57**	0.51	0.50	0.53	**0.56**	0.53
	Precision	0.53	0.54	**0.63**	0.55	0.54	0.56	**0.58**	0.55
	Recall	0.49	0.46	**0.57**	0.51	0.51	0.53	**0.56**	0.52

4.5.6 Results of Two Input Trajectory Images Classification

Since the results obtained using separately the TRAJ and SPEED techniques are encouraging, we perform additional experiments using both TRAJ and SPEED trajectory images as input to our proposed MLP DNN. Indeed, since TRAJ and SPEED images represent different features of trajectories, their combined use may increase recognition rates. This setup corresponds to the TraMiner architecture shown in Fig. 3.1 and Fig. 4.3.

The achieved results are presented in Table 4.4. Like in the previous experiments, the best results in terms of macro F_1 score are obtained using $T_s = 120s$. Also in this experiment, the worse results are obtained using threshold values of $30s$ and $180s$. Considering these results, as also shown in Fig. 4.6, it is evident that the combined use of TRAJ and SPEED features significantly improves the recognition performance with respect to the use of the single feature extraction methods. Indeed, the best achieved F_1 score is larger than 0.71, while the single feature extraction methods achieve F_1 scores close to 0.57.

The detailed results can be inspected through the confusion matrices reported in Table 4.5. By observing the confusion matrices, it is evident that the total number of samples changes depending on the chosen value of T_s. For instance, with $T_s = 30s$ we have $5, 195$ trajectories, while with $T_s = 180s$ we have only 540 trajectories. Indeed, in general, the lower the threshold for trajectory segmentation, the larger the number of generated trajectories. Hence, by using larger values of T_s we obtain a smaller number of samples, but we can encode more information in the single trajectory images since trajectories are generally longer. On the negative side, too large values of T_s may determine very involved images, which may confuse the DNN. On the contrary, too small values of T_s may determine very short trajectories, that do not encode enough information for the DNN. According to our experiments, the value $T_s = 120s$ provides a good trade-off in this sense.

Table 4.4: Trajectory images classification: results of our TRAJ+SPEED model and MLP DNN.

Class	**Measure**	**TRAJ+SPEED and MLP DNN**			
		30s	**60s**	**120**	**180s**
Cognitively healthy	F_1 score	0.79	**0.82**	0.8	0.79
	Precision	0.73	**0.81**	0.76	0.74
	Recall	**0.86**	0.84	0.85	0.84
MCI	F_1 score	0.74	0.74	**0.76**	0.72
	Precision	0.67	0.64	0.68	**0.69**
	Recall	0.84	**0.86**	**0.86**	0.78
PwD	F_1 score	0.49	0.56	**0.58**	0.52
	Precision	0.81	0.82	**0.89**	0.39
	Recall	0.35	0.43	0.43	**0.77**
Avg.	F_1 score	0.67	**0.71**	**0.71**	0.67
	Precision	0.73	0.75	**0.77**	0.61
	Recall	0.68	0.71	0.71	**0.79**

However, the achieved results, which are computed on the classification of single trajectories in isolation, are not sufficient for providing a reliable hypothesis about the

Table 4.5: Trajectory images classification: confusion matrices of our TRAJ+SPEED model and MLP DNN.

(a) $T_s = 30s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.73**	0.08	0.19
MCI	0.13	**0.67**	0.21
PwD	0.14	0.05	**0.81**

(b) $T_s = 60s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.81**	0.07	0.12
MCI	0.16	**0.64**	0.20
PwD	0.16	0.02	**0.82**

(c) $T_s = 120s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.76**	0.07	0.17
MCI	0.16	**0.68**	0.16
PwD	0.10	0.01	**0.89**

(d) $T_s = 180s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.74**	0.11	0.15
MCI	0.18	**0.69**	0.12
PwD	0.09	0.14	**0.77**

cognitive status of the individual. For this reason, in the following experiments, we evaluate the performance of the module for long-term trajectory analysis, which considers the whole history of trajectories acquired during a certain period of time.

4.5.7 Results of Long-term Trajectory Analysis

In these experiments, we apply the algorithm for the long-term analysis described in Section 4.4.2 with all the different techniques for trajectory image classification evaluated in Sections 4.5.5 and 4.5.6. Fig. 4.7 provides an overview of the achieved results.

As expected, the results achieved using DCNN with the TRAJ or GVFE feature extraction methods are rather poor. Indeed, those techniques achieve the lowest recognition rates for trajectory image classification. In particular, the TRAJ method with DCNN achieves an F_1 score slightly larger than 0.4 with $T_s = 120s$. Its F_1 score is lower than the other values of the threshold. The best result of the GVFE method with DCNN is similar but obtained with $T_s = 60s$. Overall, these two techniques do not provide significant results for cognitive assessment, even in the long term.

Results are significantly better using our MLP DNN with the TRAJ or SPEED feature extraction methods. For both techniques, the best results are obtained using $T_s = 120s$. In particular, the TRAJ method achieves a macro F_1 score of 0.7, while the SPEED method

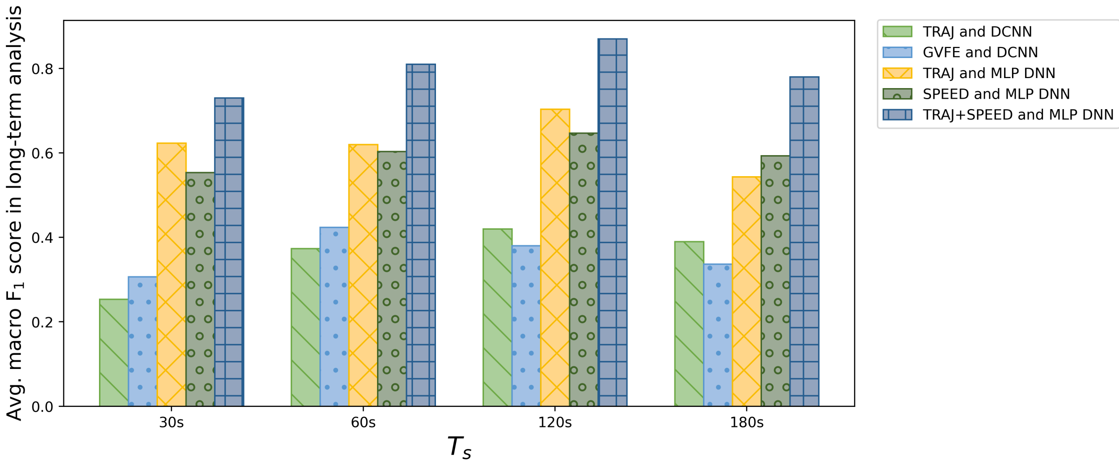


Figure 4.7: Long-term analysis: macro F_1 score for the different techniques.

Table 4.6: Long-term analysis: results obtained using two input trajectory images classification (TRAJ + SPEED features) with our MLP DNN.

Class	**Measure**	**TRAJ+SPEED and MLP DNN**			
		30s	**60s**	**120**	**180s**
Cognitively healthy	F_1 score	0.86	**0.93**	0.92	0.88
	Precision	0.85	0.94	**0.95**	0.84
	Recall	0.87	**0.93**	0.89	0.92
MCI	F_1 score	0.78	0.82	**0.87**	**0.87**
	Precision	0.69	0.74	0.8	**0.83**
	Recall	0.9	**0.93**	**0.93**	0.9
PwD	F_1 score	0.57	0.67	**0.83**	0.61
	Precision	0.79	0.84	**0.89**	0.79
	Recall	0.44	0.55	**0.77**	0.5
Avg.	F_1 score	0.73	0.81	**0.87**	0.78
	Precision	0.77	0.84	**0.88**	0.82
	Recall	0.73	0.80	**0.86**	0.77

achieves 0.65 macro F_1 score. With these techniques, the increase in recognition performance introduced by the long-term evaluation algorithm is evident. Indeed, both techniques obtain a lower macro F_1 score for trajectory image classification, which is close to 0.57. However, the results obtained with these techniques are still insufficient for providing reliable hypotheses of diagnosis about cognitive assessment.

The best results in this pool of experiments are achieved using two input trajectory images classification (TRAJ + SPEED features) with our MLP DNN. Indeed, the best results are achieved with $T_s = 120s$, with a macro F_1 score of 0.873. The detailed results are shown in Table 4.6. As it can be observed, the best results with $T_s = 120s$ are achieved for the class of cognitively healthy subjects (F_1 score = 0.92), which is the most frequent one. The class of MCI subjects obtains F_1 score = 0.87, while the class of PwD people achieves F_1 score = 0.83.

By closely inspecting the results in the confusion matrices shown in Table 4.7, we can observe that, with $T_s = 120s$, 17 PwD subjects out of 19 are correctly recognized. Among

Table 4.7: Long-term analysis: confusion matrices obtained using two input trajectory images classification (TRAJ + SPEED features) with our MLP DNN.

(a) $T_s = 30s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.85**	0.03	0.12
MCI	0.15	**0.69**	017
PwD	0.11	0.11	**0.79**

(b) $T_s = 60s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.94**	0.03	0.04
MCI	0.07	**0.74**	0.19
PwD	0.11	0.05	**0.84**

(c) $T_s = 120s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.95**	0.03	0.03
MCI	0.15	**0.80**	0.06
PwD	0.05	0.05	**0.89**

(d) $T_s = 180s$

classified as $\rightarrow$	Cognitively healthy	MCI	PwD
Cognitively healthy	**0.84**	0.04	0.12
MCI	0.07	**0.83**	0.09
PwD	0.11	0.11	**0.79**

the other ones, one subject is classified as a person with MCI, and one as a cognitively healthy person. Hence, the false negative rate of PwD is very low. Regarding false positive predictions of dementia, we observe that three persons with MCI out of 54 are classified as PwD. Out of 80 cognitively healthy subjects, only two are classified as PwD. Hence, the false positive rate of PwD is also low. Regarding the 54 persons with MCI, 43 are correctly recognized, while 8 are classified as cognitively healthy, and 3 of them as PwD. We consider these results positive since MCI is an intermediate state between cognitive health and dementia, which is difficult to diagnose, especially with automatic tools. Among the 80 cognitively healthy seniors, we achieved only 4 false positives. Indeed, two of them were classified as persons with MCI, and two of them as PwD.

4.5.8 Dashboard for Clinicians

In order to allow clinicians to inspect the predictions of our system, we have developed a user-friendly dashboard, using the Google Data Studio framework. The dashboard allows inspecting the predictions obtained through the various techniques experimented with in our work, achieved using the threshold value $T_s = 120s$. The dashboard can be freely accessed on the Web[4].

[4] https://sites.unica.it/domusafe/traminer/

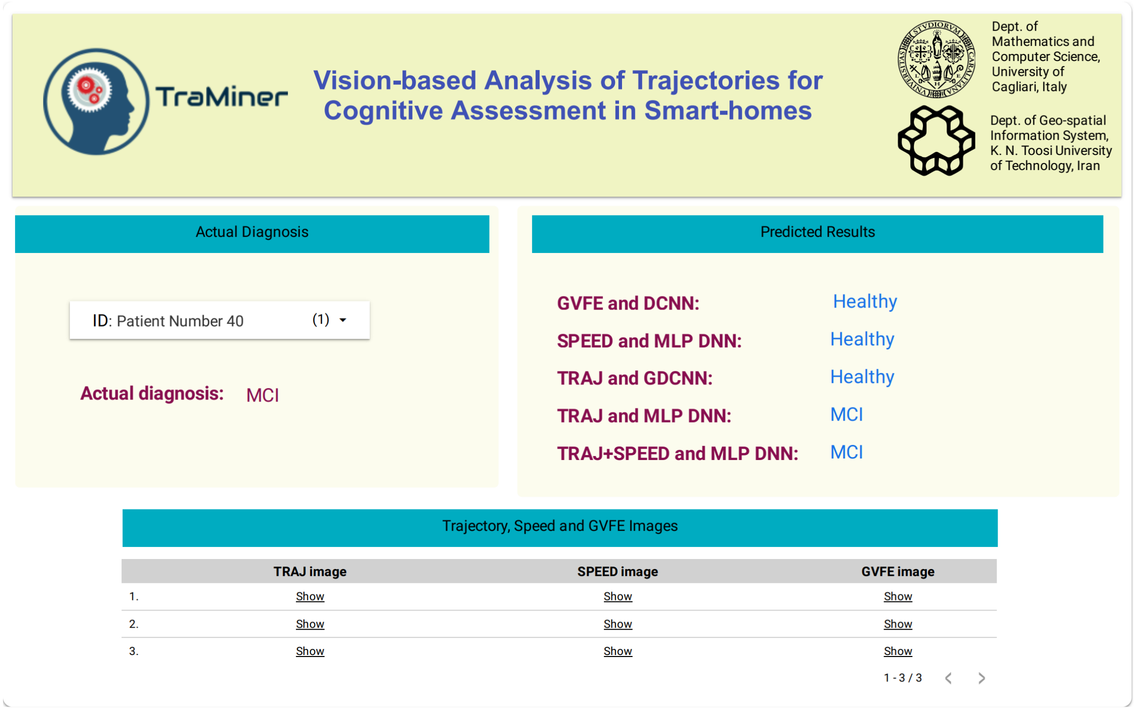


Figure 4.8: A screenshot of the TraMiner dashboard.

A screenshot of the dashboard is illustrated in Fig. 4.8. The user can select the patient through a drop-down list. The actual diagnosis for the current patient is shown on the left-hand side of the dashboard. On the right-hand side, the user can inspect the predicted diagnosis based on the five different methods: 'GVFE and DCNN', 'SPEED and MLP DNN', 'TRAJ and DCNN', 'TRAJ and MLP DNN', and 'TRAJ+SPEED and MLP DNN'. We remind that the latter is the actual method implemented by TraMiner, while the other ones are shown only as a reference.

By selecting a patient, the lower part of the dashboard shows the history of all input trajectories. For each trajectory, the user can visualize the extracted visual features, according to the three experimented methods: 'TRAJ', 'SPEED', and 'GVFE'. Those images are available in a table and can be opened in a separate window through a hyperlink. A sample of three images in the dashboard for one trajectory is shown in Fig. 4.9.

4.5.9 Discussion and Limitations

Our experimental evaluation shows that the use of our combined visual features (TRAJ and SPEED), coupled with the use of the MLP DNN, outperforms a state-of-the-art method based on a different visual feature extraction technique and on a more complex DNN. The advantage of our solution consists of the encoding of additional features, such as speed, intersections, and low-level anomaly indicators, that are not captured by existing solutions relying on images. Indeed, those locomotion features are known in the

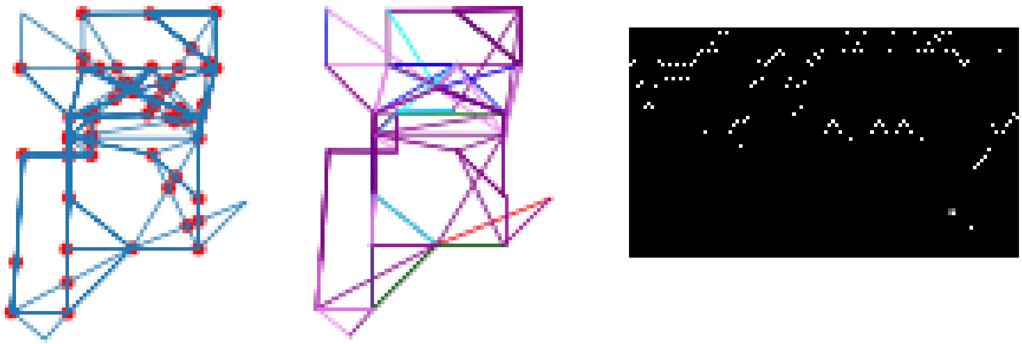


Figure 4.9: A sample of images for one trajectory in the TraMiner dashboard. From left to right, the images are obtained using the TRAJ, SPEED, and GVFE feature extraction methods, respectively.

literature to be reliable indicators of cognitive diseases.

