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DEPT. OF INFORMATION AND ELECTRICAL ENGINEERING
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Master's Degree in
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Wearable sensor platform for gait analysis and fall prevention

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We are each a patchwork quilt of those who have loved us,
those who have believed in our futures,
those who showed us empathy and kindness
or told us the truth even when it was not easy to hear.
Those who told us we could do it when there was absolutely no proof of that.

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Chapter 1

Introduction

1.1 Problem Definition

The topic of this thesis revolves around the study of the *prevention* of falls among adults and elderly. More specifically, the study is based on a wearable sensor platform, whose sensors give an insight on the the way the patient moves, to later estimate their risk of falling. Although several research studies have been published regarding the *detection* of falls using different methodologies, fall prevention remains an hot topic in the scientific community. The main difference between prevention and detection of falls is based on the idea that the first aims at identifying the risk of falling of a patient, whereas the latter aims at recognizing a fall that has already occurred.

With the ever growing scientific advances and the longer life expectancy, falls have become one of main causes of injury among the elderly. Injuries include fractures, brain damage, mobility and independence loss, and even death. According to the Centers for Disease Control and Prevention (CDC), more than one in four older adults report a fall each year.

In patients affected by Parkinson's Disease, a common problem related to the risk of falls is the Freezing of Gait (FOG). In determining whether or not this parameter could be predicted, it has been demonstrated that utilizing EEG or EMG signals led to a more accurate prediction.

As stated by [**?**], falls not only impact the patients themselves, but also their surroundings. Psychological effects take place on nurses, who feel a higher level of stress and pressure when dealing with a patient who is at risk of falling. This results in scenarios in which a nurse would limit the mobility and individual freedom of the patient as to avoid the consequences of an involuntary fall. This leads to, as stated by the nurses themselves, the loss of strength in the patients, who also have their privacy taken away: to avoid falls, nurses even accompany them in the bathroom, since a fall would get them in trouble and slow their work down. In this scenario, a different approach to fall prevention is necessary.

1.1.1 Fall Risks

The prevention of falls relies in the identification of risks associated with an increased chance of falling, and then on the mitigation of the fore mentioned risks. A study published in 2022 [?] compared all the causes that were thought to be relevant in the context of falls, and evaluated among those that increase the risk of falling in the elderly:

Older Age Falls are the most common cause for trauma in older patients. Injuries at age above 65 lead to worse head injuries, in particular hemorrhage, compared to the younger counterpart [?].

Frailty The elderly is generally considered more frail than their younger counterpart. Frailty is defined as the natural decline of the functions among organs [?].

Drugs Used Psychotropic and psychoactive drugs may increase the risk of falls in a skilled nursing facility in proportion to the total load of these agents [?].

Polypharmacy Polypharmacy is defined as the use of multiple medicines, and it is associated with adverse outcomes including mortality, falls, adverse drug reactions, increased length of stay in hospital and readmission to hospital soon after discharge [?].

Heart Disease More than 60% of patients affected by any kind of heart complication have a moderate to high risk for falls. Adults with Heart Failure and arrhythmias have an especially high risk of falls (likely because of diminished cardiac output, polypharmacy, or interaction with other comorbid conditions), with a fall rate of 13% higher if compared to people with other chronic diseases [?].

Hypertension This risk is not directly associated with the condition itself, but rather, it is related to the use of medication to control it. As stated beforehand, the use of drugs and polypharmacy are associated with an increased risk of falling, thus any pathology that leads to the addition of more medication is to relate to a risk of fall.

Fall History A study [?] demonstrated that a number of previous falls up to 4 or 5 is a predominant factor in determining whether an elderly is at risk of falling or not. The research is supported by the evidence that while a single fall might occur at random, recurrent fallers are likely to suffer from persistent deficits that result in an inability to avoid falls.

Depression Both depression and the use of antidepressant increase the risk of fall. This is due to different reasons: depression increases fall risk through psychomotor retardation, deconditioning, gait/balance abnormalities, impaired sleep/attention and fear of falling; instead, antidepressants contribute to (or cause) falling through causing sedation, impaired balance/reaction time, OH, hyponatremia, cardiac conduction delay/arrhythmia, and/or drug-induced Parkinsonism [?].

Parkinson's Disease Fall rates are higher in people affected by Parkinson's Disease (35% to 90% of patients fell at least once, with an average rate of 60.5%). Historically, falls were seen as a late manifestation of the disease caused by a progression of axial motor problems combined with the effects of aging. In this context, recurrent falling is a milestone in disease progression often linked to other events such as visual hallucinations, cognitive decline, and hospitalization [?].

Pain A research paper [?], demonstrated that the elderly subject to mild, moderate and severe pain in more that two body sites were associated with an higher risk of falling compared to those who had not, as stated by the follow up questions about history of falls during the course of two years.

Some other risk factors comprise:

Malnutrition The topic of the correlation between malnutrition and fall risk is still highly discussed in the scientific community. Most research focus on other conditions to determine the risk, hence less studies investigated the relationship between the two. Kupisz-Urbanska and Marcinowska-Suchowierska's review [?] concluded that malnutrition is indeed a factor of risk, due to the loss of muscle strength, mass and function, which also leads to more harmful falls.

Living Alone The New York Times [?] reports that people who live alone in their sixties are 24% more likely to fall than those with greater social interactions. Even for hospitalization, the rate is 23% higher in people living alone and 36 percent higher among those with the least social contact compared with those with the most.

Living in a rural area There are different theories regarding whether or not living in a rural area is an increased risk for falling. Different results were obtained by different studies, which confirmed or denied any correlation between the two. Mostly, a fall in rural area is to be attributed to both the working conditions and location of the work, which exposes the employer to dangerous environments and movements.

Alcohol Consumption A study on alcohol consumption in Chinese adults [?] highlighted that usual alcohol consumption is associated with a higher risk of falls, since it can interfere with balance, coordination, and vision.

Some other conditions related to the risk of falling that were not demonstrated by [?] to increase such risk, but on which literature does not agree are:

BMI Although BMI itself may not be a risk, consequences linked to BMI might be. Excessive weight may put additional strain on joints and lead to mobility issues. Moreover, people may be in pain or using medications.

Sex Most studies focused on fall risk identification - whether to determine if a pathology or a condition is of risk - kept into consideration biological data such as age and sex. Almost every study found a relation between sex and the increased fall risk, demonstrating that the female sex falls more often compared to their male counterparts. This result was also achieved when considering multiple conditions at once, confirming that males and females affected by the same pathology, or living in the same environments, had different fall rates.

Education level Education level is also debated. Considerations can be made regarding the age associated to education level (e.g., children may be at higher risk of falling), or a diversity in living conditions, economic status, access to healthcare, and job mobility requirements.

Diabetes While diabetes is not a condition that increases the fall risk itself, the consequences of this disease can lead to problems such as vision problems, hypoglicemia, and thus balance problems and muscle problems. Not to mention the medications needed to keep diabetes under control that may lead to an increased risk of falling in diabetic patients.

Stroke A review on the state of the art (of 2016) about the incidence of falls in stroke survivors [?] highlighted that there are contrasting opinions regarding whether or not this factor increases the chances of a fall. One reason being that more severe stroke cases may have a reduced chance of falling due to their limited mobility. Another reason being that results differ due to regional differences among stroke survivors. Moreover, some studies have limited their observations to 2 years post stroke, whereas this review confirmed from longer term studies that stroke survivors experience falls twice as likely than non-stroke controls after a median of 10 years post-stroke.

Vision Dysfunction A study from 2010 [?] concluded that vision impairment caused significant gait changes, since obstacle-crossing is more cautious when compared with that of visually normal subjects; suggesting that such individuals may be at greater risk of tripping or falling during everyday locomotion.

Cognitive Impairment Although the analysis carried out by [?] has not demonstrated the correlation of this factor with fall risk, [?] explored the steps to reduce the risk of fall in dementia patients. From their study background, people who suffer from cognitive impairment fall two to three times more than cognitively healthy older adults. The data shows that 60 to 80% of people with dementia fall annually. The regions of the brain involved in dementia are required to coordinate mobility, balance, and gait, leading to a variability in stride length and reduced walking speed.

1.1.2 Fall Risk and Balance Tests

To assess the risk of falling, literature agrees that it is useful to evaluate the movements of the patients using a variety of tests. The common denominator though, is that research shows that just one of these tests is not enough to determine if the elderly is at risk, but rather a combination of factors can be used to advance a conclusion.

Berg Balance Scale (BBS)

The Berg Balance Scale is a test made up 14 static and dynamic activities related to everyday living. The BBS assesses balance and risk for falls through direct observation of the participant's performance by trained health care professionals in a variety of settings. The patient is expected to:

- Move from a sitting to a standing position;
- Stand up unsupported;
- Sit unsupported;
- Move from a standing to a sitting position;
- Transfer from one chair to another;
- Stand up with their eyes closed;
- Stand with their feet together;
- Reach forward with an outstretched arm;
- Pick an object up off of the floor;
- Turn and look behind them;
- Turn around in a complete circle;
- Place each foot alternately on a stool in front of them;
- Stand unsupported with one food directly in front of the other;
- Stand on one leg for as long as they can.

Scoring is on a 5-point ordinal scale with 0 indicating the inability to complete the task and 4 as independent with completing the task. The maximum score of 56 indicates good balance [**?**], whereas a score below 45 indicates individuals may be at greater risk of falling. As stated before, nowadays this test is valid for predicting a fall only if supported by other tests in this category. Otherwise, it can only be an indicator for static balance.

Timed Up and Go Test(TUG)

The aim of this test is to assess the patient's mobility and fall risk. It consists of simple activities, with the objective of determining the amount of time that the subject needs to complete the tasks. The only equipment needed is a chair and a stopwatch. After marking a 3 meters line on the floor starting from the chair, the patient is asked, as soon as the stopwatch is started, to stand up from the chair, reach the target at their normal walking pace, turn

around and sit back into the chair. The timer is then stopped, and the time is recorded, in seconds.
Any older adult whose results are above or equal to 12 seconds is at risk of falling [**?**].