In general, our system achieves better results with more frequent classes. Hence, we expect that recognition rates may improve using a training set composed of larger sets of individuals with MCI and PwD. The achieved macro F_1 score suggests that TraMiner may be a useful support for clinicians to provide a clinical evaluation of the cognitive health status of the elderly. However, this hypothesis should be confirmed by a large trial with the support of clinicians and the deployment of our system in real-world conditions.

The experiments show that the recognition performance of TraMiner strongly improves by considering the whole history of trajectories. In this respect, we recall that, despite the dataset having been acquired from more than 150 individuals, each person was monitored only for a few hours in one day. Such a short observation period may be insufficient to reliably predict the cognitive status of all individuals. Hence, we expect to achieve more accurate predictions by considering a long history of observations. However, this intuition needs to be verified by additional experiments on a large trial.

4.6 Conclusion

We tackled the challenging issue of recognizing symptoms of cognitive decline based on the analysis of indoor movements. To this aim, we proposed a technique to extract visual features from indoor trajectories, and a two-input DL model for classification. Experiments with a real-world dataset collected from cognitively healthy seniors, people with MCI, and PwD, showed that our system achieves good accuracy for long-term cognitive assessment and outperforms state-of-the-art techniques.

Several directions remain open for future research. Visual feature extraction could be improved by adding some other useful characteristics related to low-level abnormal motion indicators. Our neural network model could be refined to exploit visual features. The optimal value of the temporal threshold T_s may depend on the kind of activity currently performed by the individual, and by the home shape. Hence, we will investigate techniques to fine-tune T_s considering the current context of the inhabitant. Moreover, the system could be provided with explainable AI capabilities by adopting additional models of abnormal behaviors. Finally, there is an implicit assumption that we have a fixed layout for the smart-home which can restrict data portability and generalization. The latter-mentioned challenges are the main contributions of the work that will present in Chapter 5.

Chapter 5

Augmented and Generalized TraMiner

In this chapter, we tackle the challenging issue of recognizing symptoms of NDD based on the analysis of indoor locomotion traces by acquired sensor data in smart-homes with specific attention to portability and generalization. In this regard, we adopt an approach combining STF with features extracted from images depicting the trajectories walked within a smart-home. We introduce a vision-based method to graphically represent indoor trajectories as well as a data augmentation approach based on random rotation to increase the generalization of the trained model. In order to avoid the use of obtrusive wearable sensors or privacy-invasive cameras, we rely on the acquisition of position data from environmental sensors. Moreover, we use different *HandCrafted (HC)* features designed for image analysis tasks and combine them with features extracted directly from Spatio-temporal sequences of movements. Experiments on a real-world dataset acquired in a smart-home test-bed show that the proposed approach achieves promising results.

5.1 Introduction

As locomotion traces encode Spatio-temporal information and can only be partially captured through a fixed set of numerical features, in this chapter, we adopt the vision-based approach introduced in Chapter 4. With that approach, the trajectories walked by the inhabitant are depicted in images based on the smart-home floor plan, considering speed and specific locomotion indicators. The resulting images are classified by a DNN using a labeled training set. The main purpose is to increase learning generalization by means of additional sensory, vision-based, and trajectory numerical features. We extend and improve TraMiner [16] approach providing the following contributions:

i. We propose an image augmentation strategy to generalize the approach to different smart-home layouts;
ii. We extract additional STF relevant to the cognitive assessment task;
iii. We perform a comparison with HC features;
iv. We propose a feature-merging strategy, combining STF and visual trajectory information;

v. We experimentally evaluate our methods with a real-world dataset, showing the benefits of our technique.

Experiments with a real-world dataset acquired from 99 seniors showed that the integration of heterogeneous features increases recognition accuracy.

5.2 Generalized TraMiner System Overview

Similarly, we assume a sensorized smart-home infrastructure as described in Chapter 3 , which is equipped with various types of sensors (i.e., ambient and wearable). These sensors include PIR motion sensors to detect the individual's location in the house; contact and motion sensors to track interactions with objects and their usage; power sensors to detect the use of certain electrical appliances, etc. Fig. 5.1 illustrates our system architecture. The modules highlighted in blue are those which include our contributions.

The stream processing software platform is in charge of continuously collecting positioning data through PIR and door sensors. Whenever a sensor is triggered, the platform sends to the preprocessing module the following **raw sensor event**: $e = \langle t, s\_id, v \rangle$, where t is the firing timestamp, s_id is the sensor's unique identifier, and v is the generated value.

The integration and temporal synchronization module derives Spatio-temporal information from the events based on the relative position of each sensor in the home, which is stored in the sensor position table.

The preprocessing position data module is in charge of noise reduction, data cleaning, and partitioning the temporal stream of position records into **trajectories**. For this module, we used the technique proposed in Chapter 3 and 4. For noise reduction and data cleaning similarly, we set the thresholds for the maximum possible locomotion speed of people in the house to $15\ m/s$ and the maximum distance between adjacent positions to $5\ m$, respectively. For trajectory partitioning, we rely on a given threshold T_s. A new trajectory is initialized whenever the inhabitant is not moving for a time period exceeding T_s. In this work, we set T_s to $120\ s$.

Each trajectory is passed to the modules for visual feature extraction and trajectory feature extraction. Those modules represent the trajectory as two images called TRAJ and SPEED and extract *Sensory* and *Trajectory* features considering triggered sensors for each trajectory, respectively. Moreover, the trajectory image rotation module will rotate two trajectory images by random angles to augment trajectories and provide different aspects of trajectories that can be considered as different test-bed smart-home layouts.

Likewise, classification and long-term analysis modules are in charge of classifying each trajectory combined with extracted numerical features as either walked by a cognitively healthy person or PwD and communicating the hypothesis of diagnosis to the remote healthcare center.

5.3 Trajectory Feature Extraction

The visual feature extraction module, represented in Fig. 5.1, encodes a given trajectory into two images, named TRAJ and SPEED. They highlight different visual features, i.e., the

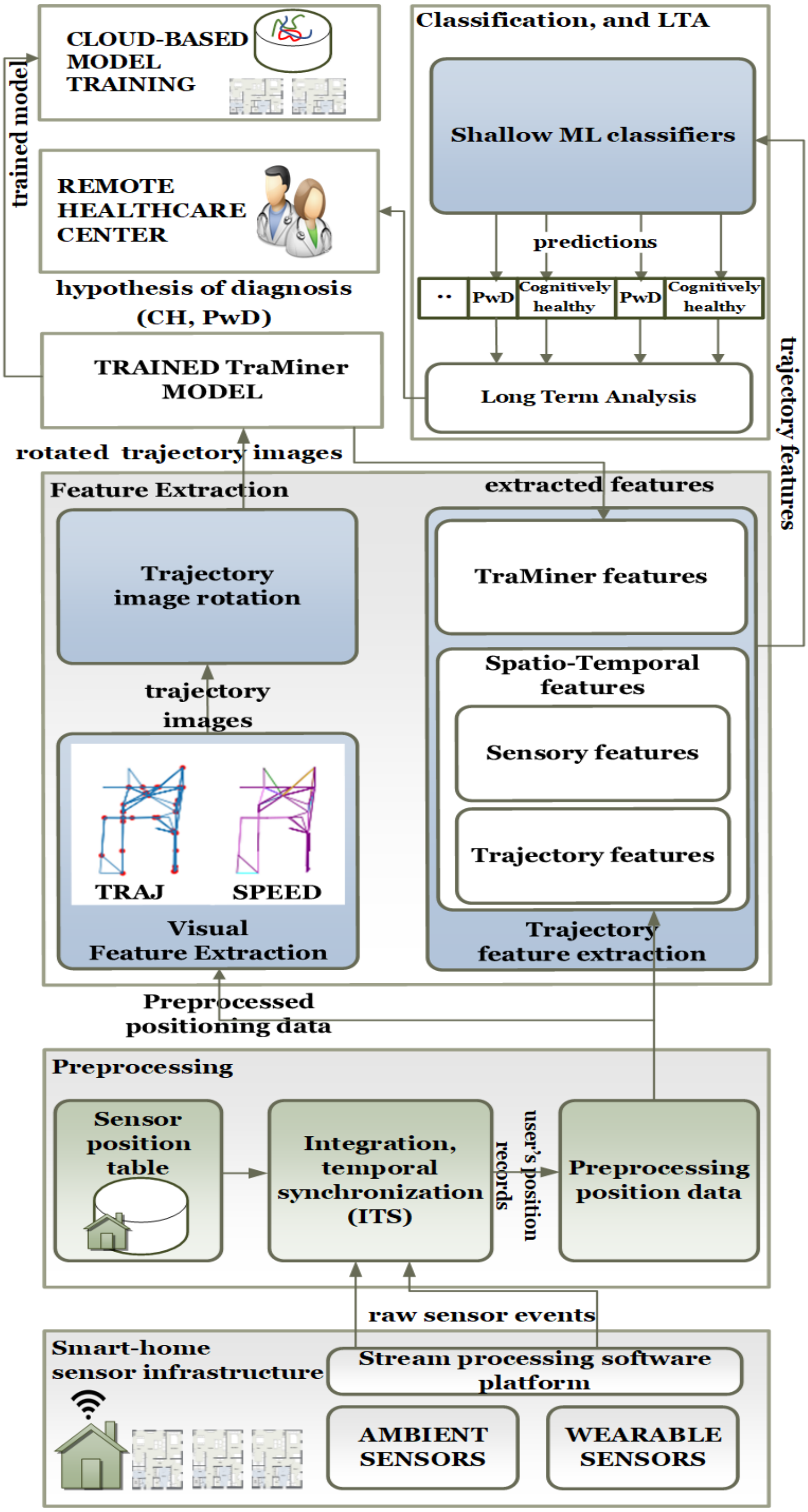
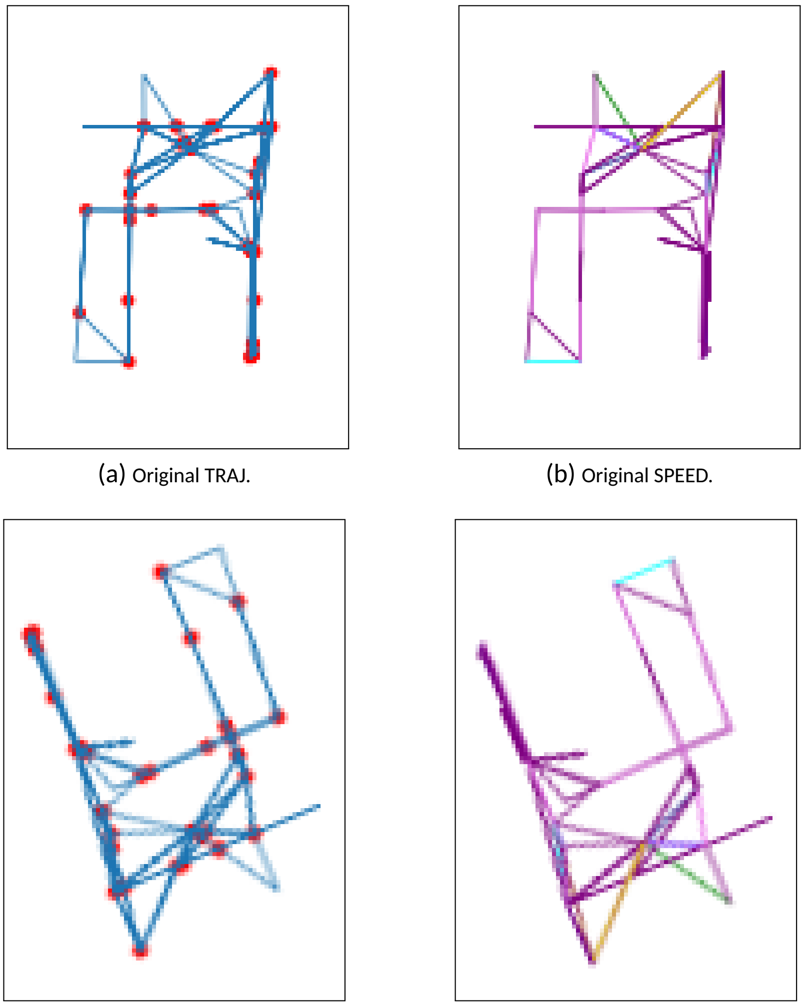


Figure 5.1: Generalized TraMiner system overview.

former represents intersection points as red dots, while the latter represents the speed of trajectory segments using different colors.

In our system, we introduce the novel trajectory image rotation module, which has been designed to generalize the vision-based approach to smart-homes with different layouts. Indeed, using patterns from a single home can limit the classification model generalization to other home layouts [170]. For this reason, the module applies a rotation of TRAJ and SPEED images by a random angle. Figure 5.2 shows the original and *Randomly Rotated (RR)* versions of the TRAJ and SPEED images.



(a) Original TRAJ. (b) Original SPEED. (c) Rotated TRAJ. (d) Rotated SPEED.

Figure 5.2: Examples of TRAJ and SPEED images.

Of course, the rotation of rectangular images may change the image layout, as in our case. Hence, we set the resolution of rotated images to 164×164 pixels unlike the Chapter 4 which was set to 100×130 pixels.

5.3.1 TraMiner as Feature Extractor

To extract high-level features from the trajectory images, in this chapter, we exploited the DNN presented in Chapter 4, already pre-trained with the full-size (164×164) original trajectories, as a feature extractor. The DNN structure is illustrated in Figure 5.3.

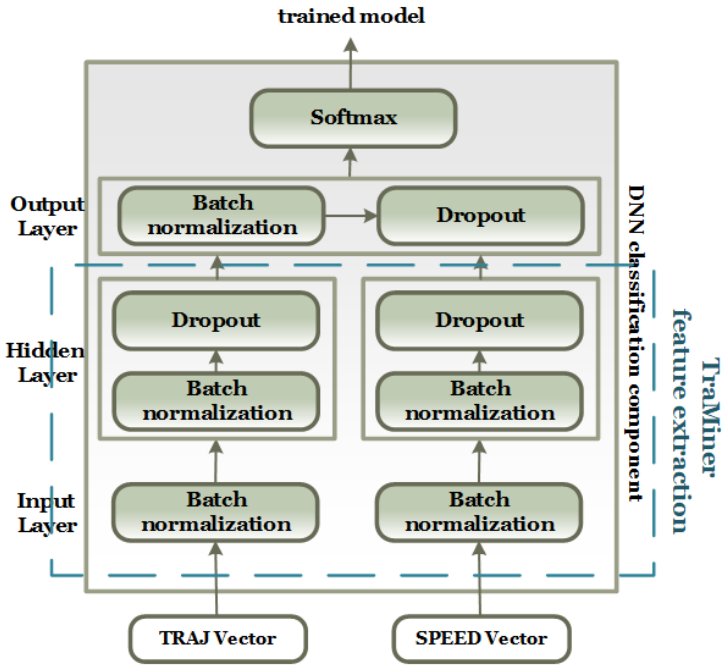


Figure 5.3: TraMiner DNN model and its feature extractor.

The trajectory images were converted into flat feature vectors based on each pixel's coordinates and color values. Normalization was applied to reduce the computational cost of training. The DNN includes two dense layers with 32 neurons each. Each layer used ReLU as the activation function, followed by batch normalization and a 0.5 dropout unit to increase reliability and reduce overfitting.

Outputs of both inputs (i.e., one per image) were concatenated, followed by batch normalization and dropout with the same drop units. Softmax was used as the activation function to calculate the probability distribution for the two classes cognitively healthy and PwD on the final output layer. Based on the maximum likelihood, it guarantees that each trajectory belongs to precisely one class [156].

After the training phase, we used the output of the hidden layers as extracted features from TRAJ and SPEED vectors of our rotated images. This part is highlighted in blue in Figure 5.3 Each image provided 64 features, which we call **TraMiner features**.

5.3.2 Spatio-Temporal Features

We also considered different categories of STF proposed in related studies [144, 160, 171] which are defined *Sensory and Trajectory features* as follows.

Sensory features are computed from raw sensor events of each trajectory:

i. IDs of the first and last activated sensor in a trajectory;

ii. Number of activated sensors;
iii. Number of activations of each sensor;
iv. Variance of the sensor IDs triggered during the trajectory's duration (each sensor is assigned a numerical ID);
v. *Time of Day (ToD)* for current trajectory based on start-time, where ToD $\in \{0, 5\}$ represents "morning" (1AM to 11AM), "noon" (11AM till 13PM), "afternoon" (13PM to 18PM), "evening" (18PM to 21PM), "night" (21PM to 23PM) or "midnight" (23PM to 1AM) by numerical order.

Trajectory features consider low-level movement indicators (explained in Chapter 2) that have been proved in the clinical literature to be indicative of cognitive decline, including *jerk* [157], *sharp angles* [159], *straightness* [158], and *path-efficiency* [62]:

i. Number of jerk episodes in the trajectory that exceed the threshold$= 1.5$;
ii. Number of sharp angles in the trajectory;
iii. Number of straightness episodes in the trajectory that exceed the threshold$= 1.5$;
iv. The ratio of the distance between the start- and end-point of a trajectory to trajectory length (path-efficiency);
v. The ratio of the number of sharp angles to the time duration of the trajectory (named *normalized change direction*);
vi. The ratio of number of triggered sensors to the trajectory duration (named *cadence*);
vii. The ratio of the total time of ambulation to trajectory duration (named *ambulation fraction*);
viii. Trajectory length;
ix. Time duration of the trajectory.

5.3.3 Handcrafted Image Features

We have also studied and exploited several well-used features for computer vision tasks, both classical ones [172–174] and other ones similar to those used in TraMiner, specifically oriented to the classification of images representing trajectories [175, 176]. In particular, we evaluated two different classes of HC image descriptors: *invariant moments* and *color features*.

For the first class, we computed *Legendre Moments (LM)* and *Zernike Moments (ZM)*. LM was introduced by Teague [177] for image analysis tasks and have been widely used due to their invariance to changes in scale, rotation, and reflection [178, 179], as well as ZM [180]. They can represent the properties of an image without redundancy or overlapping information between moments [177]. In both cases, the order of the moments is five, since a higher order would have decreased the performance of the system by adding overly specific features more useful for image reconstruction than for image classification [181].

Regarding the second class, we extracted the following *Color Histogram Features (CHF)* from the images converted to grayscale: mean, STD, smoothness, skewness, kurtosis, uniformity, and entropy. They describe the overall distribution of color in the image.

5.4 Trajectory Classification and Long-term Analysis

A machine learning algorithm classifies each trajectory as cognitively healthy or PwD according to the predicted category of the inhabitant. As shown in Section 5.5, we evaluate different machine learning classifiers in our experiments.

Based on the TraMiner work in Chapter 4, and the predictions computed by the machine learning algorithm, the long-term analysis module produces a diagnostic hypothesis about the subject's cognitive health. The diagnosis hypothesis is reported to the remote health center for further investigation by physicians. As mentioned in Chapter 4, the long-term prediction relies on the most frequently predicted class, and it is computed as ltp according to the following formula:

$$ltp = \underset{c \in \{\text{'cognitively healthy'}, \text{'PwD'}\}}{\arg\max} \; |\{c \in \{c_1, \ldots, \; c_m\}\}\,|,$$

where $c_1, ..., c_m$ is the history of predictions regarding the inhabitant's trajectories.

5.5 Experimental Evaluation

In this section, we report the experimental results which were carried out with CASAS instrumented smart-home from a large set of seniors, including cognitively healthy seniors and PwD. We explain the experimental setup and the achieved results by shallow ML classifiers.

5.5.1 Setup

Our experiments were based on the test-bed smart-home of CASAS [2]. Since we rely on locomotion data and TraMiner architecture, our experiments only consider PIR motion and door sensors as well. Since, for the sake of this study, we are interested in recognizing symptoms of dementia, we considered 99 participants' data, including 80 cognitively healthy seniors aged 60 to 74 years old and 19 PwD who were able to carry out the activities in the home. We developed a prototype of our system using Python and its libraries. All the experiments have been conducted with Leave One Person Out cross-validation, keeping one person's trajectories as the test set and the remaining persons' trajectories as the training set, and iterating over all persons. We experimentally compared different configurations of features, which are explained in the following of this section. For each configuration, we report the achieved average values of Precision, Recall, and F_1-score, where the latter is the harmonic mean of Precision and Recall. We report both weighted and macro-averaged values of those measures, where the former is averaged over all instances. The latter is averaged over the two classes cognitively healthy and PwD.

5.5.2 Experimental Results

We evaluated six classifiers, namely: NB, SVM, kNN which $k = 3$, DT, MLP (composed of 100 neurons in a hidden layer, ReLU activation function, Adam optimizer, and trained for 1000 epochs, with batch size equal to 200), and *LogitBoost (LB)*. We considered the following configurations:

- *RR-TraMiner*, which uses only the TraMiner DNN as feature extractor;
- *RR-STF*, which uses STF numerical features only;
- both RR-TraMiner and RR-STF features together;
- HC image features LM, ZM, and CHF; together, and in isolation.

The results of the first three configurations are reported in Table 5.1. Among them, RR-TraMiner features achieve the lowest results; i.e., 72.11% weighted F_1 with SVM and 53.4% macro F_1 with NB.

Features	Measures (%)		NB	SVM	kNN	DT	MLP	LB
TraMiner as feature extractor (RR-TraMiner)	Weighted	Precision	**71.55**	65.16	67	69.06	68.33	69.25
		Recall	65.81	72.72	70	66.72	**79.27**	67.81
		F1-score	68.18	**72.11**	68.4	67.82	72.01	68.5
	Macro	Precision	**54.77**	50	47.3	50.30	49.81	50.62
		Recall	**53.6**	40.36	46.66	50.26	48.66	50.57
		F1-score	**53.4**	44.66	46.84	50.17	45.9	50.55
STF numerical features (RR-STF)	Weighted	Precision	68.54	68.91	71.41	73.73	**75.13**	70.63
		Recall	76.18	70.36	74.72	73.63	**80.54**	75.45
		F1-score	71.51	69.60	71.41	73.68	**75.13**	71.96
	Macro	Precision	49.7	50.04	50.23	57.81	**59.3**	52.43
		Recall	49.29	50.04	50.40	57.76	**59.8**	53.14
		F1-score	47.97	50	49.43	57.78	**59.53**	52.47
RR-TraMiner $\cup$ and RR-STF	Weighted	Precision	68.42	68.98	69.08	75.27	**76.13**	70.12
		Recall	76	70.54	74.72	75.27	**78.18**	73.09
		F1-score	71.4	69.73	71.41	75.27	**76.96**	71.45
	Macro	Precision	49.58	50.15	50.23	**60.26**	**60.27**	51.73
		Recall	49.04	50.17	50.4	60.26	**62.85**	52.21
		F1-score	47.87	50.11	49.43	60.26	**61.17**	51.7

Table 5.1: Trajectory classification results using different features.

RR-STF features provide better results than the previous. Indeed, with those features and the MLP classifier, we achieve 75.13% weighted F_1 and 59.53% macro F_1.

The classification results improve further by using both RR-TraMiner features and RR-STF obtaining 76.96% weighted F_1 and 61.17% macro F_1 with the MLP classifier. This result indicates that the system accuracy can increase by considering the combination of heterogeneous features.

We also evaluated the classification performance achieved with the HC image features presented in Section 5.3.3. The results are reported in Table 5.2. With this class of features, LM features alone determine the lowest results in terms of macro F_1; DT achieves the best result with 48.51% macro F_1. The NB classifier achieves 51.48% macro F_1 with CHF features, while the kNN classifier obtains 51.88% macro F_1 with ZM features.

Interestingly, the use of LM, ZM, and CHF features together determines a relevant improvement in macro F_1; i.e., 57.2% with the LB classifier, indicating the need to combine different features for this recognition task.

The results obtained in weighted F_1 with HC features are more stable than the previous. Indeed, when used in isolation, all three considered kinds of features achieve their best results using the MLP classifier with around 72% or 73% weighted F_1. Also, in this

Features	Measures (%)		NB	SVM	kNN	DT	MLP	LB
LM	Weighted	Precision	68.71	67.93	64.37	67.96	**71.59**	65.58
		Recall	69.27	78.18	72.91	67.27	**80.73**	65.09
		F1-score	68.99	71.7	68.31	67.61	**72.12**	65.34
	Macro	Precision	49.72	47.78	40.72	48.55	**57.03**	44.77
		Recall	49.73	49.5	45.52	48.49	**50**	44.62
		F1-score	49.72	46.22	42.81	**48.51**	44.67	44.7
ZM	Weighted	Precision	67.11	65.78	70.49	69.88	**74.99**	68.81
		Recall	73.45	77.64	74.73	68.36	**80.73**	68.36
		F1-score	69.88	70.85	72.26	69.09	**72.78**	68.58
	Macro	Precision	46.5	42.74	53.03	51.53	**65.48**	49.89
		Recall	48.01	48.44	**52.03**	51.68	50.72	49.88
		F1-score	46.61	44.49	**51.88**	51.55	46.46	49.88
CHF	Weighted	Precision	71.14	69.71	67.03	68.23	**74.07**	69.38
		Recall	77.27	76.73	73.27	68	**80.55**	70.36
		F1-score	73.22	72.27	69.77	68.11	**73.3**	69.86
	Macro	Precision	54.68	51.74	46.36	48.95	**62.8**	50.82
		Recall	**52.17**	50.75	47.9	48.94	51.32	50.76
		F1-score	**51.48**	49.46	46.52	48.95	48.05	50.77
$ZM \cup LM \cup CHF$	Weighted	Precision	65.85	67.44	66.22	71.6	70.16	**73.38**
		Recall	61.2	**79.6**	73.22	73.41	73.22	74.5
		F1-score	63.32	71.85	69.32	72.44	71.53	**73.9**
	Macro	Precision	45.78	46.55	44.76	54.74	52.37	**57.61**
		Recall	44.74	49.68	47.17	54.1	51.83	**56.93**
		F1-score	45	45.19	45.37	54.3	51.8	**57.2**

Table 5.2: Trajectory images classification results using several HC features extracted from randomly rotated images.

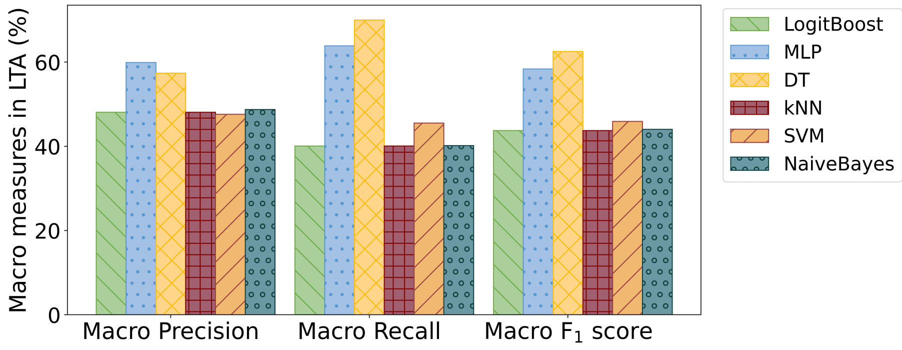
case, the best result in weighted F_1 (i.e., 73.9%) is obtained using LM, ZM, and CHF features together.

Overall, in our experiments, RR-STF features, especially when combined with RR-TraMiner ones, outperform HC image features. This result indicates that our system needs statistical information (i.e., STF) along with visual information (trajectory images) about the walked trajectories. Moreover, the results obtained in weighted F_1 are significantly better than those obtained in terms of macro F_1. This fact is probably due to class imbalance. Indeed, the dataset includes much more trajectories of cognitively healthy persons (80 individuals) than trajectories of PwD (19 individuals). Hence, the classifiers are biased toward predicting the most frequent class cognitively healthy.

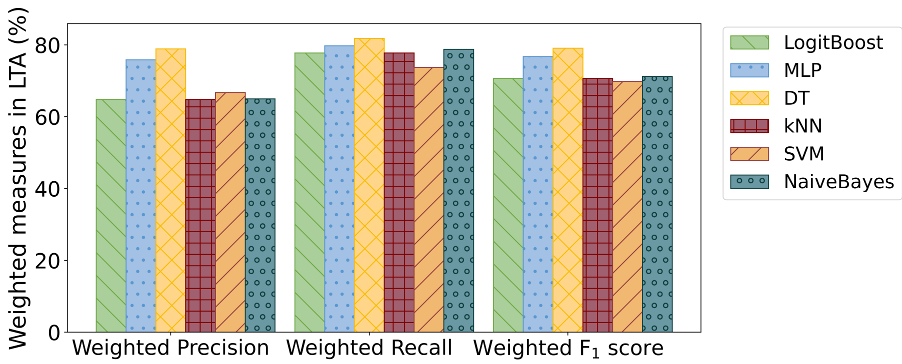
We also experimented with the algorithm for the long-term analysis described in Section 5.4, using both RR-STF and RR-TraMiner features together. As reported in Fig.5.4, the best result is obtained by the DT classifier, which achieves 62.56% macro F_1 and 79.1% weighted F_1.

5.6 Conclusion

This chapter adopts an approach to combine STF with features extracted from images depicting the trajectories walked within a smart home. We introduce a data augmentation approach based on random image rotation to increase the generalization of the



(a) Macro F_1



(b) Weighted F_1

Figure 5.4: Long-term analysis results with RR-TraMiner and RR-TF.

trained model. In order to avoid the use of obtrusive wearable sensors or privacy-invasive cameras, we rely on the acquisition of position data from environmental sensors. Experiments with a real-world dataset acquired from 99 seniors show that the integration of heterogeneous features increases recognition accuracy.

Chapter 6

Summary and Future Outlook

In this chapter we summarize the main contributions of this thesis and address open issues, future directions, and other potential locomotion analysis applications.

6.1 Technical Contributions

This thesis aims to efficiently and effectively analyze position traces to enable early detection of cognitive decline symptoms via locomotion pattern data mining. We tried to propose a framework that is non-intrusive and generalizable to various types of smart environments with different layouts considering the inhabitant's privacy.