Balance Evaluation Systems Test (BESTest)

The BESTest is comprised of a variety of tasks to assess any postural complications related to a loss of balance. It is intended for patients with neurological conditions (e.g. Parkinson's Disease, Stroke, Multiple Sclerosis and so on), vestibular disorders, cognitive impairments, and the elderly. The tasks are split into 6 sections for a maximum of 108 points:

Biomechanical Constraints This section measures the base of support (whether both feet have normal base of support or the support is subjected to pain and/or deformities), the Center of Mass Alignment, to determine if the posture is correct, ankle strength and range, hip/trunk lateral strength, the ability to sit on the floor and stand up;

Stability limits/verticality This section tests the ability to sit and lean to the side, and the capability to realign vertically after the movement. Moreover, it comprises the evaluation of the forward and lateral reach;

Transitions The activities in this section test the autonomy to stand starting from a sitting position, the stability of the keeping a balance on the toes, to stand on one leg, the ability to go up the stairs and the balance while keeping one arm raised;

Reactivity This part of the BESTest determines the overall responsiveness of the patient when pushed away from a balanced position; whether they are able to get back to a balanced positions or not. The push is tested in the forward and backward position; and also a compensatory stepping correction (how many steps the patient takes to recover equilibrium) is tested in both the forward and backward direction, with the addition of a lateral correction test;

Sensory Orientation These later activities evaluate the impact other senses have on the overall balance of the patient. In particular, they test motions the subject is asked to perform with both open and closed eyes;

Stability of Gait This set of tasks evaluates the overall ability of walking, starting from speed, observing balance and imbalance, pivot turns, the ability of stepping over obstacles and, last but not least, the patient is asked to perform the timed up and go test once on its own and one more time while asked to perform another task (counting, talking, and so on).

The test can also be performed in its *mini* form, the Mini Balance Evaluation Systems, which comprises only 14 of the 36 activities of the original test, coming from sections 3, 4, 5 and 6. The total score is 28 (32 if counting separate points for each leg).

Sit To Stand Test

The test aims at testing leg strength and endurance in older adults. It is performed using a folding chair with no arms, positioned against a wall and with rubber tips on the legs to prevent it from moving. Also defined as 30 seconds Sit to Stand, the patient is asked to stand up and sit on the chair as many times as they can before the 30 seconds mark, with their arms crossed on their chest and a foot positioned slightly in front of the other for balance reasons. The total score is equal to the number of complete, correct stands the subject achieves in the time available. A below average number of stands for the patient's age group indicates a high risk of falls [**?**].

Single Leg Stance Test (SLST)

The Single Leg Stance (SLS) Test is used to assess static postural and balance control in clinical settings, to monitor neurological and musculoskeletal conditions. This evaluation method is usually used to determine the balance level of people who are at major risk of fall. The patient is asked to stand on one leg without assistance, keeping their eyes open and their hands on their hips.

Age Group	Below Average	Average	Above Average
60 - 64	<14	14 to 19	>19
65 - 69	<12	12 to 18	>18
70 – 74	<12	12 to 17	>17
75 – 79	<11	11 to 17	>17
80 – 84	<10	10 to 15	>15
85 – 89	<8	8 to 14	>14
90 – 94	<7	7 to 12	>12

Table 1.1: Number of average repetitions completed by men

Age Group	Below Average	Average	Above Average
60 - 64	<12	12 to 17	>17
65 - 69	<11	11 to 16	>16
70 – 74	<10	10 to 15	>15
75 – 79	<10	10 to 15	>15
80 – 84	<9	9 to 14	>14
85 – 89	<8	8 to 13	>13
90 – 94	<4	4 to 11	>11

Table 1.2: Number of average repetitions completed by women

Once the movement is initiated, a timer is started. If the equilibrium is lost or one of the hands leaves the hips, the stopwatch is stopped. The subject is determined at greater risk of injury from fall, if the balance is kept for less than 5 seconds [**?**], since the movement is significantly impaired by: neurological conditions like multiple sclerosis, Parkinson's disease, Alzheimer's disease, and dementia; stroke; traumatic brain injury; or lower extremity pathology, which usually affect the geriatric population.

Functional Reach Test (FRT)

The FRT test is comprised of a single activity to evaluate static balance through maximal forward reach from a fixed base of support. It is usually targeted for the elderly and frail adults. The patient is first asked to stand, and later to extend their arm. Once in position, the subject is requested to reach forward with their lifted arm the most they can standing still, and without losing their balance.

Once the subject completes the task, the distance reached (measured as the difference of their hand's ending position and their hand's initial position) can be interpreted as a measure of their fall risk if compared to the performance of their peers.

It has been observed that a greater distance equals to a better balance and decreased fall risk. Thus, in community dwelling elders, a value below 17.5 cm suggests limited mobility skills, inability to leave the neighborhood without help, and restriction in performing any kind of activity of daily living (ADL) [?]. Instead, in frail elderly patients, a value below 18.5 cm reach indicates fall risk [?]. Based on a Canada-wide sample of 2,305 elderly people, the median distance was 29 cm in cognitively unimpaired subjects [?].

Some research [?] [?] found that a decreased spinal flexibility and the movement strategy affects the distance reached, questioning the ability of the test to differentiate elderly non-fallers and fallers. A research [?] also noted that trunk mobility has a greater contribution to the test than the centre of pressure displacement.

Tinetti Performance Oriented Mobility Assessment (POMA)

The Tinetti Scale is a test comprised of different activities, developed for the aim of assessing the older adult's gait and balance abilities. Each activity is graded on a scale of 0 to 2 points, according to a given criteria. Overall, the total score (gait and balance tests) is 28 points, with

- below 19, high fall risk;
- 19 to 24, medium fall risk;
- 25 to 28, low fall risk.

For the balance tests, the movements tested are:

Tasks	Metrics	Points
Sitting balance	Leans or slides in chair	0
	Steady	1
Rising	Unable without help	0
	Able with help	1
	Able without help	2
Attempt to rise	Unable without help	0
	Able with more than 1 trial	1
	Able in 1 trial	2
Immediate standing balance (first 5 seconds)	Unsteady (swaggers, moves feet, trunk sway)	0
	Steady but uses walker or other support	1
	Steady without walker or other support	2
Standing Balance	Unsteady	0
	Steady but wide stance (median heels more than 4 inches apart) and uses cane or other support	1
	Narrow stance without support	2
Nudged (subject at maximum position with feet as close together as possible, examiner pushes lightly on subject's sternum with palm of hand 3 times)	Begins to fall	0
	Staggers, grabs, catches self	1
	Steady	2

Eyes Closed (at maximum position of item 6)	Unsteady	0
	Steady	1
Turning 360 Degrees	Discontinuous steps	0
	Continuous steps	1
	Unsteady (grabs, staggers)	0
	Steady	1
Sitting Down	Unsafe (misjudged distance, falls into chair)	0
	Uses arms or not a smooth motion	1
	Safe, smooth motion	2

Table 1.3: Tinetti Scale Tasks

Tasks	**Metrics**	**Points**
Initiation of Gait (immediately after told to "go")	Any hesitancy or multiple attempts to start	0
	No hesitancy	1
Step Length and Height (Right swing foot)	Does not pass left stance foot with step	0
	Passes left stance foot	1
	Right foot does not clear floor completely With step	0
	Right foot completely clears floor	1

Step Length and Height (Left swing foot)	Does not pass right stance foot with step	0
	Passes right stance foot	1
	Left foot does not clear floor completely With step	0
	Left foot completely clears floor	1
Step Symmetry	Right and left step length not equal (estimate)	0
	Right and left step length appear equal	1
Step Continuity	Stopping or discontinuity between steps	0
	Steps appear continuous	1
Path (estimated in relation to floor tiles, 12-inch diameter; observe excursion of 1 foot over about 10 ft. of the course)	Marked deviation	0
	Mild/moderate deviation or uses walking aid	1
	Straight without walking aid	2
Trunk	Marked sway or uses walking aid	0
	No sway but flexion of knees or back or Spreads arms out while walking	1

	No sway, no flexion, no use of arms, and no Use of walking aid	2
Walking Stance	Heels apart	0
	Heels almost touching while walking	1

Table 1.4: Tinetti Scale Tasks Gait Tasks

1.2 Relevance of the problem in the context of computer engineering

Although the problem of fall prevention is already discussed in the medical field, the biological solutions to the problem include the use of the tests discussed above for the determination of the gait asymmetries that influence the patient, to evaluate, according to some criteria, if the patient might be at risk. After the examination, the patient is either adviced to perform exercises that can increase their mobility, or to use devices that can prevent sudden falls. Apart from the biological tests, that are dependent on the medical staff's considerations, computer engineering can lead to advances in the solution to the problem, by making use of different methodologies such as wearable sensors and machine learning. Wearable sensors allow for a continuous moniroting of the patient's movements, and include accelerometers, gyroscopoes, magnetoscopes and pressure insoles, whereas machine learning can bring a new insight on the problem by highlighting problem-specific features that are mostly associated with an inbalanced gait and risk of falls. By giving a new perspective on the problem, both of these means can help the medical staff in the identification of the predominant factors that make patients at risk. Since the application is related to the medical field, the machine learning algorithms used need to be of the explainable or interpretable type. Using more complex (such as Deep Learning) models or those who hide their solution (such as Neural Networks) is not an option, mainly for two reasons: the available data is usually limited because it should be acquired from patients who are not always willing to share their information (privacy reasons), and because the medical staff has to be aware of the criteria used by the model to make the prediction, since the results need to be validated and understood by the community to be effective. One problem with said methods is that the subjects should feel at ease while making use of them. Therefore, an optimal solution to the problem is one that makes use of technologies that are not defined as burdens by the patients who need to make use of them. Therefore, even in the use o0f sensors, those need to be configured so that the subject feels no discomfort in wearing them. One available solution that has the least amount of discomfort is make of pressure insoles that can be worn inside of shoes to monitor in real time the walking motion of the patient, and assign a risk score when the signals are analyzed. One complication of this approach emerges when considering that the persons who are usually the target of the analysis are mostly elderly or affected by impairements. Thus, a continuous analysis is probably not feasible if the monitored subject forgets to wear their sensors of forgets to charge them (since the whole system should be equipped with a battery). Despite this evident limitation, the solution remains valid as it can be used for monthly or yearly checks to determine if the patient has improved their gait, or has become more at risk.