The first proposed framework, in Chapter 3, consists in representing the trajectories walked by the resident depicted into images based on the smart-home floor plan as well as speed and other specific locomotion indicators and utilizing DNN for image classification for supporting cognitive impairment diagnosis. DNNs help to effectively capture discriminative features without feature engineering efforts.

In the TraMiner system, introduced in Chapter 4, we tried to extend and refine the preliminary version of our framework by transforming each locomotion segment into two images that capture different aspects related to the clinical indicators of locomotion anomalies. However, it is assumed that smart-homes have a fixed layout which can restrict data portability and generalization.

Therefore, in a later work discussed in Chapter 5, we introduced a data augmentation approach based on image rotation by random angles to increase the generalization of the trained model. Moreover, we augmented the image features with handcrafted features extracted from sensors triggered by the inhabitant's movements. Experimental results show that the proposed approach is promising, and it merits further research and improvements.

However, in our experimental test-bed, we relied on PIR sensors and door sensors to track the inhabitant's location, which provides coarse-grained position data. The system accuracy could be enhanced by using more precise localization technologies, like UWB positioning systems.

6.2 Open Issues and Future Directions

Several issues, both practical and theoretical, still have to be deeply investigated to make an effective and viable solution for detecting cognitive decline symptoms through locomotion analysis. We identify the following as the main open issues:

i. Explainability;
ii. Data portability
iii. Public benchmarks availability
iv. Ethics and privacy
v. Activity recognition and locomotion anomaly detection

6.2.1 Explainability

A limitation of our vision-based method is the difficulty of manually analyzing the reasons that determined the actual hypothesis of diagnosis. Indeed, it is not straightforward for a human observer to distinguish the trajectory images produced by our feature extraction techniques for the different classes of seniors. In order to provide explainable AI capabilities, these kinds of systems should be complemented with other methods for cognitive assessment, possibly considering other behavioral models of cognitive decline based on overt [182] or subtle anomalies [183], which are easier to interpret by a domain expert. In order to recognize those behavioral anomalies, the locomotion analysis system should be extended with additional sensors and algorithms to recognize activities at a fine-grained level.

6.2.2 Data Portability

Given the nature of the datasets used in our experiments, all the patients' data were acquired in the same smart-home context. Whether the learned model is portable to a different context is still an open research question. We believe that advanced transfer learning methods specifically designed for image classification may enable training data portability [184], but this aspect should be confirmed by additional experiments with other datasets.

Even without the use of transfer learning methods to enhance data portability, our system could be applied to important domains. In particular, a residence for elderly people may consist of several similar apartments. The DNN model could be trained based on the trajectories walked by those inhabitants for which a cognitive status diagnosis is known. That model could be used for the cognitive assessment of the other inhabitants.

6.2.3 Public Benchmarks Availability

The accurate evaluation of proposed tools and methods necessarily relies on extensive experiments in naturalistic conditions. However, in this domain, the setup of experimental test-beds and the experimentation with a large set of participants, including both people with NDD and healthy control seniors, is particularly complex and expensive. Moreover, acquired data contain sensitive information. For these reasons, there is a lack of large datasets acquired for long time periods on a significant number of individuals, that are publicly available.

This fact limits the possibility of experimentally comparing different solutions for AI-based neurocognitive disease assessment using common test-bed datasets. A potential solution for this problem could be the option to integrate external evaluation pipelines into the computation infrastructure of the institution holding the dataset, allowing external researchers to evaluate their hypotheses without the risk of data privacy violation.

It should be mentioned that most collected datasets that are used as a benchmark are based on certain cultural regions. Therefore, there is a need to enrich data sources by considering the customs, and cultural differences of different regions. The gender, interests, and daily habits of subjects could be considered to create an interactive environment. There can be a progressive profile for each resident, which is constantly evolving according to the feedback it receives from the person and the environment.

6.2.4 Ethics and Privacy

Since the average age of the population is projected to increase significantly in the near future, the early diagnosis of cognitive decline among elderly people is becoming a key objective of healthcare systems worldwide [20]. This dissertation explored different technologies and methods that have been demonstrated to be successful in detecting symptoms of NDD based on locomotion sensor data and AI algorithms.

However, given the sensitivity of the task, particular care should be taken before introducing these technologies into medical practice. The first fundamental challenge in sensor-based healthcare systems is the protection of privacy. The use of sensor data and AI methods for neurocognitive disease assessment raises serious ethical and legal concerns, including informed consent acquisition, safety, transparency, data ownership, algorithmic fairness, and biases [185].

Indeed, it is well known that the release of location data determines serious privacy issues [186]. Of course, the continuous observation of movements and locomotion patterns may reveal not only medical conditions, but also personal routines, activities, and preferences. This problem is particularly evident in systems based on outdoor location. For instance, recurring presence in specific locations may reveal sensitive data such as political opinions or religious beliefs, while frequent co-occurrence with other people may expose private contacts. The continuous observation of indoor locomotion traces at home may also challenge the individual's privacy, revealing the presence of other people or the execution of private ADL.

These concerns are becoming more important when RC systems are designed to be used by vulnerable people with cognitive impairments who often lack the capacity to provide informed consent to their use [187, 188].

In the last decade, we have witnessed significant endeavors in striking a balance between ethical and policy considerations and assistive technologies, and a growing interest in AI ethics [188, 189]. However, there is still a lack of a structural framework to thoroughly consider different aspects of sensor-based AI-related technologies in RC for people with cognitive impairments in terms of ethical and policy-oriented concerns. Furthermore, there are some major gaps between developing clinically relevant AI-powered diagnosis systems and their acceptance and reliability [190]. For this reason, a privacy-by-design technology must be adopted when designing and implementing locomotion-based healthcare systems [114].

Furthermore, novel tools and methodologies are needed to provide training and guidelines to explain the benefits of introducing medical AI for people with cognitive impairments and their families. Investigating the views and needs of both patients and relevant stakeholders at the cross-section of technology development and healthcare is considered a useful way to prospectively assess the practical, technical, clinical, and ethical challenges associated with RC smart-homes for people with cognitive impairments and their caregivers [191]. The future prospect could be focusing on challenges, preventive strategies, and the possibility of improving ethical and policy-oriented training to provide proper counseling to the patients about the risks and benefits of using RC in smart-homes which are crucial to building trust between patients and clinical staff. Particularly, there is a need to do:

- A systematic qualitative research about opportunities and issues related to ethics and policy in AI-powered assistive systems for people with cognitive impairments.
- An analysis of challenges and the proposal of a comparison structure to map major issues and possible solutions.
- A quantitative research by a user study approach considering neurological, geriatric, and geropsychiatric clinicians and older adults to understand the needs, expectations, and acceptance of RC smart-home systems.
- A structural approach for training and providing guidelines for the end-users of assistive systems.

Together with privacy, it is important to adopt effective cyber-security mechanisms in order to protect sensitive data regarding the individual. This requirement is particularly important in IoT systems, which are prone to different kinds of attacks [192]. From a technological point of view, the need for continuous data acquisition and processing challenges the power requirements of portable or wearable systems. Novel edge computing solutions such as Federated Learning [193, 194] optimized for the execution of ML algorithms and supported by privacy and security mechanisms need to be put in place [195]. There is also the need for optimized, energy efficient, and effective noise suppression algorithms for accurate localization and location data processing [93].

6.2.5 Activity Recognition and Locomotion Anomaly Detection

Frail people, especially those with cognitive impairments, are at risk of declining levels of independence, and safety issues, therefore, the main purpose of RC technologies is to support them to improve their quality of life [6]. RC technologies in smart-homes enable time-dependent and location-based monitoring in order to manage ADL by a variety of assistive technologies [7].

Studies showed that the relation between locomotion and ADL patterns is significantly correlated with a person's health and cognitive status, if changes in human behavior can be detected, situations that require further health evaluation will be identified [146, 196]. Moreover, indoor movements are affected by the variability of activity execution as well. In fact, recognizing activities is a challenging problem as there are no direct ways to relate data recorded via sensors to specific activities. In fact, a person could carry out an activity with significant variations compared to the performance of another person. In this way, the data collected by the sensors will also vary. Some of these changes are detectable in the short term, such as frequent use of the toilet, which may indicate a urinary tract infection, or behavioral changes that are detectable in the long term, such as taking longer to prepare food and shorter reading the newspaper. It may indicate MCI or a more serious form of dementia [197]. Furthermore, they can be classified using different perspectives and granularity levels, as well as requiring a dense sensing infrastructure which may lead to privacy issues and increasing recognition complexity due to the number of residents in an indoor environment [198].

Therefore, human activity recognition in elderly healthcare systems is the way to facilitate healthcare work in order to treat and care for the elderly, reduce the workload for caregivers, reduce hospital stays, reduce costs, and improve quality of life. Experts in the field of medicine in general and in geriatrics, in particular, believe that one of the best ways to identify and discover emerging medical conditions is to examine changes in people's daily activities before these conditions become serious [199].

In general, abnormal behaviors of individuals more specifically during multi-stage activities such as cooking can be identified based on observations and they can be divided into three main categories [200]:

- Problem with experience: Lack of sufficient experience with multi-stage activities has led to difficulty in performing this activity effectively. Also, not having enough experience in doing the activity leads to slowing down each stage of the activity and a lot of time will be spent doing it.
- Difficulty in following the steps and instructions for the activity: participants face productivity and safety problems during the activity and constantly ask questions to receive approval from observers.
- Cognitive/Emotional Problems: The results show that using a method that is controlled by the user leads to less distraction. However, some people need the help of supervisors to prevent mistakes to follow activities.

Since in most sensor-based applications, the focus is on sensing object interaction and tracking locations visited [201], as s future research direction, a novel unobtrusive activity recognition system based on indoor locomotion analysis for the recognition of participants' activities through encoding the trajectories and manipulated objects into images which represented the performed activities through graphics could be useful.

Moreover, considering the goals while the person is executing the actions, in order to detect errors in behavior, assess the skills of initiation, organization, the inclusion of all steps, sequencing, safety and judgment, and completion while the task is being performed [202–204], and to reason about the causes of these errors. It can be done using Computational Causal Behavior Models [205] which is a compact symbolic structure with a powerful probabilistic inference engine.

These kinds of systems are the most preferred solution for monitoring daily activities specifically regarding elderly people who live alone and they prefer non-intrusive systems rather than a camera and wearable devices-based systems.

6.3 Other potential application areas

Locomotion analysis other than healthcare applications is valuable in different kinds of domains such as military and surveillance environments, entertainment, sports, and for validation of computer vision and robots.

Motion and locomotion detection and analysis in surveillance and security environments can be used in order to automatically detect anomalous activities to warn relevant authorities about potentially dangerous or criminal or terrorist behaviors, monitor the safety of a place, and track individuals or groups of people. Therefore, when an emergency situation arises it also leads to facilitate the evacuation of that area. This application is helpful to coordinate the activities of firefighters who need to work in parallel but differently divided groups. Automatic recognition and tracking of group movement patterns along with activities will be useful for team training in emergency situations as well as for helping groups to coordinate their actions in complex situations In filmmaking and video game development, it refers to recording the locomotion of human actors and using that information to animate digital character models in 2D or 3D computer animation.

“Locomotion" by itself is a general term that is considered as “Walking" in the current dissertation. However, there are other types of locomotion including rolling, hopping, metachronal motion, slithering, swimming, brachiating, and hybrid locomotions which can be considered as locomotion in multiple modes. Furthermore, it can be categorized according to one of four types of environment: terrestrial (on the earth), aerial (in the air), aquatic (in the water), or fossorial (in the earth). Considering different kinds of environments and variations of locomotions, they can have different sorts of applications, especially in developing robots’ locomotion capabilities to autonomously decide how, when, and where to move.

Bibliography

[1] E. Khodabandehloo, D. Riboni, and A. Alimohammadi, "Healthxai: Collaborative and explainable ai for supporting early diagnosis of cognitive decline," *Future Generation Computer Systems*, vol. 116, pp. 168–189, 2021.

[2] D. J. Cook, M. Schmitter-Edgecombe, A. Crandall, C. Sanders, and B. Thomas, "Collecting and disseminating smart home sensor data in the CASAS project," in *Proceedings of the CHI Workshop on Developing Shared Home Behavior Datasets to Advance HCI and Ubiquitous Computing Research*, 2009.

[3] M. Gochoo, T.-H. Tan, V. Velusamy, S.-H. Liu, D. Bayanduuren, and S.-C. Huang, "Device-free non-privacy invasive classification of elderly travel patterns in a smart house using pir sensors and dcnn," *IEEE Sensors Journal*, vol. 18, no. 1, pp. 390–400, 2017.

[4] B. Rechel, E. Grundy, J.-M. Robine, J. Cylus, J. P. Mackenbach, C. Knai, and M. McKee, "Ageing in the european union," *The Lancet*, vol. 381, no. 9874, pp. 1312–1322, 2013.

[5] M. Prince, M. Prina, and M. Guerchet, "World alzheimer report 2013: Journey of caring," Alzheimer's Disease International, Tech. Rep., September 2013.

[6] P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," *IEEE journal of biomedical and health informatics*, vol. 17, no. 3, pp. 579–590, 2012.

[7] M. Amiribesheli, A. Benmansour, and A. Bouchachia, "A review of smart homes in healthcare," *Journal of Ambient Intelligence and Humanized Computing*, vol. 6, no. 4, pp. 495–517, 2015.

[8] Z. Wang, J. Xin, Z. Wang, H. Gu, Y. Zhao, and W. Qian, "Computer-aided dementia diagnosis based on hierarchical extreme learning machine," *Cognitive Computation*, pp. 1–15, 2020.

[9] J. C. Castillo, Á. Castro-González, A. Fernández-Caballero, J. M. Latorre, J. M. Pastor, A. Fernández-Sotos, and M. A. Salichs, "Software architecture for smart emotion recognition and regulation of the ageing adult," *Cognitive Computation*, vol. 8, no. 2, pp. 357–367, 2016.

[10] A. C. Rodríguez, C. Roda, F. Montero, P. González, and E. Navarro, "An interactive fuzzy inference system for teletherapy of older people," *Cognitive Computation*, vol. 8, no. 2, pp. 318–335, 2016.

[11] P. Pires, L. Mendes, J. Mendes, R. Rodrigues, and A. Pereira, "Integrated e-healthcare system for elderly support," *Cognitive Computation*, vol. 8, no. 2, pp. 368–384, 2016.

[12] D. Riboni, C. Bettini, G. Civitarese, Z. H. Janjua, and R. Helaoui, "Smartfaber: Recognizing fine-grained abnormal behaviors for early detection of mild cognitive impairment," *Artificial Intelligence in Medicine*, vol. 67, pp. 57–74, 2016.

[13] D. Riboni and F. Murru, "Unsupervised recognition of multi-resident activities in smart-homes," *IEEE Access*, vol. 8, pp. 201 985–201 994, 2020.

[14] S. Zolfaghari, E. Khodabandehloo, and D. Riboni, "Towards vision-based analysis of indoor trajectories for cognitive assessment," in *Proceedings of the 2020 IEEE International Conference on Smart Computing (SMARTCOMP)*. IEEE, 2020, pp. 290–295.

[15] Q. Lin, D. Zhang, X. Huang, H. Ni, and X. Zhou, "Detecting wandering behavior based on gps traces for elders with dementia," in *2012 12th International Conference on Control Automation Robotics*. IEEE, 2012, pp. 672–677.

[16] S. Zolfaghari, E. Khodabandehloo, and D. Riboni, "Traminer: Vision-based analysis of locomotion traces for cognitive assessment in smart-homes," *Cognitive Computation*, pp. 1–22, 2021.

[17] D. Martino-Saltzman, B. B. Blasch, R. D. Morris, and L. W. McNeal, "Travel behavior of nursing home residents perceived as wanderers and nonwanderers," *The Gerontologist*, vol. 31, no. 5, pp. 666–672, 1991.

[18] S. Zolfaghari, A. Loddo, B. Pes, and D. Riboni, "A combination of visual and temporal trajectory features for cognitive assessment in smart home," in *2022 23rd IEEE International Conference on Mobile Data Management (MDM)*. IEEE, 2022, pp. 343–348.

[19] S. Schaat, P. Koldrack, K. Yordanova, T. Kirste, and S. Teipel, "Real-time detection of spatial disorientation in persons with mild cognitive impairment and dementia," *Gerontology*, vol. 66, no. 1, pp. 85–94, 2020.

[20] B. Rechel, E. Grundy, J.-M. Robine, J. Cylus, J. P. Mackenbach, C. Knai, and M. McKee, "Ageing in the european union," *The Lancet*, vol. 381, no. 9874, pp. 1312–1322, 2013.

[21] D. J. Gelb, E. Oliver, and S. Gilman, "Diagnostic criteria for parkinson disease," *Archives of neurology*, vol. 56, no. 1, pp. 33–39, 1999.

[22] K. D. Sethi, "Clinical aspects of parkinson disease," *Current opinion in neurology*, vol. 15, no. 4, pp. 457–460, 2002.

[23] C. Ahlrichs and M. Lawo, "Parkinson's disease motor symptoms in machine learning: A review," *arXiv preprint arXiv:1312.3825*, 2013.

[24] C. Punin, B. Barzallo, R. Clotet, A. Bermeo, M. Bravo, J. P. Bermeo, and C. Llumiguano, "A non-invasive medical device for parkinson's patients with episodes of freezing of gait," *Sensors*, vol. 19, no. 3, 2019. [Online]. Available: https://www.mdpi.com/1424-8220/19/3/737

[25] N. Georgiou-Karistianis, R. Scahill, S. J. Tabrizi, F. Squitieri, and E. Aylward, "Structural mri in huntington's disease and recommendations for its potential use in clinical trials," *Neuroscience & Biobehavioral Reviews*, vol. 37, no. 3, pp. 480–490, 2013.

[26] G. P. Bates, R. Dorsey, J. F. Gusella, M. R. Hayden, C. Kay, B. R. Leavitt, M. Nance, C. A. Ross, R. I. Scahill, R. Wetzel *et al.*, "Huntington disease," *Nature reviews Disease primers*, vol. 1, no. 1, pp. 1–21, 2015.

[27] A. Albahri, A. Alnoor, A. Zaidan, O. Albahri, H. Hameed, B. Zaidan, S. Peh, A. Zain, S. Siraj, A. Alamoodi *et al.*, "Based on the multi-assessment model: towards a new context of combining the artificial neural network and structural equation modelling: a review," *Chaos, Solitons & Fractals*, vol. 153, p. 111445, 2021.

[28] A. Albahri, A. Alnoor, A. Zaidan, O. Albahri, H. Hameed, B. Zaidan, S. Peh, A. Zain, S. Siraj, A. Masnan *et al.*, "Hybrid artificial neural network and structural equation modelling techniques: a survey," *Complex & Intelligent Systems*, vol. 8, no. 2, pp. 1781–1801, 2022.

[29] S. S. Joudar, A. Albahri, and R. A. Hamid, "Triage and priority-based healthcare diagnosis using artificial intelligence for autism spectrum disorder and gene contribution: A systematic review," *Computers in Biology and Medicine*, p. 105553, 2022.

[30] Q. Lin, D. Zhang, L. Chen, H. Ni, and X. Zhou, "Managing elders' wandering behavior using sensors-based solutions: A survey," *International Journal of Gerontology*, vol. 8, no. 2, pp. 49–55, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1873959814000295

[31] W. Zeng and C. Wang, "Classification of neurodegenerative diseases using gait dynamics via deterministic learning," *Information Sciences*, vol. 317, pp. 246–258, 2015.

[32] W. Pirker and R. Katzenschlager, "Gait disorders in adults and the elderly," *Wiener Klinische Wochenschrift*, vol. 129, no. 3-4, pp. 81–95, 2017.

[33] D. L. Algase, D. H. Moore, C. Vandeweerd, and D. Gavin-Dreschnack, “Mapping the maze of terms and definitions in dementia-related wandering,” *Aging & mental health*, vol. 11, no. 6, pp. 686–698, 2007.

[34] E. Khodabandehloo and D. Riboni, “Collaborative trajectory mining in smart-homes to support early diagnosis of cognitive decline,” *IEEE Transactions on Emerging Topics in Computing*, 2020.

[35] I. T. G. de Oliveira Gondim, C. d. C. B. de Souza, M. A. B. Rodrigues, I. M. Azevedo, M. d. G. W. de Sales, O. G. Lins *et al.*, “Portable accelerometers for the evaluation of spatio-temporal gait parameters in people with parkinson’s disease: an integrative review,” *Archives of Gerontology and Geriatrics*, p. 104097, 2020.

[36] W. D. Kearns, V. Nams, and J. L. Fozard, “Tortuosity in movement paths is related to cognitive impairment,” *Methods of information in medicine*, vol. 49, no. 06, pp. 592–598, 2010.

[37] P. Esser, H. Dawes, J. Collett, and K. Howells, “Insights into gait disorders: walking variability using phase plot analysis, parkinson’s disease,” *Gait & posture*, vol. 38, no. 4, pp. 648–652, 2013.

[38] T. Rantalainen, W. Teo, N. Ridgers, N. Nuzum, L. Valente, and H. Macpherson, “Laboratory-based gait variability and habitual gait entropy do not differentiate community-dwelling older adults from those with subjective memory complaints,” *Gait & Posture*, vol. 80, 2020.

[39] T. IJmker and C. J. Lamoth, “Gait and cognition: the relationship between gait stability and variability with executive function in persons with and without dementia,” *Gait & posture*, vol. 35, no. 1, pp. 126–130, 2012.

[40] J. H. Hollman, E. M. McDade, and R. C. Petersen, “Normative spatiotemporal gait parameters in older adults,” *Gait & posture*, vol. 34, no. 1, pp. 111–118, 2011.

[41] S. Gillain, E. Warzee, F. Lekeu, V. Wojtasik, D. Maquet, J.-L. Croisier, E. Salmon, and J. Petermans, “The value of instrumental gait analysis in elderly healthy, mci or alzheimer’s disease subjects and a comparison with other clinical tests used in single and dual-task conditions,” *Annals of physical and rehabilitation medicine*, vol. 52, no. 6, pp. 453–474, 2009.

[42] J. M. Hausdorff, I. Hillel, S. Shustak, S. Del Din, E. M. Bekkers, E. Pelosin, F. Nieuwhof, L. Rochester, and A. Mirelman, “Everyday stepping quantity and quality among older adult fallers with and without mild cognitive impairment: initial evidence for new motor markers of cognitive deficits?” *The Journals of Gerontology: Series A*, vol. 73, no. 8, pp. 1078–1082, 2018.

[43] N. Toosizadeh, B. Najafi, E. M. Reiman, R. M. Mager, J. K. Veldhuizen, K. O'Connor, E. Zamrini, and J. Mohler, "Upper-extremity dual-task function: an innovative method to assess cognitive impairment in older adults," *Frontiers in aging neuroscience*, vol. 8, p. 167, 2016.

[44] A. S. Buchman, R. J. Dawe, S. E. Leurgans, T. A. Curran, T. Truty, L. Yu, L. L. Barnes, J. M. Hausdorff, and D. A. Bennett, "Different combinations of mobility metrics derived from a wearable sensor are associated with distinct health outcomes in older adults," *The Journals of Gerontology: Series A*, vol. 75, no. 6, pp. 1176–1183, 2020.

[45] A. Dalton, H. Khalil, M. Busse, A. Rosser, R. van Deursen, and G. ÓLaighin, "Analysis of gait and balance through a single triaxial accelerometer in presymptomatic and symptomatic huntington's disease," *Gait & posture*, vol. 37, no. 1, pp. 49–54, 2013.

[46] A. K. Rao, L. Quinn, and K. S. Marder, "Reliability of spatiotemporal gait outcome measures in huntington's disease," *Movement disorders: official journal of the Movement Disorder Society*, vol. 20, no. 8, pp. 1033–1037, 2005.

[47] A. Delval, S. Bleuse, C. Simonin, M. Delliaux, B. Rolland, A. Destee, L. Defebvre, P. Krystkowiak, and K. Dujardin, "Are gait initiation parameters early markers of huntington's disease in pre-manifest mutation carriers?" *Gait & posture*, vol. 34, no. 2, pp. 202–207, 2011.

[48] R. Mc Ardle, S. Del Din, B. Galna, A. Thomas, and L. Rochester, "Differentiating dementia disease subtypes with gait analysis: feasibility of wearable sensors?" *Gait & Posture*, vol. 76, pp. 372–376, 2020.

[49] H. Ehsani, M. J. Mohler, K. O'connor, E. Zamrini, C. Tirambulo, and N. Toosizadeh, "The association between cognition and dual-tasking among older adults: the effect of motor function type and cognition task difficulty," *Clinical interventions in aging*, vol. 14, p. 659, 2019.

[50] J. Kondragunta, R. Seidel, and G. Hirtz, "Machine learning based identification of elderly persons with cognitive impairment using dynamic time warping," *Current Directions in Biomedical Engineering*, vol. 6, no. 3, pp. 360–363, 2020.

[51] C. Caramia, D. Torricelli, M. Schmid, A. Muñoz-Gonzalez, J. Gonzalez-Vargas, F. Grandas, and J. L. Pons, "Imu-based classification of parkinson's disease from gait: A sensitivity analysis on sensor location and feature selection," *IEEE journal of biomedical and health informatics*, vol. 22, no. 6, pp. 1765–1774, 2018.

[52] Q. Lin, D. Zhang, X. Huang, H. Ni, and X. Zhou, "Detecting wandering behavior based on gps traces for elders with dementia," in *2012 12th International Conference on Control Automation Robotics & Vision (ICARCV)*. IEEE, 2012, pp. 672–677.

[53] W. Aziz and M. Arif, "Complexity analysis of stride interval time series by threshold dependent symbolic entropy," *European journal of applied physiology*, vol. 98, no. 1, pp. 30–40, 2006.

[54] D. Trojaniello, A. Ravaschio, J. M. Hausdorff, and A. Cereatti, "Comparative assessment of different methods for the estimation of gait temporal parameters using a single inertial sensor: application to elderly, post-stroke, parkinson's disease and huntington's disease subjects," *Gait & posture*, vol. 42, no. 3, pp. 310–316, 2015.

[55] A. Martínez-Ramírez, I. Martinikorena, P. Lecumberri, M. Gómez, N. Millor, A. Casas-Herrero, F. Zambom-Ferraresi, and M. Izquierdo, "Dual task gait performance in frail individuals with and without mild cognitive impairment," *Dementia and geriatric cognitive disorders*, vol. 42, no. 1-2, pp. 7–16, 2016.

[56] A. K. Rao, L. Muratori, E. D. Louis, C. B. Moskowitz, and K. S. Marder, "Spectrum of gait impairments in presymptomatic and symptomatic huntington's disease," *Movement disorders: official journal of the Movement Disorder Society*, vol. 23, no. 8, pp. 1100–1107, 2008.

[57] ——, "Clinical measurement of mobility and balance impairments in huntington's disease: validity and responsiveness," *Gait & posture*, vol. 29, no. 3, pp. 433–436, 2009.

[58] I. Mulas, V. Putzu, G. Asoni, D. Viale, I. Mameli, and M. Pau, "Clinical assessment of gait and functional mobility in italian healthy and cognitively impaired older persons using wearable inertial sensors," *Aging clinical and experimental research*, pp. 1–12, 2020.

[59] H. Zhou, H. Lee, J. Lee, M. Schwenk, and B. Najafi, "Motor planning error: toward measuring cognitive frailty in older adults using wearables," *Sensors*, vol. 18, no. 3, p. 926, 2018.

[60] M. Gietzelt, K.-H. Wolf, M. Kohlmann, M. Marschollek, and R. Haux, "Measurement of accelerometry-based gait parameters in people with and without dementia in the field," *Methods of information in medicine*, vol. 52, no. 04, pp. 319–325, 2013.

[61] W.-H. Wang, Y.-L. Hsu, M.-C. Pai, C.-H. Wang, C.-Y. Wang, C.-W. Lin, H.-L. Wu, and P.-C. Chung, "Alzheimer's disease classification based on gait information," in *2014 International Joint Conference on Neural Networks (IJCNN)*. Beijing, China: IEEE, 2014, pp. 3251–3257.

[62] A. Kumar, C. T. Lau, M. Ma, S. Chan, and W. Kearns, "Trend analysis in the trajectory of the dementia patients," in *Proc. of ICSEC*. IEEE, 2017, pp. 1–5.

[63] A. Delaunay and J. Guérin, "Wandering detection within an embedded system for alzheimer suffering patients," in *2017 AAAI Spring Symposium Series*, 2017.

[64] F. Ferreira, M. F. Gago, E. Bicho, C. Carvalho, N. Mollaei, L. Rodrigues, N. Sousa, P. P. Rodrigues, C. Ferreira, and J. Gama, "Gait stride-to-stride variability and foot clearance pattern analysis in idiopathic parkinson's disease and vascular parkinsonism," *Journal of biomechanics*, vol. 92, pp. 98–104, 2019.

[65] W.-H. Wang, P.-C. Chung, G.-L. Yang, C.-W. Lin, Y.-L. Hsu, and M.-C. Pai, "An inertial sensor based balance and gait analysis system," in *2015 IEEE International Symposium on Circuits and Systems (ISCAS)*. Lisbon, Portugal: IEEE, 2015, pp. 2636–2639.

[66] E. Stack, V. Agarwal, R. King, M. Burnett, F. Tahavori, B. Janko, W. Harwin, A. Ashburn, and D. Kunkel, "Identifying balance impairments in people with parkinson's disease using video and wearable sensors," *Gait & posture*, vol. 62, pp. 321–326, 2018.

[67] K. Sheehan, B. Greene, C. Cunningham, L. Crosby, and R. Kenny, "Early identification of declining balance in higher functioning older adults, an inertial sensor based method," *Gait & posture*, vol. 39, no. 4, pp. 1034–1039, 2014.

[68] P. Pérez-Toro, J. Vásquez-Correa, T. Arias-Vergara, E. Nöth, and J. Orozco-Arroyave, "Nonlinear dynamics and poincaré sections to model gait impairments in different stages of parkinson's disease," *Nonlinear Dynamics*, vol. 100, no. 4, pp. 3253–3276, 2020.

[69] H. Carvajal-Castano, J. Lemos-Duque, and J. Orozco-Arroyave, "Effective detection of abnormal gait patterns in parkinson's disease patients using kinematics, nonlinear, and stability gait features," *Human Movement Science*, vol. 81, p. 102891, 2022.

[70] M. Kirchner, P. Schubert, M. Liebherr, and C. T. Haas, "Detrended fluctuation analysis and adaptive fractal analysis of stride time data in parkinson's disease: stitching together short gait trials," *PloS one*, vol. 9, no. 1, p. e85787, 2014.