Chapter 2

State Of The Art

This chapter will focus on a review of the available literature on fall prevention using wearable sensors and machine learning techniques, to highlight the common approaches used in the last few years.

Moreover, there will be an overview on the available datasets for the purpose of the thesis, and their characteristics, linked with their availability.

Lastly, a brief explanation on the challenges of the available state of the art, emerging trends and conclusion.

2.1 Literature Review

2.1.1 Common Approaches

A first review on the state of the art was proposed by [?]. The paper aims at identifying the most common technologies utilized to recognize the risk of fall by evaluating selected articles, from 2002 to 2019, based on a predefined criteria,to detect a fall and to classify the elderly as "faller" and "not faller". Focusing on fall risk prediction articles, the authors highlighted that the most common wearable sensor used is the accelerometer, together with the gyroscope. These devices were used in the 17.2% of the publications to capture gait data. In particular, the best locations to identify the level of risk are the lumbar and waist areas, which were the most popular among the articles considered. Moreover, their sampling rate were mostly 50Hz or 100Hz, although the parameters ranged from 4Hz to 256 Hz. Lastly, the methodology most used is the feature extraction, compared to machine learning alone.

2.1.2 Tinetti Scale to automatically determine fall risk

Predicting falls is a task most centered around the elderly who should be, first of all, classified at risk of falling. An experiment carried out by Rivolta et al. [?], studied the data acquired from 90 participants (79 elderly and 11 healthy volunteers) located into two rehabilitation centers in Northen Italy to asses their risk of falling using the data captured by only one accelerometer attached to the waist. The aim of the study was to create an automated system that could be used at home to predict the risk of a fall. The study is based on the Tinetti Scale; therefore, the tasks that the participants were asked to perform were both the Gait and Balance activities that comprise the test. Later, this data was used to first study the features obtained by pre-processing the data to establish the differences between high risk fallers and low risk fallers. Secondly, the features were selected using a linear regression to determine those related to the Tinetti Scale; Thirdly, the reduced feature set was used to train two classification models (linear model and artificial neural network) to automatically detect those affected by the risk of fall; Lastly, the scores from the Tinetti Scale were tested to determine which ones were more affected by misjudgments.

As for the first task, the authors found out that 12 out of 21 features were different among the two groups, such as age and gender, while BMI is not significative to determine the difference between high and low risk. Moreover, as regards balance, the Standing UP Duration, Balance Recovery after nudge and regularity of standing were highly different; whereas the 360 degree turn and the sitting down activities do not differ between the two groups. As for gait, instead, all the features differ (Step Frequency, Step Regularity - vertical axis, Surrogated Step Height and Trunk Lateral Sway) except Step Regularity computed on the horizontal axis.

For the second task, Rivolta et al. used LASSO with parameter $\lambda = 0.7$ to reduce the set to 9 features: Triangle duration along the Anterior/Posterior axis (determined intersecting two straight lines having the maximum and minimum slopes, with the AP baseline before and after standing up), Immediate Standing Unbalance for the Standing Up Tinetti Task, Lateral Oscillations of the participant's body when nudged by the specialist, Sample Entropy for Task 5 of the test, and Step Regularity on the vertical axis and Trunk Lateral Sway for the walking task, BMI, Gender and Age.

The classification task involves one regression and one binary classification. The regression performance was measured by the Pearson's correlation coefficient while classification performances were assessed using sensitivity and specificity. First, the linear regression was trained on the parameters of the Tinetti scores in the training set. Then the artificial neural network was used to understand if it would have a lower number of misclassifications compared to the first approach. First, a standard linear regression was used to fit the LM parameters on the Tinetti scores of the training set. The model was applied on the test set and the estimated scores were dichotomized at 18 as in the regular Tinetti test. Second, an ANN was used to verify whether a non-linear transformation of the feature set could provide a lower misclassification error. For the regression, the obtained sensitivity was of 0.71 and the specificity was 0.81. For the artificial network, the obtained sensitivity was of 0.86 and the specificity was 0.90 on the test set.

For the last task, to assess the importance of a misjudgement of the parameters of the Tinetti test in deciding the fall risk, each element was changed in value (choosing from the possible value ranges) and the authors assessed how many participants changed class (from high risk to low risk and viceversa).

For the balance parts, the most important features were standing balance with eyes closed, nudge and standing balance with eyes opened, while the less important was sitting balance. For the gait parts, path related to the floor, trunk sway and walking stance showed the highest classification error when changed, together with walking stance, a determining factor to classify the patients as low risk when changed to 1. For both parts, a wrong standing balance led to the highest error rate.

2.1.3 Random Forest Classifiers

Another article used random forest algorithms to classify frailty and falling history in seniors using plantar pressure measurement insoles [?]. This study aimed at providing an analysis on the gait of the elderly using insoles able to capture seven signals coming from each foot. Then, the data has been processed to obtain the determining features of the gait, obtaining up to 182 features later analyzed using random forest algorithms. The dataset used for the study is comprised of 774 elderly people from Japan. The experiment involved different tasks:

- A 45s standing balance test;
- 20m walking trail (10m in forward direction, then a turn and another 10m in the backward direction)

A total of 203 subjects were considered frail by using the Kihon checklist, while 45 subjects who could not remember whether they had fallen in the 12 months prior to the study were excluded. Another 17 subjects were excluded from the analysis due to errors during the collection of the data. Overall, 712 subjects were used for the study. A total of 5 categories for features were extracted from the walking data:

Frequency Domain Analysis A fast Fourier transform was performed after the output of the 14 sensors was summed at each sampling point to integrate the temporal information on only one time series.This category includes four extracted features.

Peak analysis and area under the curves First, three parameters were extracted for each isolated step and each sensor: maximum pressure,the time at which this maximum pressure occurred relative to the total stance time, the area under the pressure curve was extracted for each isolated step and for each sensor. Second, the four following data features were calculated for each trial and each of the three parameters: the average of all the left foot steps, the standard deviation of all the left foot isolated steps, the standard deviation of all isolated steps of both feet, and the left and right foot average difference. Thus, this results in 84 extracted features in this category.

1-foot COP trajectory analysis The COP trajectory was computed for each stance phase of each isolated step. First, the following 13 parameters were extracted: the minimum and maximum values on x and y, x and y coordinates at the double to single stance and single to double stance points, x coordinates of COP at the y coordinates of the center midfoot and center forefoot sensors, respectively; the range of variations on x and y; and the center of pressure excursion index, calculated as the ratio of COP trajectory excursion on the distance between the lateral and medial forefoot sensors. Second, the four following data features were calculated for each trial and each of the 13 parameters: the average of all the left foot isolated steps, the standard deviation of all the left foot isolated steps,the standard deviation of all isolated steps of both feet, and the left and right foot average difference. This category included 52 extracted features.

Gait phase analysis The following two parameters were computed for each isolated step: stance phase duration and percentage of double support duration relative to the whole stance phase. Then, the following four features were extracted for each trial and each of the two parameters: average of all the steps from the left foot, standard deviation of all the steps from the left foot, the standard deviation of all isolated steps of both feet, and the left and right foot average difference. This subcategory includes a total of 8 extracted features.

Wavelet analysis For each stance phase of each isolated step, the envelope of the 7-sensor of the left foot was computed. This category of features is based on the characteristics of the two waves, which characterize the plantar pressure pattern during the stance phase. First, the following 15 parameters were computed: the distance between the first and second peaks, height of the first peak, height of the second peak, height of valley, the difference between the heights of the peaks, ratio of the height of the first peak to one of the valleys, ratio of the height of the second peak to one of the valleys, difference between these two ratios, width of the first peak, width of second peaks, difference between these two widths, slope rate from the starting point of the stance phase to the first peak, slope rate from the first peak to valley, slope rate from valley to the second peak, slope rate from the second peak to the endpoint of stance phase. Second, the average and standard deviation of all the steps from the left foot were calculated, resulting in the extraction of two features for 15 parameters. This category included 30 extracted features.

Lastly, random forest models were trained to classify the frail from the healthy using scikit-learn. The training procedure was set so that each forest model was composed of 200 decision trees. Each tree is built by successfully splitting its nodes until the Gini impurity score equals zero until all data points in the leaf nodes correspond to the same class. Models showed low classification performances (average balanced accuracy: 0.57±0.05, weighted F1-score: 0.556±0.034). Then, the models were validated using a 5-fold cross-validation procedure. Alternatively, random forest models were constructed and tested using a nested cross-validation procedure. The random forest classifiers showed an average balanced accuracy of 0.75±0.04 and an average weighted F1-score of 0.77±0.03 for the recognition of frail vs. non-frail subjects.

2.1.4 STM32 wearable device

A novel approach was proposed by Andò et al [?]. A wearable sensor platform was deployed using STM32 components, which allow for the introduction of an AI Core to detect postural movements in real time. The authors differentiated between four different postures, starting from stable to unstable. A limitation of this study is its data acquisition. The movements are simulated through the use of a mannequin, which is personally moved to emulate human movements. A better approach would have been the participation of real older adults, and study their own movements as they wore the device. The data is acquired using a tri-axial accelerometer, positioned on what would be the chest area of a real individual. The main features extracted for the classification task are:

1. maximum displacement in the AP (Anterior - Posterior) direction;
2. maximum displacement in the ML (Medio Lateral) direction;
3. ellipse area which includes 95% of the stabilogram plot, i.e. a plot of the variation in time of the movements of the Center of Pressure of the individual;
4. Root Mean Square (RMS) displacement.

These features embed information related to the distance between the sensor and the hips of the subject, and the distance between the sensor and the ground.

The adopted classification strategy is comprised of the simplest architecture available, a Multi-Layer-Perceptron.