[71] J. M. Hausdorff, S. L. Mitchell, R. Firtion, C.-K. Peng, M. E. Cudkowicz, J. Y. Wei, and A. L. Goldberger, "Altered fractal dynamics of gait: reduced stride-interval correlations with aging and huntington's disease," *Journal of applied physiology*, vol. 82, no. 1, pp. 262–269, 1997.

[72] E. Sejdić, K. A. Lowry, J. Bellanca, M. S. Redfern, and J. S. Brach, "A comprehensive assessment of gait accelerometry signals in time, frequency and time-frequency domains," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 3, pp. 603–612, 2013.

[73] P. Prabhu, A. K. Karunakar, H. Anitha, and N. Pradhan, "Classification of gait signals into different neurodegenerative diseases using statistical analysis and recurrence quantification analysis," *Pattern Recognition Letters*, vol. 139, pp. 10–16, 2020.

[74] C. Kamath, "A novel perspective to assessment of neurodegenerative disorder gait," *Sci. Postprint*, vol. 1, p. e00051, 2015.

[75] T.-Y. Li, Y.-W. Chien, C.-C. Chou, C.-F. Liao, W.-T. Cheah, L.-C. Fu, C. C.-H. Chen, C.-C. Chou, and I.-A. Chen, "A fast and low-cost repetitive movement pattern indicator for massive dementia screening," *IEEE Transactions on Automation Science and Engineering*, vol. 17, no. 2, pp. 771–783, 2019.

[76] N. Vuong, S. Chan, C. T. Lau, S. Chan, P. L. K. Yap, and A. Chen, "Preliminary results of using inertial sensors to detect dementia-related wandering patterns," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Milan, Italy: IEEE, 2015, pp. 3703–3706.

[77] D. L. Algase, E. R. Beattie, S. A. Leitsch, and C. A. Beel-Bates, "Biomechanical activity devices to index wandering behaviour in dementia," *American Journal of Alzheimer's Disease & Other Dementias®*, vol. 18, no. 2, pp. 85–92, 2003.

[78] D. Chen, A. J. Bharucha, and H. D. Wactlar, "Intelligent video monitoring to improve safety of older persons," in *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2007, pp. 3814–3817.

[79] D. H. Moore, D. L. Algase, G. Powell-Cope, S. Applegarth, and E. R. Beattie, "A framework for managing wandering and preventing elopement," *American Journal of Alzheimer's Disease & Other Dementias®*, vol. 24, no. 3, pp. 208–219, 2009.

[80] L. Costa, M. F. Gago, D. Yelshyna, J. Ferreira, H. David Silva, L. Rocha, N. Sousa, and E. Bicho, "Application of machine learning in postural control kinematics for the diagnosis of alzheimer's disease," *Computational intelligence and neuroscience*, vol. 2016, p. 15, 2016.

[81] S. Cullen, M. Montero-Odasso, L. Bherer, Q. Almeida, S. Fraser, S. Muir-Hunter, K. Li, T. Liu-Ambrose, C. A. McGibbon, W. McIlroy *et al.*, "Guidelines for gait assessments in the canadian consortium on neurodegeneration in aging (ccna)," *Canadian Geriatrics Journal*, vol. 21, no. 2, p. 157, 2018.

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

[83] A. P. T. Association), "Unified parkinson's disease rating scale (updrs), movement disorders society (mds) modified unified parkinson's disease rating scale (mds-updrs)," 2021.

[84] M. M. Hoehn, M. D. Yahr *et al.*, "Parkinsonism: onset, progression, and mortality," *Neurology*, vol. 50, no. 2, pp. 318–318, 1998.

[85] S. L. Mitchell, D. W. Harper, A. Lau, and R. Bhalla, “Patterns of outcome measurement in parkinson’s disease clinical trials,” *Neuroepidemiology*, vol. 19, no. 2, pp. 100–108, 2000.

[86] M. El-Gohary, S. Pearson, J. McNames, M. Mancini, F. Horak, S. Mellone, and L. Chiari, “Continuous monitoring of turning in patients with movement disability,” *Sensors*, vol. 14, no. 1, pp. 356–369, 2014.

[87] R. Ramsperger, S. Meckler, T. Heger, J. van Uem, S. Hucker, U. Braatz, H. Graessner, D. Berg, Y. Manoli, J. A. Serrano *et al.*, “Continuous leg dyskinesia assessment in parkinson’s disease–clinical validity and ecological effect,” *Parkinsonism & related disorders*, vol. 26, pp. 41–46, 2016.

[88] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, W. Poewe, C. Sampaio, M. B. Stern, R. Dodel *et al.*, “Movement disorder society-sponsored revision of the unified parkinson’s disease rating scale (mds-updrs): scale presentation and clinimetric testing results,” *Movement disorders: official journal of the Movement Disorder Society*, vol. 23, no. 15, pp. 2129–2170, 2008.

[89] N. Naghavi and E. Wade, “Prediction of freezing of gait in parkinson’s disease using statistical inference and lower–limb acceleration data,” *IEEE transactions on neural systems and rehabilitation engineering*, vol. 27, no. 5, pp. 947–955, 2019.

[90] J. Collett, P. Esser, H. Khalil, M. Busse, L. Quinn, K. DeBono, A. Rosser, A. H. Nemeth, and H. Dawes, “Insights into gait disorders: Walking variability using phase plot analysis, huntington’s disease,” *Gait & posture*, vol. 40, no. 4, pp. 694–700, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0966636214006638

[91] S. J. Pyo, H. Kim, I. S. Kim, Y.-M. Park, M.-J. Kim, H. M. Lee, and S.-B. Koh, “Quantitative gait analysis in patients with huntington’s disease,” *Journal of movement disorders*, vol. 10, no. 3, p. 140, 2017.

[92] A. Mannini, D. Trojaniello, U. Della Croce, and A. M. Sabatini, “Hidden markov model-based strategy for gait segmentation using inertial sensors: application to elderly, hemiparetic patients and huntington’s disease patients,” in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Milan, Italy: IEEE, 2015, pp. 5179–5182.

[93] G. A. Oguntala, R. Abd-Alhameed, S. M. R. Jones, J. M. Noras, M. Patwary, and J. Rodriguez, “Indoor location identification technologies for real-time iot-based applications: An inclusive survey,” *Comput. Sci. Rev.*, vol. 30, pp. 55–79, 2018.

[94] R. F. Brena, J. García-Vázquez, C. E. Galván-Tejada, D. M. Rodríguez, C. V. Rosales, and J. F. Jr., “Evolution of indoor positioning technologies: A survey,” *J. Sensors*, vol. 2017, pp. 2 630 413:1–2 630 413:21, 2017.

[95] W. E. Sakpere and M. O. Adeyeye, "Can near field communication solve the limitations in mobile indoor navigation?" in *RFID technology integration for business performance improvement*. IGI Global, 2015, pp. 52–79.

[96] G.-X. Liu, L.-F. Shi, S. Chen, and Z.-G. Wu, "Focusing matching localization method based on indoor magnetic map," *IEEE Sensors Journal*, vol. 20, no. 17, pp. 10 012–10 020, 2020.

[97] T. Sanpechuda and L.-o. Kovavisaruch, "A review of rfid localization: Applications and techniques," in *2008 5th international conference on electrical engineering/electronics, computer, telecommunications and information technology*, vol. 2. IEEE, 2008, pp. 769–772.

[98] T. Liu, Y. Inoue, and K. Shibata, "A wearable ground reaction force sensor system and its application to the measurement of extrinsic gait variability," *Sensors*, vol. 10, no. 11, pp. 10 240–10 255, 2010.

[99] W. Zhu, B. Anderson, S. Zhu, and Y. Wang, "A computer vision-based system for stride length estimation using a mobile phone camera," in *Proceedings of the 18th International ACM SIGACCESS Conference on Computers and Accessibility*. New York, NY, USA: Association for Computing Machinery, 2016, pp. 121–130.

[100] S. Wan, Y. Liang, Y. Zhang, and M. Guizani, "Deep multi-layer perceptron classifier for behavior analysis to estimate parkinson's disease severity using smartphones," *IEEE Access*, vol. 6, pp. 36 825–36 833, 2018.

[101] R. Graça, R. S. e Castro, and J. Cevada, "Parkdetect: Early diagnosing parkinson's disease," in *2014 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*. IEEE, 2014, pp. 1–6.

[102] P. Serra-Añó, J. F. Pedrero-Sánchez, M. Inglés, M. Aguilar-Rodríguez, I. Vargas-Villanueva, and J. López-Pascual, "Assessment of functional activities in individuals with parkinson's disease using a simple and reliable smartphone-based procedure," *International journal of environmental research and public health*, vol. 17, no. 11, p. 4123, 2020.

[103] S. Mazilu, U. Blanke, A. Calatroni, E. Gazit, J. M. Hausdorff, and G. Tröster, "The role of wrist-mounted inertial sensors in detecting gait freeze episodes in parkinson's disease," *Pervasive and Mobile Computing*, vol. 33, pp. 1–16, 2016.

[104] B. Ganesan, T. Gowda, A. Al-Jumaily, K. Fong, S. Meena, and R. Tong, "Ambient assisted living technologies for older adults with cognitive and physical impairments: a review," *European review for medical and pharmacological sciences*, 2019.

[105] N. Homdee, R. Alam, S. Wolfe, and J. Lach, "Mind the gaps: Edge-based monitoring for continuous room-level location tracking," *Smart Health*, vol. 9, pp. 297–306, 2018.

[106] R. Sharma, L. Pillai, A. Glover, and T. Virmani, "Objective impairment of tandem gait in parkinson's disease patients increases with disease severity," *Parkinsonism and Related Disorders*, vol. 68, pp. 33–39, 2019.

[107] J. Shah, L. Pillai, D. K. Williams, S. M. Doerhoff, L. Larson-Prior, E. Garcia-Rill, and T. Virmani, "Increased foot strike variability in parkinson's disease patients with freezing of gait," *Parkinsonism & related disorders*, vol. 53, pp. 58–63, 2018.

[108] K.-W. Kim, J. Kwon, C.-G. Lee, and J. Han, "Accurate indoor location tracking exploiting ultrasonic reflections," *IEEE Sensors Journal*, vol. 16, no. 24, pp. 9075–9088, 2016.

[109] S. Tsukagoshi, M. Furuta, K. Hirayanagi, N. Furuta, S. Nakazato, M. Fujii, Y. Yuminaka, and Y. Ikeda, "Noninvasive and quantitative evaluation of movement disorder disability using an infrared depth sensor," *Journal of Clinical Neuroscience*, vol. 71, pp. 135–140, 2020.

[110] A. Procházka, O. Vyšata, M. Vališ, O. Ťupa, M. Schätz, and V. Mařík, "Bayesian classification and analysis of gait disorders using image and depth sensors of microsoft kinect," *Digital Signal Processing*, vol. 47, pp. 169–177, 2015.

[111] X. Meng, H. Yu, and M. P. Tham, "Gait phase detection in able-bodied subjects and dementia patients," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2013, pp. 4907–4910.

[112] M. Gwak, E. Woo, and M. Sarrafzadeh, "The role of accelerometer and gyroscope sensors in identification of mild cognitive impairment," in *2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. IEEE, 2018, pp. 434–438.

[113] A. Chaudhary, H. P. Gupta, K. Shukla, and T. Dutta, "Sensor signals-based early dementia detection system using travel pattern classification," *IEEE Sensors Journal*, vol. 20, no. 23, pp. 14 474–14 481, 2020.

[114] C. Bettini and D. Riboni, "Privacy protection in pervasive systems: State of the art and technical challenges," *Pervasive and Mobile Computing*, vol. 17, pp. 159–174, 2015.

[115] S. T. Moore, H. G. MacDougall, J.-M. Gracies, H. S. Cohen, and W. G. Ondo, "Long-term monitoring of gait in parkinson's disease," *Gait & posture*, vol. 26, no. 2, pp. 200–207, 2007.

[116] S. Viteckova, R. Krupicka, V. Cejka, P. Kutilek, Z. Szabo, E. Růžička, and P. Dusek, "Waveform skewness: Parameter for timed up & go turn assessment," *Biomedical Signal Processing and Control*, vol. 52, pp. 347–352, 2019.

[117] C. Buckley, B. Galna, L. Rochester, and C. Mazzà, "Upper body accelerations as a biomarker of gait impairment in the early stages of parkinson's disease," *Gait & posture*, vol. 71, pp. 289–295, 2019.

[118] U. M. Fietzek, L. Stuhlinger, A. Plate, A. Ceballos-Baumann, and K. Bötzel, "Spatial constraints evoke increased number of steps during turning in parkinson's disease," *Clinical Neurophysiology*, vol. 128, no. 10, pp. 1954–1960, 2017.

[119] E. Rastegari, V. Marmelat, L. Najjar, D. Bastola, and H. H. Ali, "Using gait parameters to recognize various stages of parkinson's disease," in *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. Kansas City, MO, USA: IEEE, 2017, pp. 1647–1651.

[120] S. V. Perumal and R. Sankar, "Gait and tremor assessment for patients with parkinson's disease using wearable sensors," *Ict Express*, vol. 2, no. 4, pp. 168–174, 2016.

[121] M. R. Daliri, "Chi-square distance kernel of the gaits for the diagnosis of parkinson's disease," *Biomedical Signal Processing and Control*, vol. 8, no. 1, pp. 66–70, 2013.

[122] D. Joshi, A. Khajuria, and P. Joshi, "An automatic non-invasive method for parkinson's disease classification," *Computer Methods and Programs in Biomedicine*, vol. 145, pp. 135–145, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169260716306484

[123] M. G. Tsipouras, A. T. Tzallas, G. Rigas, S. Tsouli, D. I. Fotiadis, and S. Konitsiotis, "An automated methodology for levodopa-induced dyskinesia: assessment based on gyroscope and accelerometer signals," *Artificial intelligence in medicine*, vol. 55, no. 2, pp. 127–135, 2012.

[124] I. El Maachi, G.-A. Bilodeau, and W. Bouachir, "Deep 1d-convnet for accurate parkinson disease detection and severity prediction from gait," *Expert Systems with Applications*, vol. 143, p. 113075, 2020.

[125] J. C. Vásquez-Correa, T. Arias-Vergara, J. R. Orozco-Arroyave, B. Eskofier, J. Klucken, and E. Nöth, "Multimodal assessment of parkinson's disease: a deep learning approach," *IEEE journal of biomedical and health informatics*, vol. 23, no. 4, pp. 1618–1630, 2018.

[126] C.-W. Cho, W.-H. Chao, S.-H. Lin, and Y.-Y. Chen, "A vision-based analysis system for gait recognition in patients with parkinson's disease," *Expert Systems with applications*, vol. 36, no. 3, pp. 7033–7039, 2009.

[127] L. Gong, J. Li, M. Yu, M. Zhu, and R. Clifford, "A novel computer vision based gait analysis technique for normal and parkinson's gaits classification," in *2020 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf*

on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), 2020, pp. 209–215.

[128] T. Khan, J. Westin, and M. Dougherty, “Motion cue analysis for parkinsonian gait recognition,” *The open biomedical engineering journal*, vol. 7, p. 1, 2013.

[129] Ö. F. Ertuğrul, Y. Kaya, R. Tekin, and M. N. Almalı, “Detection of parkinson’s disease by shifted one dimensional local binary patterns from gait,” *Expert Systems with Applications*, vol. 56, pp. 156–163, 2016.