2.1.5 Gait Heat Maps and CNNs

A different approach was suggested by Brome et al [?]. Instead of transforming the data to obtain meaningful features to feed to a machine learning algorithm, the authors decided to encode the information about the gait of the patients analyzing the gait as a cyclostationary process, whose statistical properties repeat over a certain period. The data was collected through insoles inserted into special shoes which recorded two pressure points (heel and toes) for each foot. This data was later pre-processed both in frequency and in time so that the entire data was held within the cyclic frequencies associated with the characteristic cycles of the signal. The information about the spectral correlation function, i.e. a function that determines the correlation between two frequencies components of the signals with respect to their frequency difference, was then used to create the heat maps where brighter colors where associated with higher values of the function. The image was then fed to a Convolutional Neural Network, which was able to distinguish between fallers and non - fallers reading the spatial information encoded in the images.

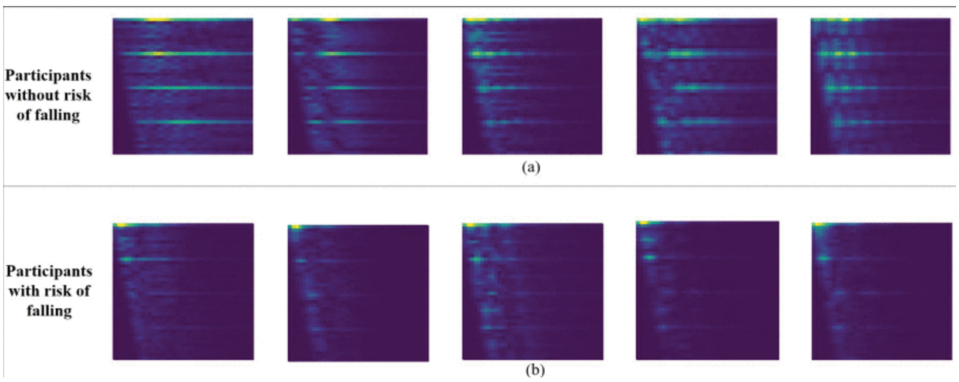

Figure 2.1: Example of heatmaps generated by the pre - processing

2.1.6 Dual Task Timed Up and Go for Fall Risk Assessment

A take on the problem of fall risk assessment was proposed by [?]. The analysis is based on the observation that mostly every study that uses insoles to detect the risk of falling, have their subjects only perform the activity of walking when capturing the data. The author suggest that the individual's gait changes when distracted, such as performing a second task while moving. Thus, the experiment carried out was comprised of two tasks: first, the patient had to walk 23ft ($\sim$ 7 meters) at their normal pace; second, they were asked to repeat the first task but holding a cup of water in their hand. This ensured that the subject would be focused on not dropping the water. The data was recorded using insoles and a couple of accelerometers positioned on the heel and first metatarsal area. From the data acquired with the sensors, gait phases and parameters (such as symmetry) are extracted, with a total of 63 gait features and 864 accelerometer features to use to detect the risk of a fall. After determining the most important features, the authors tested random forest classifiers, support vectors machine and k nearest neighbors. The results show that the Parkinson's Disease patients change their stride symmetry in task 2, a change that is not seen with Control Group subjects. Moreover, although the gait features did not differ much, the accelerometers features did, showing completely different directions. A classification using both gait and accelerometer features shows that the latter is more significant in differentiating healthy from Parkinson's patients, with an increased accuracy when considering the data coming from Task 2.

2.1.7 Foreseeing falls comparing accelerometer data and TUG test seconds

When comparing sensors data and clinical tests, [?] demonstrated that the data captured from an accelerometer positioned in the chest area of the patients as they performed different variations of the TUG test (simple TUG, TUG + cup of water, TUG + cognitive task) were more indicative of a risk of fall in the patients compared to the number of seconds they took to complete the different tasks. Starting from the raw data of the accelerometer, the authors extracted features about the signal of the gait in the frequency domain. After collecting data about the number of falls the subjects had experienced in the following 12 months, the most accurate predictions (among 74 elderly who were healthy, and had no history of falls in the previous six months) were given by the measures about the energy compression of the signal, and the frequencies that characterize it. Moreover, from their analysis, the data about the gait was better at indicating which of the elderly would fall in three months following the acquisition of the data, rather than recognizing a faller with data about the gait of the previous 12 months. Instead, the seconds necessary to complete all of the variations of the TUG test were different in two groups, but the sensitivity achieved by the classification used was low, demonstrating a great number of false negatives.

2.2 Data Availability

A common problem in applications involving data acquired from any sort of patient is the data availability. Since new systems aim at improving the quality of therapies, make them easily accessible, or help professionals in their everyday activities, these objectives need data directly acquired from those affected to define and create systems that work in the correct way. This involves problems related to the privacy of the patients who make their information accessible to only the part that expressively asked for the data. This usually comes with a (rightful) prohibition of distribution of the fore mentioned data, which usually includes private information about the patients involved. The downside is a limitation of the progress of the research. A few public datasets containing the anonymized data are available for everyone to use; other can be accessed upon request, and others are not publicly available. The focus of this thesis revolves around data that has not been processed prior to the release of the dataset to the scientific community. This information is referred to as raw data.

2.2.1 Public Datasets

A first public dataset is *PlantPre* [?], comprised of data comimg from 2-3 minutes of plantar pressure data from a total of 48 elderly people, along with their Berg Balance Scale score as their falling risk labels. The test were conducted in the First Affiliated Hospital of Jinan University (Guangzhou Overseas Chinese Hospital).The content of the experiment mainly includes three parts:

Personal Health Information information included subjects' sex, age, height and weight, history of fall, past medical history, drug use, exercise frequency and home life status;

Berg Balance Scale Test Before collecting plantar pressure, clinical doctors conducted the Berg Balance Scale on the elderly to evaluate their postural control and stability: subjects with a total score of less than 40 were labelled as high falling risk, while subjects with a total score equal to and more than 40 were classified as low falling risk;

Walking Experiment plantar pressure monitoring shoes were used to collect the walking data associated to the subject. The monitoring shoes collected the plantar pressure data at a frequency of 20Hz, recording 8 pressure points per foot. After adapting to the shoes, the subjects walked in the hospital corridor at a comfortable speed for 2-3 minutes accompanied by the experimenter. The data was sent to an application through bluetooth. The unit of measure is Pascal.

The three-axis accelerometer model was LIS3DHTR (STMicroelectronics, Switzerland).

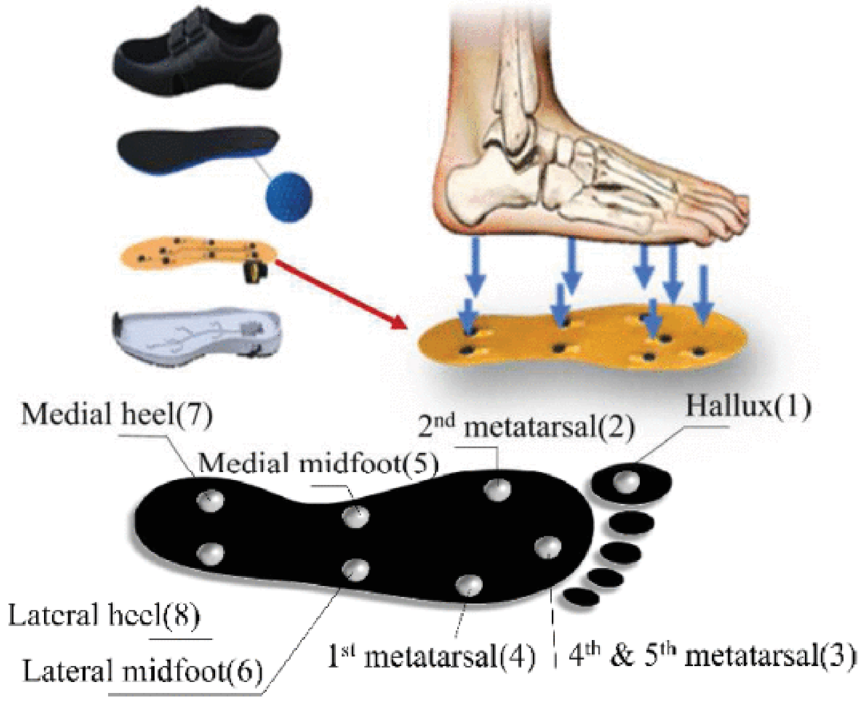

Figure 2.2: Location of the 8 sensors of the insole

2.2.2 Datasets available upon request

A first dataset available upon request is *The Smart Insole Dataset* [?]. This dataset is comprised of raw data coming from a pair of pressure sensors insoles. The participants, 29 persons of different age groups and health conditions (healthy adults, elderly, Parkinson's disease patients), performed two sets of tests. The first group is the control group, in which healthy adults aged between 20–59 years were included; the second group includes elderly citizens, in which people above the age of 60 years were included; the third group relates to Parkinson's disease patients, irrespective of their age. The data is acquired from *Moticon SCIENCE* insole sensors, with a sampling rate of 100Hz. The total number of features is 50 (with 25 coming from the right foot and 25 coming from the left foot), plus a timestamp. The raw data is measured in:

- timestamp, in ms;
- pressure points (1 to 16) in N/cm^2;

- acceleration on the c, y, z axes in g;
- The angular rate $\omega x, \omega y, \omega z$ in dps;
- The computed center of pressure in the x, y coordinates;
- The total force N.

The tests to measure gait information involved the Walking Straight and Turn test and a modified version of the Timed Up and Go test, which are made up of the following activities: for the Walking Straight and Turn test, participants were requested to walk in a straight route for 10m starting from a standing position. At the end of the 10m route, they turned 180° and returned to the starting position. The test was repeated two times and at three different walking speeds, slow, normal, and fast, as perceived by each participant; for the modified Timed Up and Go Test, participants were asked to rise from the chair, and immediately start walking straight for 10m. Then, after a turn of 180°, they were instructed to return to their chair, and sit down. As for the first test, this task was also repeated twice.

The labeling of the recorded data was performed following a two-level annotation process. In the first level of annotation, data were described as activities of daily living (ADLs) that included 12 different labels (Tab **??**). The second level of annotation was focused on labeling the characteristic events of a gait cycle (Tab **??**), for both the right and left leg.

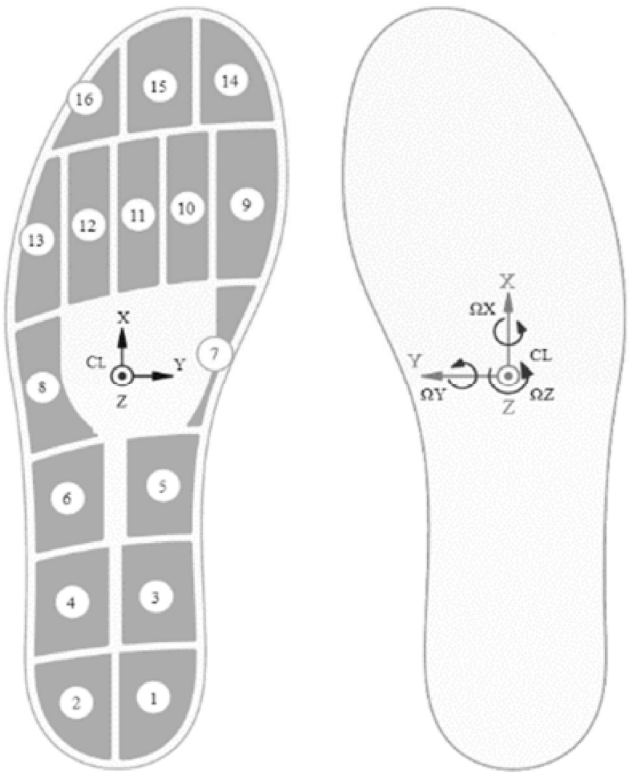

Figure 2.3: The Smart Insole Dataset: Pressure Points

Label	Activity	Description
STD	Standing	Standing with subtle movements
STE	Standing Eyes closed	Standing with eyes closed
WAL	Walking	Normal walking
WAS	Walking Slow	Walking in a slow rhythm
WAF	Walking Fast	Walking in a fast rhythm
SCH	Sit on chair	Sitting on a chair
CHU	Chair up	Getting up from a chair
SIT	Sitting	Sitting with subtle movements
TUR	Turning	Turning 180 degrees at a normal speed at the end of the 10 m aisle
TUS	Turning Slow	Turning 180 degrees at a slow speed at the end of the 10 m aisle
TUF	Turning Fast	Turning 180 degrees at a fast speed at the end of the 10 m aisle

Table 2.1: ADL labels of The Smart Insole Dataset

Label	Activity	Description
HES	Heel Strike	Heel contacts the floor
HER	Heel Rise	Heel rises of the floor
TOF	Toe Off	Toe leaves the floor
FOF	Foot Flat	Foot is flat on the floor; both heel and toe contact the floor.

Table 2.2: Gait labels of The Smart Insole Dataset

2.3 Challenges

The current state of the art has limitations regarding the availability of the data and the means used to analyse the data.

The principal limitation relies in data acquisition. Most of the studies are based on a personal acquisition of the data that is later not shared nor publicly available. This leads to two consequences: first, the results of the analysis proposed cannot be reproduced to assess their correctness and validity; second, this limits the advancement in the research as the data is not available. Another limitation regarding the data is based on the amount of the data that is usually acquired for those studies, as the number of patients is usually very limited to a 100, or most likely, less than 50, making the results of the research less valuable.

Another limitation of the long term monitoring studies is that patients are not always willing or available to repeat tests after six, nine, or twelve months, making the available data even fewer.

The limitation regarding the machine learning algorithms used to analyze the data is then related to the complexity of the algorithm to use, since it is necessary that the models chosen can be trained using very few samples.

Last but not least, the results greatly depend on the quality of the wearable sensors employed in the studies, as higher quality sensors can lead to better analysis, whereas lower quality sensors can lead to samples with many missing data points.

2.4 Emerging Trends

As the literature review suggests, the machine learning approaches constitute the emerging trends on this topic, as a few years ago the main analysis was comprised of the analytical filtering and considerations made regarding the signals themselves. Additionally, the results of the Fall Risk Tests were used to assess the gait imbalance and asymmetries of the patients.

2.5 Conclusion

In the realm of fall risk assessment, wearable sensors and pressure insoles have emerged as valuable tools for gathering data related to gait and balance. Various approaches have been explored to analyze this data and predict the risk of falls among elderly individuals and those with specific health conditions. These approaches encompass a range of methodologies and techniques, from traditional statistical analyses to machine learning and deep learning models.

Several noteworthy findings and strategies have been highlighted in the literature. Notably, the use of accelerometers and gyroscopes as common sensors for capturing gait data, particularly when positioned in the lumbar and waist areas, has been prevalent. The selection of relevant features from the data is a crucial step, with feature extraction being favored over machine learning alone in many studies. Moreover, different tasks, such as the Tinetti Scale assessment and dual-task walking, have been employed to assess fall risk.

Several public datasets and requestable datasets have become valuable resources for researchers in this field, enabling them to develop and validate their models and techniques. These datasets typically include raw data, often collected from a diverse group of participants, including healthy individuals, the elderly, and patients with specific medical conditions.

In conclusion, the research on fall risk assessment using wearable sensors and pressure insoles is advancing rapidly. This area has the potential to significantly improve the quality of care for individuals at risk of falling by enabling early detection and intervention. However, challenges related to data privacy and availability need to be addressed to facilitate further progress in this field. Researchers and healthcare professionals continue to explore innovative approaches to enhance fall risk assessment, ultimately contributing to better outcomes for individuals at risk of falls.

Chapter 3

Original contribution to the solution of the problem

3.1 Introduction

The contribution to the problem relies in the definition of a pipeline comprised of a first phase of extraction of human readable and understandable features, and a second phase of classification. Due to the nature of the problem, and the available data, the focus of this thesis shifts from the original aim of classification into high and low risk for falls, to, rather, the differentiation of gait movements of elderly but healthy patients, Parkinson's Disease patients, and adults, to identify any possible complications that may show in an asymmetrical gait and which features are the most indicative of said condition.

The feature extraction is based on a previous pre-processing of the raw information, whereas the classification is performed using different explainable machine learning algorithms, where both the accuracy and relevant features are taken into consideration to identify the best model to reach the objective of this work.

3.2 Dataset

The dataset chosen for the application is *The Smart Insole Dataset*, comprised of raw pressure information coming from *Moticon Science* insoles, made up of 16 pressure points distributed throughout the sensor. The whole dataset contains several trials performed by 29 persons in total. The patients are distinguished as follows: 13 Adults aged 20-59 years old, 10 Elderly patients whose age is above 60 to 85, and 7 Parkinson's Disease patients whose age is the range 63 to 83. The subjects are all males, with the exception of two elderly women. The patients had to perform both the Walk and Turn test and the TUG test. The first has the patient walk 10mt, then turn and walk back to their initial position; the latter, instead, should have the patient get up from the chair, walk 3mt, turn and go back to their initial position. Finally, the patient should sit. The TUG test has been performed differently compared to its standard version: instead of having the patients walk 3mt, the authors asked them to walk 10mt for the TUG test as well. Each TUG test is repeated twice in accordance with the patient's ability of motion, whereas the Walk and Turn Test is repeated twice for each version chosen by the authors: Walk and Turn Slow Speed, Walk and Turn Normal Speed, Walk and Turn High Speed.

For each patient, the available tests are:

Patient	**Walk and Turn**	**TUG**
PD001	N/A	N/A
PD002	1X[Slow,High]+2X[Normal]	2X[TUG]
PD003	None	1X[TUG]
PD004	2X[Slow]+1X[Normal,High]	2X[TUG]
PD005	None	3X[TUG]
PD006	2X[Slow,Normal,High]	2X[TUG]
PD007	1X[Slow,Normal,High]	1X[TUG]
PD008	1X[Normal]	1X[TUG]
EL001	2X[Slow,Normal,High]	2X[TUG]
EL002	2X[Slow,Normal]+1X[High]	2X[TUG]

EL003	2X[Slow,Normal,High]	2X[TUG]
EL004	2X[Slow,Normal,High]	2X[TUG]
EL006	2X[Slow,Normal,High]	2X[TUG]
EL007	2X[Slow,Normal,High]	2X[TUG]
EL008	2X[Slow,Normal,High]	2X[TUG]
EL009	2X[Slow,Normal,High]	2X[TUG]
EL010	2X[Slow,Normal,High]	2X[TUG]
S001	2X[Slow,Normal,High]	2X[TUG]
S002	2X[Slow,Normal,High]	2X[TUG]
S003	2X[Slow,Normal,High]	2X[TUG]
S004	2X[Slow,Normal,High]	2X[TUG]
S005	2X[Slow,Normal,High]	2X[TUG]
S006	2X[Slow,Normal,High]	2X[TUG]
S007	2X[Slow,Normal,High]	2X[TUG]
S008	2X[Slow,Normal,High]	2X[TUG]
S009	2X[Slow,Normal,High]	2X[TUG]
S010	2X[Slow,Normal,High]	2X[TUG]
S011	2X[Slow,Normal,High]	2X[TUG]
S012	2X[Slow,Normal,High]	2X[TUG]
S013	2X[Slow,Normal,High]	2X[TUG]

Table 3.1: The Smart Insole Dataset Trials

For the recordings, the sampling rate was set at 100Hz. The generated file for each recording includes 51 features in total. Specifically, 25 values for the left and 25 values for the right leg plus the timestamp:

- The Timestamp (cs);
- The pressure from 1 to 16 sensors (N/cm^2);
- The acceleration in the X, Y, Z axes (g);

- The angular rate in $\omega x, \omega y, \omega z$ (dps);
- The computed center of pressure in the X, Y axes;
- The computed total force (N).

The dataset is labelled so that each sample (of each test, for each patient) displays both the activity performed by the patient and the gait phase associated with that activity. As a conclusion, the dataset is not labelled to differentiate between high and low risk for falls, neither to distinguish between classes. Therefore, a label has been added to identify the elderly patients as "0", the Parkinson's Disease Patients as "1", and the adults as "2".