[130] E. Rastegari and H. Ali, “A bag-of-words feature engineering approach for assessing health conditions using accelerometer data,” *Smart Health*, vol. 16, p. 100116, 2020.

[131] A. Ferrari, P. Ginis, M. Hardegger, F. Casamassima, L. Rocchi, and L. Chiari, “A mobile kalman-filter based solution for the real-time estimation of spatio-temporal gait parameters,” *IEEE transactions on neural systems and rehabilitation engineering*, vol. 24, no. 7, pp. 764–773, 2015.

[132] S. Fahn, “Members of the updrs development committee. unified parkinson’s disease rating scale,” *Recent developments in Parkinson’s disease*, vol. 2, pp. 293–304, 1987.

[133] R. Bhidayasiri and D. Tarsy, *Parkinson’s Disease: Hoehn and Yahr Scale*. Totowa, NJ: Humana Press, 2012, pp. 4–5. [Online]. Available: https://doi.org/10.1007/978-1-60327-426-5_2

[134] F. Hulzinga, A. Nieuwboer, B. W. Dijkstra, M. Mancini, C. Strouwen, B. R. Bloem, and P. Ginis, “The new freezing of gait questionnaire: unsuitable as an outcome in clinical trials?” *Movement disorders clinical practice*, vol. 7, no. 2, pp. 199–205, 2020.

[135] G. Paragliola and A. Coronato, “A deep learning-based approach for the classification of gait dynamics in subjects with a neurodegenerative disease,” in *Proceedings of SAI Intelligent Systems Conference*. Springer, 2020, pp. 452–468.

[136] J. Wojtusiak and R. M. Nia, “Location prediction using gps trackers: Can machine learning help locate the missing people with dementia?” *Internet of Things*, vol. 13, p. 100035, 2019.

[137] M. Yoneyama, H. Mitoma, N. Sanjo, M. Higuma, H. Terashi, and T. Yokota, “Ambulatory gait behavior in patients with dementia: a comparison with parkinson’s disease,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 8, pp. 817–826, 2015.

[138] S. Schaat, P. Koldrack, K. Yordanova, T. Kirste, and S. Teipel, "Real-time detection of spatial disorientation in persons with mild cognitive impairment and dementia," *Gerontology*, vol. 66, no. 1, pp. 85–94, 2020.

[139] B. Filtjens, P. Ginis, A. Nieuwboer, P. Slaets, and B. Vanrumste, "Automated freezing of gait assessment with marker-based motion capture and multi-stage spatial-temporal graph convolutional neural networks," *Journal of NeuroEngineering and Rehabilitation*, vol. 19, no. 1, pp. 1–14, 2022.

[140] A. M. Seelye, M. Schmitter-Edgecombe, D. J. Cook, and A. Crandall, "Naturalistic assessment of everyday activities and prompting technologies in mild cognitive impairment," *J Int Neuropsychol Soc*, vol. 19, no. 4, pp. 442–452, 2013.

[141] P. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, "Automated cognitive health assessment using smart home monitoring of complex tasks," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 43, no. 6, pp. 1302–1313, 2013.

[142] D. L. Algase, "Wandering: a dementia-compromised behavior," *Journal of Gerontological Nursing*, vol. 25, no. 9, pp. 10–16, 1999.

[143] Q. Lin, W. Zhao, and W. Wang, "Detecting dementia-related wandering locomotion of elders by leveraging active infrared sensors," *Journal of Computer and Communications*, vol. 6, no. 05, p. 94, 2018.

[144] E. Khodabandehloo and D. Riboni, "Collaborative trajectory mining in smart-homes to support early diagnosis of cognitive decline," *IEEE Transactions on Emerging Topics in Computing*, 2020.

[145] W. D. Kearns, J. L. Fozard, V. O. Nams, and J. D. Craighead, "Wireless telesurveillance system for detecting dementia," *Gerontechnology*, p. 90, 2011.

[146] H. Dodge, N. Mattek, D. Austin, T. Hayes, and J. Kaye, "In-home walking speeds and variability trajectories associated with mild cognitive impairment," *Neurology*, vol. 78, no. 24, pp. 1946–1952, 2012.

[147] T. Kieu, B. Yang, C. Guo, and C. S. Jensen, "Distinguishing trajectories from different drivers using incompletely labeled trajectories," in *Proceedings of the 27th ACM international conference on information and knowledge management*, 2018, pp. 863–872.

[148] Y. Endo, H. Toda, K. Nishida, and J. Ikedo, "Classifying spatial trajectories using representation learning," *International Journal of Data Science and Analytics*, vol. 2, no. 3-4, pp. 107–117, 2016.

[149] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov, "Improving neural networks by preventing co-adaptation of feature detectors," *arXiv preprint arXiv:1207.0580*, 2012.

[150] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: a simple way to prevent neural networks from overfitting,” *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[151] Y. Bengio, “Practical recommendations for gradient-based training of deep architectures,” in *Neural networks: Tricks of the trade*. Springer, 2012, pp. 437–478.

[152] D. J. Cook, A. S. Crandall, B. L. Thomas, and N. C. Krishnan, “CASAS: A smart home in a box,” *Computer*, vol. 46, no. 7, pp. 62–69, 2013.

[153] P. W. Burgess, “Strategy application disorder: the role of the frontal lobes in human multitasking,” *Psychological research*, vol. 63, no. 3-4, pp. 279–288, 2000.

[154] P. Rashidi, D. J. Cook, L. B. Holder, and M. Schmitter-Edgecombe, “Discovering activities to recognize and track in a smart environment,” *IEEE Trans. Knowl. Data Eng.*, vol. 23, no. 4, pp. 527–539, 2011.

[155] R. C. Petersen and J. C. Morris, “Mild cognitive impairment as a clinical entity and treatment target,” *Archives of neurology*, vol. 62, no. 7, pp. 1160–1163, 2005.

[156] R. Das and S. Chaudhuri, “On the separability of classes with the cross-entropy loss function,” *arXiv preprint arXiv:1909.06930*, 2019.

[157] S. Dabiri and K. Heaslip, “Inferring transportation modes from gps trajectories using a convolutional neural network,” *Transportation research part C: emerging technologies*, vol. 86, pp. 360–371, 2018.

[158] X. Li, “Using complexity measures of movement for automatically detecting movement types of unknown gps trajectories,” *Am. J. Geogr. Inf. Syst*, vol. 3, no. 2, pp. 63–74, 2014.

[159] Q. Lin, D. Zhang, X. Huang, H. Ni, and X. Zhou, “Detecting wandering behavior based on GPS traces for elders with dementia,” in *12th International Conference on Control Automation Robotics & Vision*. IEEE, 2012, pp. 672–677.

[160] E. Khodabandehloo, D. Riboni, and A. Alimohammadi, “HealthXAI: Collaborative and explainable AI for supporting early diagnosis of cognitive decline,” *Future Generation Computer Systems*, vol. 116, pp. 168–189, 2021.

[161] E. Frank, M. A. Hall, G. Holmes, R. Kirkby, and B. Pfahringer, “WEKA - A machine learning workbench for data mining,” in *The Data Mining and Knowledge Discovery Handbook*. Springer, 2005, pp. 1305–1314.

[162] I. Rish *et al.*, “An empirical study of the Naive Bayes classifier,” in *IJCAI 2001 workshop on empirical methods in artificial intelligence*, vol. 3, no. 22, 2001, pp. 41–46.

[163] S. Le Cessie and J. C. Van Houwelingen, "Ridge estimators in logistic regression," *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, vol. 41, no. 1, pp. 191–201, 1992.

[164] J. Shawe-Taylor and N. Cristianini, *Support vector machines*. Cambridge University Press Cambridge, 2000, vol. 2.

[165] D. W. Aha, D. Kibler, and M. K. Albert, "Instance-based learning algorithms," *Machine learning*, vol. 6, no. 1, pp. 37–66, 1991.

[166] W. W. Cohen, "Fast effective rule induction," in *Machine learning proceedings 1995*. Elsevier, 1995, pp. 115–123.

[167] J. R. Quinlan, *C4.5: Programs for Machine Learning*. Morgan Kaufmann, 1993.

[168] S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE transactions on systems, man, and cybernetics*, vol. 21, no. 3, pp. 660–674, 1991.

[169] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[170] M. ElSayed, A. Alsebai, A. Salaheldin, N. El Gayar, and M. ElHelw, "Ambient and wearable sensing for gait classification in pervasive healthcare environments," in *The 12th IEEE International Conference on e-Health Networking, Applications and Services*. IEEE, 2010, pp. 240–245.

[171] M. R. Keyvanpour and S. Zolfaghari, "Augmented feature-state sensors in human activity recognition," in *2017 9th International Conference on Information and Knowledge Technology (IKT)*. IEEE, 2017, pp. 71–75.

[172] Y. Ren, J. Yang, Q. Zhang, and Z. Guo, "Ship recognition based on hu invariant moments and convolutional neural network for video surveillance," *Multim. Tools Appl.*, vol. 80, no. 1, pp. 1343–1373, 2021.

[173] J. Zhao and X. Wang, "Vehicle-logo recognition based on modified HU invariant moments and SVM," *Multim. Tools Appl.*, vol. 78, no. 1, pp. 75–97, 2019.

[174] X. Ji, H. Guo, and M. Hu, "Features extraction and classification of wood defect based on hu invariant moment and wavelet moment and bp neural network," in *Proceedings of the 12th International Symposium on Visual Information Communication and Interaction*, ser. VINCI'2019. New York, NY, USA: Association for Computing Machinery, 2019.

[175] I. Kontopoulos, A. Makris, D. Zissis, and K. Tserpes, "A computer vision approach for trajectory classification," in *2021 22nd IEEE International Conference on Mobile Data Management (MDM)*, 2021, pp. 163–168.

[176] A. Makris, I. Kontopoulos, E. Psomakelis, and K. Tserpes, “Semi-supervised trajectory classification using convolutional auto-encoders,” in *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Animal Movement Ecology and Human Mobility*, ser. HANIMOB ’21. New York, NY, USA: Association for Computing Machinery, 2021, p. 27–32.

[177] M. R. Teague, “Image analysis via the general theory of moments,” *J. Opt. Soc. Am.*, vol. 70, no. 8, pp. 920–930, 1980.

[178] C.-W. Chong, P. Raveendran, and R. Mukundan, “Translation and scale invariants of Legendre moments,” *Pattern Recognition*, vol. 37, no. 1, pp. 119–129, 2004.

[179] Z. Ma, B. Kang, and J. Ma, “Translation and scale invariant of Legendre moments for images retrieval,” *J. Inf. Comput. Sci.*, vol. 8, no. 11, pp. 2221–2229, 2011.

[180] M. Oujaoura, B. Minaoui, and M. Fakir, “Image annotation by moments,” in *Moments and Moment Invariants - Theory and Applications*, vol. 1, 2014, pp. 227–252.

[181] C. Di Ruberto, L. Putzu, and G. Rodriguez, “Fast and accurate computation of orthogonal moments for texture analysis,” *Pattern Recognition*, vol. 83, pp. 498–510, 2018.

[182] M. F. Schwartz, M. Segal, T. Veramonti, M. Ferraro, and L. J. Buxbaum, “The naturalistic action test: A standardised assessment for everyday action impairment,” *Neuropsychol Rehabil*, vol. 12, no. 4, pp. 311–339, 2002.

[183] S. C. Seligman, T. Giovannetti, J. Sestito, and D. J. Libon, “A new approach to the characterization of subtle errors in everyday action: Implications for mild cognitive impairment,” *Clin Neuropsychol*, vol. 28, pp. 97–115, 2014.

[184] C. Deng, Y. Xue, X. Liu, C. Li, and D. Tao, “Active transfer learning network: A unified deep joint spectral–spatial feature learning model for hyperspectral image classification,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 3, pp. 1741–1754, 2018.

[185] S. Gerke, T. Minssen, and G. Cohen, “Ethical and legal challenges of artificial intelligence-driven healthcare,” in *Artificial intelligence in healthcare*. Elsevier, 2020, pp. 295–336.

[186] D. Riboni, L. Pareschi, and C. Bettini, “Privacy in georeferenced context-aware services: A survey,” in *Privacy in location-based applications*. Springer, 2009, pp. 151–172.

[187] J. Pool, S. Akhlaghpour, F. Fatehi, and L. C. Gray, “Data privacy concerns and use of telehealth in the aged care context: An integrative review and research agenda,” *International Journal of Medical Informatics*, p. 104707, 2022.

[188] J. Morley, C. C. Machado, C. Burr, J. Cowls, I. Joshi, M. Taddeo, and L. Floridi, "The ethics of ai in health care: a mapping review," *Social Science & Medicine*, vol. 260, p. 113172, 2020.

[189] H. Siala and Y. Wang, "Shifting artificial intelligence to be responsible in healthcare: A systematic review," *Social Science & Medicine*, p. 114782, 2022.

[190] C. Han, L. Rundo, K. Murao, T. Nemoto, and H. Nakayama, "Bridging the gap between ai and healthcare sides: towards developing clinically relevant ai-powered diagnosis systems," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*. Springer, 2020, pp. 320–333.

[191] M. Ienca, T. Wangmo, F. Jotterand, R. W. Kressig, and B. Elger, "Ethical design of intelligent assistive technologies for dementia: a descriptive review," *Science and engineering ethics*, vol. 24, no. 4, pp. 1035–1055, 2018.

[192] E. Toch, C. Bettini, E. Shmueli, L. Radaelli, A. Lanzi, D. Riboni, and B. Lepri, "The privacy implications of cyber security systems: A technological survey," *ACM Computing Surveys (CSUR)*, vol. 51, no. 2, pp. 1–27, 2018.

[193] Q. Li, Z. Wen, Z. Wu, S. Hu, N. Wang, Y. Li, X. Liu, and B. He, "A survey on federated learning systems: vision, hype and reality for data privacy and protection," *IEEE Transactions on Knowledge and Data Engineering*, 2021.

[194] C. Zhang, Y. Xie, H. Bai, B. Yu, W. Li, and Y. Gao, "A survey on federated learning," *Knowledge-Based Systems*, vol. 216, p. 106775, 2021.

[195] A. A. Abdellatif, A. Mohamed, C. F. Chiasserini, M. Tlili, and A. Erbad, "Edge computing for smart health: Context-aware approaches, opportunities, and challenges," *IEEE Network*, vol. 33, no. 3, pp. 196–203, 2019.

[196] L. G. Fahad, A. Ali, and M. Rajarajan, "Learning models for activity recognition in smart homes," in *Information science and applications*. Springer, 2015, pp. 819–826.

[197] H. Alemdar, C. Tunca, and C. Ersoy, "Daily life behaviour monitoring for health assessment using machine learning: bridging the gap between domains," *Personal and Ubiquitous Computing*, vol. 19, no. 2, pp. 303–315, 2015.

[198] S. Zolfaghari and M. R. Keyvanpour, "Human activity recognition in smart homes: Research challenges classification," *changes*, vol. 14, p. 15, 2017.

[199] H. Fang, L. He, H. Si, P. Liu, and X. Xie, "Human activity recognition based on feature selection in smart home using back-propagation algorithm," *ISA transactions*, vol. 53, no. 5, pp. 1629–1638, 2014.