3.3 Data Pre - processing

The first step of the analysis consists in a pipeline of data pre-processing. Since the dataset contains raw data coming from the insoles, it is likely that there exists samples for which the information of certain sensors might be missing. Therefore, each of the trials is checked for NaN (missing) values. If the trial contains any, then two different approaches are taken depending on the position of the individual sample considered: a chunk of the samples coming from the initial and final phase of the trial are removed if they contain a consecutive number of missing values. Instead, if the samples coming from the middle of trial contain missing values, then they are imputed using a KNN Imputer, a type of univariate imputation algorithm, which imputes values in the i-th feature dimension using only non-missing values in that feature dimension. The imputer is a "k-Nearest Neighbors" algorithm, meaning that each sample's missing values are imputed using the mean value from k nearest neighbors found in the training set. The number of neighbors K is a hyper-parameter of the algorithm, which is set to 5 in this particular instance. Moreover, the neighbors to the missing value are weighted by the inverse of their distance, meaning that closer neighbors of a missing data point will have a greater influence than neighbors which are further away. This particular technique is chosen since the data is a time-series, which changes over time with a certain regularity, or period.

Two approaches are chosen because it is necessary to remove any missing values before proceeding with any further step, but it is mandatory to preserve data quality. By removing some samples, the data quality is not diminished, and at the same time the number of imputations included in the data is reduced to the minimum.

An example below.

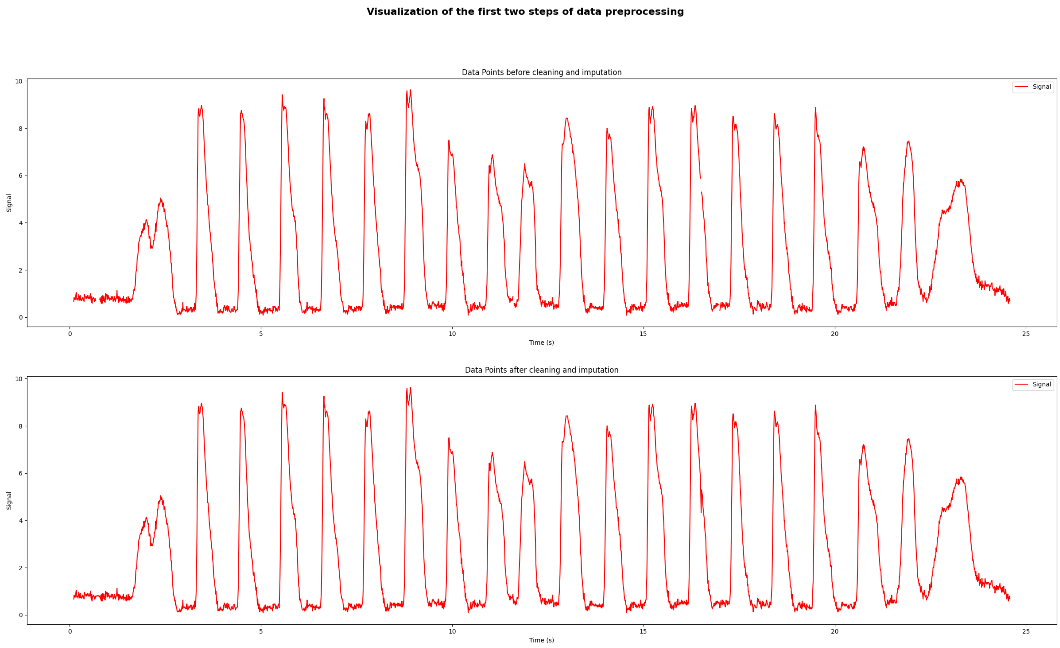

Figure 3.1: Example of value imputated during pre - processing

The second step is data scaling. The values of each individual feature are scaled in the range [-1, 1] using a MaxAbsScaler since the unit of measures differ among measurements. The choice for this particular scaler relies in robustness of the scaler to very small standard deviations of features and its ability to preserve zero entries in sparse data. Moreover, there are no assumptions on the distribution of the data, and, since the dataset contains acceleration values, these are positive or negative depending on the direction of the movement with respect to the coordinate axis, so it is important to keep negative values.

3.4 Gait Phases Extraction Algorithm

The human readable gait features can be extracted only if the information about gait phases for each sample is available. Gait is a skill, defined in [?] as the cyclic motion of lower and upper limbs that aims to move the body forward. Gait analysis is the procedure that observes, records, analyzes, and interprets movement patterns performed as part of the skill of gait. The process of Gait Analysis starts with the definition of the *Gait Cycle*, which is composed by the sequence of movements performed when one foot makes contact with the ground and ends when that same foot contacts the ground again. It is usually divided into two periods, stance and swing. The stance period is the time during which the foot is in contact with the ground, whereas the swing period follows the stance period and is the time during which the same foot is in the air. The separation of the two periods is discerned by the toe-off. Normally, the stance period represents the first 60% of the Gait Cycle and the swing the latter 40%, with the Single Leg Support representing the 40% of the stance phase, and the Double Leg Support the latter 20%. Although gait literature expands on different definitions of gait phases, for the objective of this thesis only four gait phases are relevant: heel strike, foot flat, heel rise and toe off.

Heel strike is defined as the initial contact of the foot with the ground; Foot Flat begins with initial contact and continues until the contra-lateral foot leaves the ground; Heel Rise, instead, begins when the heel leaves the floor and continues until the contra-lateral foot contacts the ground; lastly, Toe off begins when the contra-lateral foot contacts the ground and continues until the ipsilateral foot leaves the ground. It provides the final burst of propulsion as the toes leave the ground.

To extract gait phases, the values of the individual samples are first averaged to obtain two different signals: the first 6 sensors are used to compute the mean value of the pressure in the heel area of the patient; the last 8 sensors are, instead, used to compute the mean value of the pressure in the toe area. Two sensors are left unused: the 7th and 8th sensor, located in the middle of

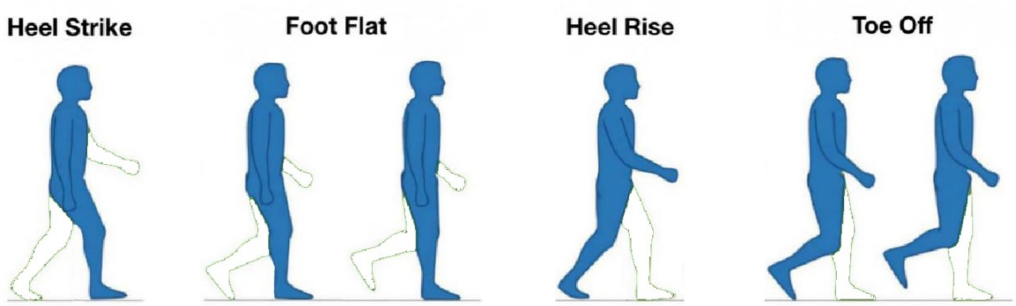

Figure 3.2: Gait Phases referred to the right leg (in blue)

the foot, as their contributions to the overall signals were irrelevant.

Using these signals, a gait phase extraction algorithm is defined. Since the data is previously scaled, a consideration can be made regarding the value of the two mean signals when the heel strike, foot flat and toe off phases are occurring. Heel strike is characterized by an increasing slope of the average heel signal up until a local maximum; for foot flat, the two mean signals are around the same value; for toe off, the mean toe signal increases as the foot starts leaving the ground and then decreases towards 0.

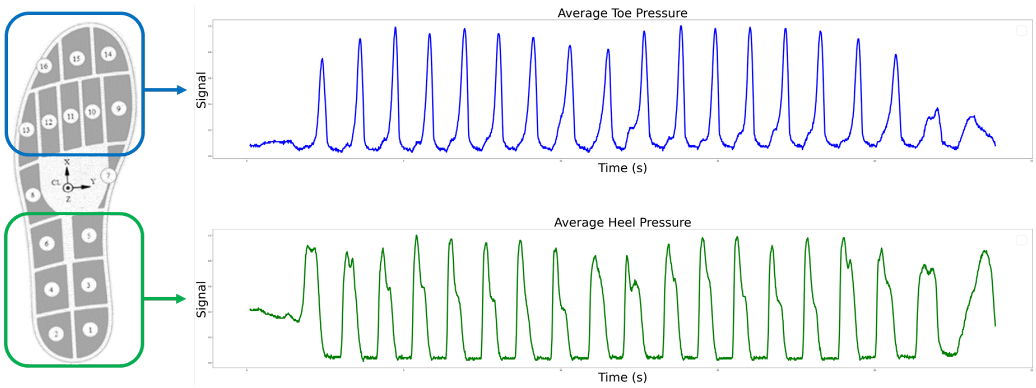

Figure 3.3: Example of the Average Heel and Toe Pressure Signals on patient EL001.

Taking all of this into consideration, to define gait phases the mean toe signal is subtracted to the mean heel signal. This allows to have, in time, a signal whose maximums are in correspondence of heel strikes, and the minimums correspond to toe offs. Additionally, the values above the mean (which is around 0) correspond to foot flats, whereas the ones below correspond to heel rises.

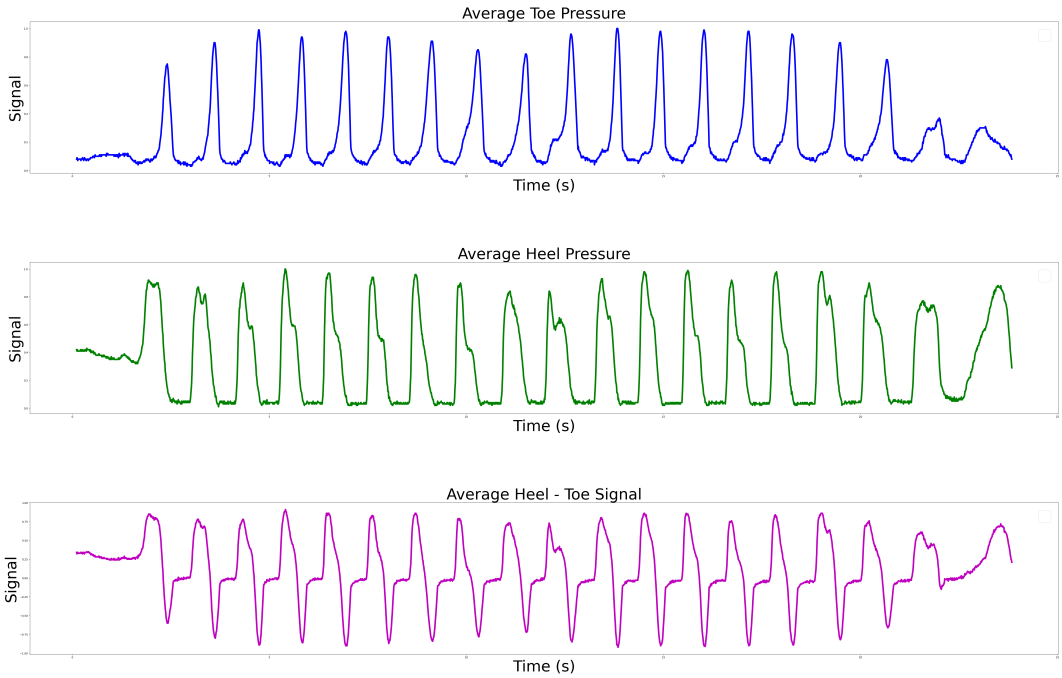

Figure 3.4: Example of the Average Heel - Toe Pressure Signal on patient EL001.