[200] J. Wang, H. Mahajan, P. Toto, A. McKeon, M. McCue, and D. Ding, "Comparison of two prompting methods in guiding people with traumatic brain injury in cooking tasks," in *International Conference on Smart Homes and Health Telematics*. Springer, 2014, pp. 83–92.

[201] S. S. Akter and L. B. Holder, "Activity recognition using graphical features," in *2014 13th International Conference on Machine Learning and Applications*. IEEE, 2014, pp. 165–170.

[202] C. Baum and D. F. Edwards, "Cognitive performance in senile dementia of the alzheimer's type: The kitchen task assessment," *The American Journal of Occupational Therapy*, vol. 47, no. 5, pp. 431–436, 1993.

[203] A. Serna, H. Pigot, and V. Rialle, "Modeling the progression of alzheimer's disease for cognitive assistance in smart homes," *User Modeling and User-Adapted Interaction*, vol. 17, no. 4, pp. 415–438, 2007.

[204] K. Yordanova, A. Hein, and T. Kirste, "Kitchen task assessment dataset for measuring errors due to cognitive impairments," in *2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. IEEE, 2020, pp. 1–6.

[205] F. Krüger, M. Nyolt, K. Yordanova, A. Hein, and T. Kirste, "Computational state space models for activity and intention recognition. a feasibility study," *PloS one*, vol. 9, no. 11, p. e109381, 2014.

[206] R. N. Noella, D. Gupta, and J. Priyadarshini, "Diagnosis of parkinson's disease using gait dynamics and images," *Procedia Computer Science*, vol. 165, pp. 428–434, 2019.

Appendix

Table A.1: Selected papers after four phases of literature search method.

Ref.	Disease	Location	#Subjects	Monitoring duration	Lab/Real	Algorithms	Sensors	Year
[77]	Dementia	Indoor	178	16 hours	Real	Multi-modality	Actillume, StepWatch, Step Sensor, and TriTrac-R3D	2003
[53]	Huntington	Indoor	64	few min	Lab	Temporal assessment methods	2-bit on-board analog-to-digital converter, 4 sensitive switches	2006
[44]	Dementia	General	1249	3.6 years	Real	Low-level motion indicator assessment	accelerometer, gyroscope	2020
[117]	Parkinson	General	134	few min.	Lab	Statistical analysis	Accelerometers, GAITRite	2019
[51]	Parkinson	Indoor	54	-	Real	ML based assessment methods	8 IMU sensors	2018
[69]	Parkinson	Indoor	134	60 meter walk	Lab	NLD, SVM	smartphone, accelerometers and gyroscopes	2022
[113]	Dementia	Indoor	5 CASAS dataset	-	Real	Pattern-based methods	PIR	2020
[78]	Dementia	Indoor	19	600 hours	Real	Single-modality	Computer vision	2007
[126]	Parkinson	Indoor	14	-	Lab	Image processing based method	SONY HDR-HC3 camcorder	2009
[90]	Huntington	Indoor	85	-	Lab	Hybrid assessment methods	IMU attached to the trunk	2014
[80]	Dementia	Indoor	72	few sec.	Lab	Feature-based methods	accelerometer, gyroscope	2016
[121]	Parkinson	General	166	few min.	Lab	ML based assessment methods	8 sensors underneath each foot	2013
[45]	Huntington	General	34	-	Lab	Hybrid assessment methods	accelerometer	2013
[63]	Dementia	Outdoor	182	few min.	Real	Multi-modality	GPS,accelerometer	2017
[47]	Huntington	Indoor	99	50 m walk	Lab	Hybrid assessment methods	force platforms + 6 infrared camera + 15 spherical, retroreflective marker	2011
[49]	Dementia	Indoor	100	25 steps	Lab	Task-oriented assessment	3D kinematics, gyroscope	2019
[86]	Parkinson	Indoor	40	7 days	Lab	Multi-task assessment methods	wearable sensors, gyroscope, opal inertial sensors	2014
[124]	Parkinson	General	166	few min.	Lab	ML based assessment methods	8 foot sensors measuring the vertical ground reaction force (VGRF)	2020
[129]	Parkinson	General	166	few min.	Lab	ML based assessment methods	force sensors	2016
[37]	Parkinson	General	24	few min.	Real	Temporal assessment methods	IMU	2013

Table A.1 – continued from previous page

Ref.	Disease	Location	#Subjects	Monitoring duration	Lab/Real	Algorithms	Sensors	Year
[131]	Parkinson	Indoor	28	few min.	Real	Pattern-based methods	mobile device, Kalman filter and off-the-shelf shoe-worn inertial sensors	2016
[64]	Parkinson	Indoor	45	13 hours	Lab	Clinical assessment methods	accelerometer, gyroscope, magnetometer, and a barometric pressure sensor	2019
[118]	Parkinson	General	56	few min.	Lab	Clinical assessment methods	accelerometers	2017
[139]	Parkinson	Indoor	42	-	Lab	Multi-modality methods	Vicon 3D motion analysis system	2022
[60]	Dementia	Indoor	20	5 months	Real	Feature-based methods	accelerometer	2013
[41]	Dementia	Indoor	65	-	Lab	Task-oriented assessment	accelerometer	2009
[127]	Parkinson	General	301	-	Real	Image processing based method	-	2020
[101]	Parkinson	Indoor	35	25 sec	real	Statistical analysis	smartphone app, sensors, accelerometer	2014
[112]	Dementia	General	53	-		Feature-based methods	accelerometer, gyroscope	2019
[42]	Dementia	General	136	7 days	both	Task-oriented assessment	accelerometer	2018
[71]	Huntington	Indoor	46	few min.	Lab	Single-task assessment	Force-sensitive switches placed inside the shoe	1997
[105]	Dementia	Indoor	different approach	1 month	Real	Multi-modality	doorway sensors, accelerometer	2018
[39]	Dementia	Indoor	41	few min	Lab	Task-oriented assessment	accelerometer	2012
[122]	Parkinson	General	31	5 min.	Real	ML based assessment methods	force sensitive resistors	2017
[36]	Dementia	Indoor	14	30 days	Real	Low-level motion indicator assessment	UW sensor network	2010
[128]	Parkinson	Indoor	7	20 second	Lab	Image processing based method	-	2013
[34]	Dementia	Indoor	200	2 years	Real	Pattern-based methods	PIR, door sensors	2020
[1]	Dementia	Indoor	192	2 years	Real	Pattern-based methods	PIR, doorway sensors	2021
[70]	Parkinson	Indoor	39	49.2 meter walk	Real	NLD based apporach	Wireless Medilogic foot pressure insoles	2014
[50]	Dementia	Indoor	+250	3 years	Lab	Feature-based methods	Kinect sensor	2020
[62]	Dementia	Indoor	10	1 year	Real	Feature-based methods	UW location data	2017
[75]	Dementia	Indoor	252	2 to 4 hours	Real	Pattern-based methods	ambient sensors	
[52]	Dementia	Outdoor	7	7days	Real	Single-modality	GPS	2012
[92]	Huntington	general	30	-	Lab	Hybrid assessment methods	accelerometer, gyroscope,gait pressure mat	2015
[55]	Dementia	Indoor	41	2 weeks	Lab	Task-oriented assessment	inertial sensor	2016
[17]	Dementia	Indoor	40	4 weeks	Lab	Multi-modality	RFID, GPS, GSM and GIS, vision-based	1991
[48]	Dementia	General	80	few min.	Lab	Low-level motion indicator assessment	accelerometer	2020
[111]	Dementia	Indoor	9	few sec.	Lab	Threshold-based methods	accelerometers, gyroscopes, magnetometers	2013
[115]	Parkinson	General	17	-	Both	Clinical assessment methods	accelerometers	2007
[58]	Dementia	Indoor	213	30m walk	Real	Low-level motion indicator assessment	wearable inertial sensors	2020
[206]	Parkinson	General	166	few min.	Lab	ML based assessment method	pressure sensors	2019
[135]	Parkinson, Huntington	Indoor	64	few min	Lab	ML based assessment method	sensorized walkway, force-sensitive	2021

Table A.1 – continued from previous page

Ref.	Disease	Location	#Subjects	Monitoring duration	Lab/Real	Algorithms	Sensors	Year
[68]	Parkinson	Indoor	90	20 meter walking with a stop at 10 meter	lab	NLD based apporach	tri-axial accelerometer and a tri-axial gyroscope	2020
[120]	Parkinson	General	182	few sec.	Lab	Feature-based assessment methods	8 foot sensors measuring the vertical ground reaction force (VGRF)	2016
[73]	Parkinson, Huntington	Indoor	64		lab	Feature-based: Non-linear feature, SVM, probabilistic neural network	Force-sensitive resistors	2020
[110]	Parkinson	Indoor	51	few min	Lab	ML based assessment method	Kinect	2015
[91]	Huntington	Indoor	14	walk to the end of the hallway	Lab	Hybrid assessment methods	GaitRite. CIR system	2017
[24]	Parkinson	Indoor	8	few sec.	Real	Multi-task assessment method	accelerometer	2019
[87]	Parkinson	Indoor	36	12 weeks	Both	Clinical assessment methods	accelerometer	2016
[38]	Dementia	General	60	8 days	Both	Task-oriented assessment	accelerometer, instrumented walkway	2020
[56]	Huntington	Indoor	65	4.6 m walk	Lab	Hybrid assessment methods	instrumented walkway with force sensors embedded in its surface	2008
[57]	Huntington	Indoor	30	walk to the end of the hallway	Lab	Hybrid assessment methods	GaitRite. CIR system	2009
[46]	Huntington	Indoor	24	4.6m walk	Lab	Hybrid assessment methods	six sensor pads encapsulated in a roll-up carpet	2005
[130]	Parkinson	General	20	40m walk	Lab	ML based assessment methods	accelerometer, gyroscope	2020
[119]	Parkinson	Indoor	10	few min	Lab	Clinical assessment methods	accelerometer, gyroscope	2017
[138]	Dementia	Outdoor	15	few sec.	Real	Multi-modality	accelerometers, GPS	2020
[72]	Parkinson	Indoor	34	3 min walk	lab	Feature-based approach, Hoehn and Yahr scale	tri-axial accelerometer	2014
[102]	Parkinson	Indoor	60	Walk 3meter twice with 15 min interval	real	Statistical analysis	device sensor, 3-axis gyroscope, 3-axis accelerometer, and a Digital Motion Processor	2020
[107]	Parkinson	Indoor	102	few sec.	Lab	Clinical assessment methods	pressure sensors on the floor	2018
[106]	Parkinson	Indoor	102	few sec.	Lab	Clinical assessment methods	pressure sensors on the floor	2019
[66]	Parkinson	Indoor	24	few min.	Lab	Clinical assessment methods	video and wearable	2018
[43]	Dementia, Parkinson	Indoor	67	few sec.	Lab	Feature-based methods	gyroscope, accelerometer	2016
[82]	Dementia	Indoor	28	6 min	Real	Single-modality	QR codes	2016
[54]	Parkinson, Huntington	General	40	few min.	Lab	Temporal assessment methods	accelerometer, gyroscope	2015
[123]	Parkinson	General	16	1 hour	Lab	ML based assessment method	accelerometers, gyroscopes	2012
[109]	Parkinson	General	100	-	Lab	Clinical assessment method	infrared depth sensor (Kinect)	2020
[125]	Parkinson	Indoor	44	1 hour	Lab	Feature-based assessment methods	Bio-signals and gait information by eGaIT system	2018

Table A.1 – continued from previous page

Ref.	Disease	Location	#Subjects	Monitoring duration	Lab/Real	Algorithms	Sensors	Year
[116]	Parkinson	General	73	10m walk	Lab	Clinical assessment method	gyroscope, accelerometers	2019
[76]	Dementia	Indoor	7	1 hour	Lab	Threshold-based methods	accelerometer, gyroscope, magnetometer	2015
[100]	Parkinson	Outdoor	62	6 months	real	Feature-based assessment method	smartphone, accelerometers and gyroscopes	2018
[65]	Dementia	Indoor	46	3 meters	Lab	Threshold-based methods	accelerometer, gyroscope	2015
[61]	Dementia	Indoor	30	40m walk	Lab	Feature-based methods	accelerometer, gyroscope	2014
[136]	Dementia	Outdoor		14 days	Real	Single-modality	GPS	2019
[137]	Dementia, Parkinson	Outdoor	65	24 hours	Real	Single-modality	accelerometer	2016
[31]	Huntington, Parkinson	Indoor	64	few min.	Lab	Hybrid assessment methods	Force sensitive switches in the shoes	2015
[59]	Dementia	Indoor	28	few min.	Lab	Task-oriented assessment	accelerometer, gyroscope, magnetometer	2018
[99]	Parkinson	Indoor	55	14 days	Real	Image processing based assessment methods	mobile phone	2016
[16]	Dementia	Indoor	153	2 years	Real	Pattern-based methods	PIR, doorway sensors	2021

Abbreviations

AD Alzheimer's disease

ADL Activities of Daily Living

AI Artificial Intelligence

AIR Active InfraRed

BBS Berg Balance Scale

CASAS Center for Advanced Studies in Adaptive Systems

CCNA Canadian Consortium on Neurodegeneration in Aging

CD Correlation Dimension

CHF Color Histogram Features

CNN Convolutional Neural Networks

DCNN Deep CNN

DFA Detrended Fluctuation Analysis

DL Deep Learning

DMLP Deep MLP

DNN Deep neural network

DOTs Day Out Tasks

DT Decision Tree

FoG Freezing of Gait

FoG-Q FoG-Questionnaire

FRT Functional Reach Test

GPU Graphics Processing Unit

GVFE Gochoo Visual Feature Extraction

HC HandCrafted

HD Huntington’s Disease

HD-ADL HD Activities of Daily Living

HE Hurst Exponent

HMM Hidden Markov Models

HR Harmonic Ratio

IMU Inertial Measurement Unit

IoT Internet of Things

kNN K-Nearest Neighbour

LB LogitBoost

LDA Linear Discriminant Analysis

LED Light-Emitting Diode

LLE Largest Lyapunov Exponent

LM Legendre Moments

LR Logistic Regression

LZC Lempel Ziv Complexity

MDS-UPDRS Movement Disorder Society-sponsored version of the UPDRS

MEMS MicroElectro Mechanical Systems

ML Machine Learning

MLP Multi-Layer Perceptron

MMSE Mini-Mental State Examination

MoCA Montreal Cognitive Assessment

NB Naive Bayes

NDD Neuro-Degenerative Diseases

NFoG-Q New FoG-Questionnaire

NLD Non-Linear Dynamics

PCA Principal Component Analysis

PD Parkinson’s Disease

PIR Passive InfraRed

PNN Probabilistic Neural Network

PwD People with Dementia

PwHD People with HD

PwPD People with PD

RB Romberg Balance

RC Remote Care

R-CNN Regional-CNN

ReLU Rectified Linear Units

RF Random Forest

RFID Radio-Frequency Identification

RNN Recurrent Neural Network

RQA Recurrence Quantification Analysis

RR Randomly Rotated

SPPB Short Physical Performance Battery

STD STandard Deviation

STF Spatio-Temporal Features

SVM Support Vector Machine

TDoA Time Difference of Arrival

THD Total Harmonic Distortion

ToA Time of Arrival

ToD Time of Day

TUG Timed Up & Go

UB Upper Body

UHDRS Unified HD rating scale

UPDRS Unified PD Rating Scale

UWB Ultra-Wide Band

WSU Washington State University

ZM Zernike Moments