Since the patient is not already walking when the pressure data points are registered, a multivariate analysis is performed using both the acceleration values and the pressure values to determine the beginning and the ending of the walking stage. Since the acceleration along the X,Y and Z axes is scaled as well, the mean value of these signals is still along 0. The walking motion can be set to begin when the acceleration is above a certain threshold, and it can be set to end when it is below said threshold. By taking the exact mean value and the standard deviation of the acceleration, the threshold is defined as

$$threshold = mean + 1 \times standarddeviation \tag{3.1}$$

for the positive threshold, and

$$threshold = mean - 1 \times standarddeviation \tag{3.2}$$

for the negative threshold.

The samples whose acceleration is found in the range [- threshold, threshold] are labelled as foot flat occurrences, since the patient is not walking, but either standing or sitting.

The general idea of the whole algorithm is defined as follows:

First, the acceleration along the X axis is used to determine two phases: initial stance phase and final stance phase. The initial stance is comprised of all of the samples that lie in the range [-threshold, threshold] at the beginning of the signal, ending as soon as one of the acceleration samples lies outside the previously defined range. This is the time when the walking stage begins. The final stance phase is defined in the same way, with the only difference brings that the phase *begins* with the first sample lying in the range. This is the time when the walking stage ends.

Before computing the gait phases during the walking stage, the algorithm searches for the local maximums and minimums of the Mean Heel - Mean Toe signal, removing from these lists (peaks, minimums) the ones lying in the stance phases of the signal.

During the walking stage, the samples are split into two main categories: the pressure samples above the mean, and the pressure samples below the mean.

For the samples above the mean the algorithm checks if a local peak is closer than a local minimum. When this condition is true, it means that the signal is characterized by an increasing slope towards the local maximum. Therefore, the samples are categorized as being Heel Strikes. On the contrary, if a local minimum is closer than a local maximum, the signal is decreasing towards said minimum, and thus, the samples are characterized as being Foot Flat instances down until the signal reaches its mean.

For the samples below the mean, the behavior of the algorithm is similar: if a minimum is closer than a peak, the signal is still decreasing, therefore the samples are categorized as being heel rises (when the signal is negative, the heel pressure is lower than the toe pressure) until a minimum is reached. The opposite is true for the toe offs, defined as the range of samples that go from

Algorithm 1 Gait Phases Extraction Algorithm

```
while signal − index ≤ len(signal) do
                          ▷ 1st case: Current value of the signal below the mean
    if signal[signal − index] ≤ mean then
        if mins − index ≤ peaks − index then
            while signal − index ≤ mins − index do
                GaitPhase ← HeelRise
            end while
        end if
        if peaks − index ≤ mins − index then
            while signal − index ≤ mean do
                GaitPhase ← ToeOff
                signal-index = signal-index + 1
            end while
        end if
    end if        ▷ 2nd case: Current value of the signal above the mean
    if signal[signal − index] ≥ mean then
        if mins − index ≤ peaks − index then
            while signal − index ≤ mins − index do
                GaitPhase ← FootFlat
            end while
        end if
        if peaks − index ≤ mins − index then
            while signal − index ≤ mean do
                GaitPhase ← HeelStrike
            end while
        end if
    end if
end while
```

the local minimum up until the mean of the signal is reached.

An example of the output of the algorithm on an elderly patient is shown below.

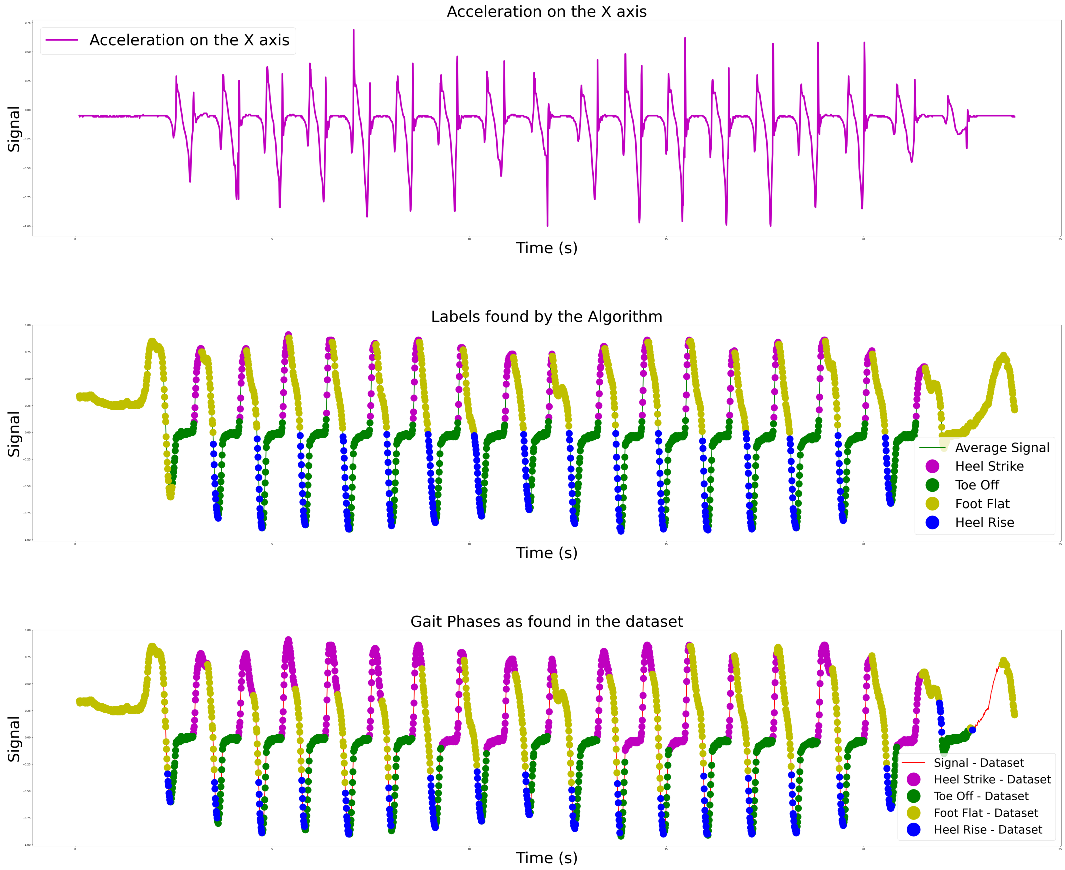

Figure 3.5: Example of the labels computed by the algorithm on patient EL001. (1st Figure) represents the value of the acceleration on the X axis; (2nd Figure) the labels computed by the algorithm - with foot flats at the beginning and at the end of the signal in accordance with the threshold defined using the acceleration; (3rd Figure) the labels computed in The Smart Insole Dataset

Samples in which the two algorithms differ greatly are the trials performed by Parkinson's Disease Patients, where the algorithm used by the authors of the dataset fails to capture gait phases. The acceleration of the fore mentioned trials is also indicative of a walking motion rather than a standing or sitting motion. Therefore, the results are considered valid.

An example is shown below.

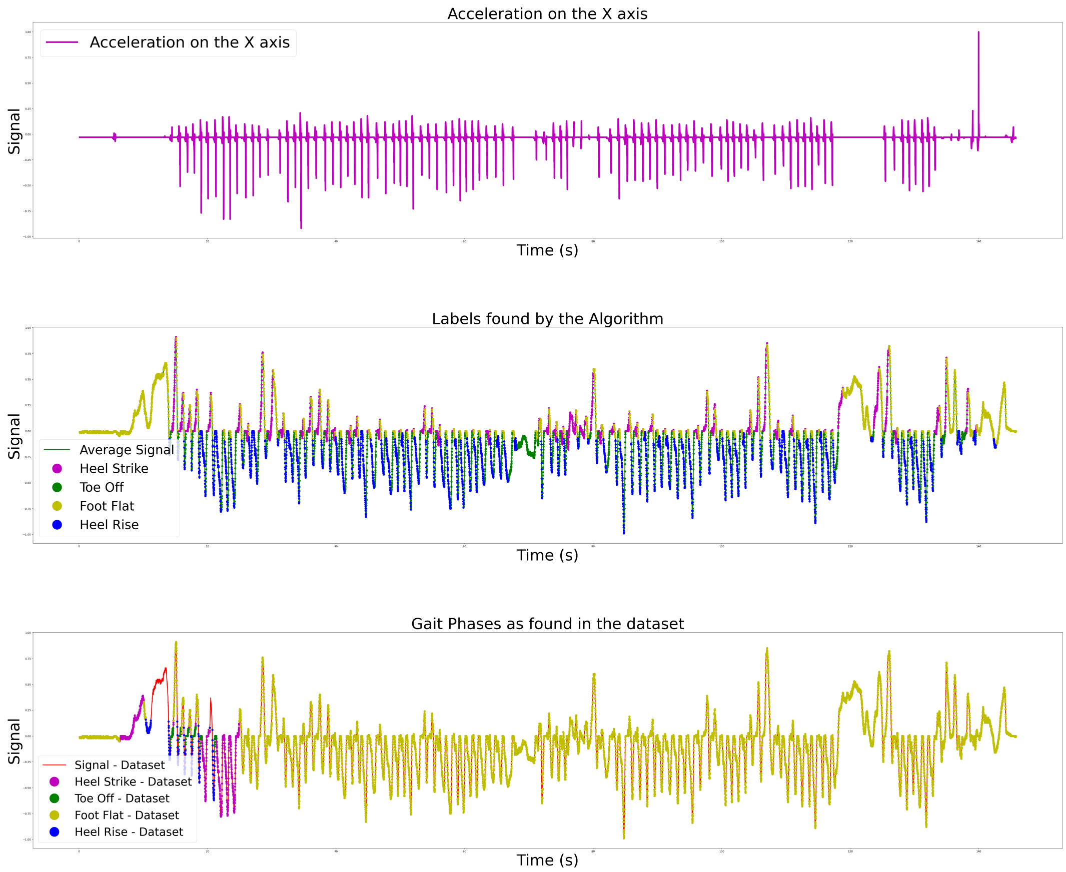

Figure 3.6: Example of the labels computed by the algorithm on patient PD003. (1st Figure) represents the value of the acceleration on the X axis; (2nd Figure) the labels computed by the algorithm - with foot flats at the beginning and at the end of the signal in accordance with the threshold defined using the acceleration; (3rd Figure) the labels computed in The Smart Insole Dataset

3.5 Feature Extraction

Both gait associated features and statistical features are extracted from gait phases and signal values according to literature. A total of 107/108 features characterize each sample of the dataset, where each sample is now intended as each trial successfully completed by one patient. Thus, the total number of samples is 201/202.

According to [?] the features extracted include:

Step Time (s) is described as the time between two successive Heel Strikes of different foot.

$$HeelStrike_{foot2_j} - HeelStrike_{foot1_j} \tag{3.3}$$

Step Length (m) is calculated by dividing the total distance covered (20 m) to the total number of steps (Steps Number) which is specified as the number of Heel Strikes during gait.

$$\frac{Distance}{StepNumber} \tag{3.4}$$

Step Frequency (steps/min) also called *Cadence* or *Walking Rate*, describes the number of steps in the unit of time. It is given by the ratio of the steps number to the time of gait, multiplied by 60 to be expressed in minutes.

$$\frac{StepNumber}{Time} \times 60 \tag{3.5}$$

Stride Time (s) is equal to the time between two successive Heel Strikes of the same foot.

$$HeelStrike_{j+1} - HeelStrike_j \tag{3.6}$$

Stride Length (m) is calculated by dividing the total distance covered (20 m) to the total number of strides (Strides Number).

$$\frac{Distance}{StrideNumber} \tag{3.7}$$

Gait Velocity (m/s), which describes the displacement in the unit of time, is given by the ratio of the total distance to the total time, or by the ratio of the mean values of stride length to stride time.

$$\frac{StrideLength}{StrideTime} \tag{3.8}$$

Gait Variability refers to the difference between the duration of the strides.

$$StandardDeviation(StrideTimes) \tag{3.9}$$

Stance Time (s) describes the total time during a gait cycle where the foot is in contact with the ground. Specifically, it is described as the time where the heel of one foot, contacts the ground until the toe of the same foot leaves the ground.

$$ToeOff_{j+1} - HeelStrike_j \tag{3.10}$$

Stance Phase (%) it represents the percentage of gait cycle covered during Stance. It is defined as:

$$\frac{StanceTime}{GaitCycle} \times 100 \tag{3.11}$$

Swing Time (s) describes the time from the Toe Off of the one foot until the Heel Strike of the same foot.

$$HeelStrike_{j+1} - ToeOff_j \tag{3.12}$$

Swing Phase (%) it represents the percentage of gait cycle in which the patient swings. It is defined as:

$$\frac{SwingTime}{GaitCycle} \times 100 \tag{3.13}$$

Walk Ratio (mm/step/min), represents the relationship between the width (base of gait) and the frequency of steps and is given by the ratio of step length to Step Frequency.

$$\frac{StepLength}{StepFrequency} \tag{3.14}$$

Single Support Time (s), is the sub - period of the gait cycle during which one foot is in the air. It describes the time from the Toe Off of one foot until the Heel Strike of the other foot.

$$(HeelStrike_j - ToeOff_{j-1}) + (HeelStrike_{j+1} - ToeOff_j) \tag{3.15}$$

Single Support Phase (%) it represents the percentage of gait cycle in which the patient keeps only one on the ground. It is defined as:

$$\frac{SingleSupportTime}{GaitCycle} \times 100 \tag{3.16}$$

Double Support Time (s), it is the sub - period of the Gait Cycle during which both feet are in contact with the ground. It describes the time from the Heel Strike of the first foot until the Toe Off of the other foot. It is defined as:

$$(ToeOff_j - HeelStrike_j) + (ToeOff_{j-1} - HeelStrike_{j-1}) \tag{3.17}$$

Double Support Phase (%) it represents the percentage of gait cycle in which the patient keeps both feet on the ground. It is defined as:

$$\frac{DoubleSupportTime}{GaitCycle} \times 100 \tag{3.18}$$

Gait Speed (m/s) is calculated by dividing the total distance covered (20 m) to the total time needed to complete the exercise.

$$\frac{Distance}{Time} \times 100 \tag{3.19}$$

Ratio (R) Index Evaluated for different measures: Ratio of the average heel pressure and average toe pressure on one foot; Ratio of the average heel pressure and average toe pressure on both feet.

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point.

Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.

Approximate Entropy is a technique used to quantify the amount of regularity and the unpredictability of fluctuations over time-series data. It is computed using the *EntropyHub* library.

3.6 Classification Algorithms

The problem is evaluated using different Machine Learning techniques. The ones chosen are all part of the explainable machine learning algorithms and are analyzed so that each model suggests the most important features in the identification of the patients belonging to the Elderly, Adults or Parkinson's Disease classes. Apart from considering features that are able to distinguish between the three, there is an additional study on the peculiar features that discriminate each class. The models used are presented below.

3.6.1 Random Forest

Random Forest is a type of Decision Tree, a non-parametric model used for classification and regression that gives good results both numerical and categorical features. It automatically ignores irrelevant features making few assumptions on the input data. Staring from a set of training data with N observations and P features, each internal node divides the patterns into groups using a test on the value of a single feature. The process is repeated recursively using the children of the node, until a leaf node is reached. A leaf node represents groups of patterns that are easy to classify (e.g. using the class of the majority of them) or to regress (e.g. using a constant value corresponding to the average y of the group). Since decision trees suffer from high variance, i.e. splitting the training data into two parts at random, the results of the two parts may be quite different. Bootstrap aggregation, or bagging, is a general-purpose procedure for reducing the variance of a statistical learning method: by taking many training sets from the population and builing a separate prediction model using each training set, the resulting predictions are averaged to obtain the final classification or regression value. Random forests provide an improvement over bagged trees by way of a small tweak that decorrelates the trees. It is a multi-classifier approach: combining many (possibly independent) decision trees, a more robust classifier is obtained, that is, a Random Forest. Usually a simple combination rule, like majority voting, is used to combine the results of the individual trees into a single output. In Random Forests a high number of tree classifiers (e.g. 100 or more) is trained using the same algorithm. For the purpose of this thesis, the dataset has been bootstraped to train each tree using only a subset of the training set, obtained by random sampling. Usually

$\frac{2}{3}$ of the full training set are used to train the trees, whereas the the last third, called out of bag samples, are used as a validation set.

3.6.2 Support Vector Machine

Support Vector Machine (SVM) is an approach for classification based on the idea that samples in the P dimensional feature space can be separated through and hyperplane. A hyperplane is a flat affine su-space of dimension $P-1$. In general, if the data can be perfectly separated using a hyperplane, then there will exist an infinite number of such hyperplanes. This is because a given separating hyperplane can usually be shifted a tiny bit up or down, or rotated, without coming into contact with any of the observations. In order to construct a classifier based upon a separating hyperplane, a decision regarding which of the infinite possible separating hyperplanes to use is to be made. A natural choice is the maximal margin hyperplane (also known as the optimal separating hyperplane), which is the separating hyperplane that is farthest from the training observations. That is, by computing the (perpendicular) distance from each training observation to a given separating hyperplane, the margin is known as the minimal distance from the observations to the hyperplane. The maximal margin hyperplane is the separating hyperplane for which the margin is largest—that is, it is the hyperplane that has the farthest minimum distance to the training observations. Test observations are then classified based on which side of the maximal margin hyperplane it lies. This is known as the maximal margin classifier. Although the maximal margin classifier is often successful, it can also lead to overfitting when p is large. The points that lie along the margin are called support vectors, vectors in p-dimensional space that “support” the maximal margin hyperplane in the sense that if these points were moved slightly then the maximal margin hyperplane would move as well. Interestingly, the maximal margin hyperplane depends directly on the support vectors, but not on the other observations: a movement to any of the other observations would not affect the separating hyperplane. The maximal margin classifier is a very natural way to perform classification, if a separating hyperplane exists. However, in many cases no separating hyperplane exists. This is also the case of noisy data with outliers leading to poor solutions. Therefore, the concept of a separating hyperplane can be extended in order to develop a hyperplane that almost separates the classes, using a so-called soft margin. The generalization of the maximal margin classifier to the non-separable case is known as the support vector classifier. The support vector classifier, sometimes called a soft margin classifier, rather than seeking the largest possible margin so that every observation is not only on the correct side of the hyperplane but also on the correct side of the margin, instead allows some observations to be on the incorrect side of the margin, or even the incorrect side of the hyperplane. The support vector classifier classifies a test observation depending on which side of a hyperplane it lies. The hyperplane is chosen to correctly separate most of the training observations into the classes, but may misclassify a few observations. The support vector classifier is a natural approach for classification in the two-class setting, if the boundary between the two classes is linear. However, as it is the case with the data used for this thesis, there exist non-linear class boundaries. In the case of the support vector classifier, the problem of possibly non-linear boundaries between classes can be addressed by enlarging the feature space using quadratic, cubic, and even higher-order polynomial functions of the predictors. The support vector machine (SVM) is an extension of the support vector classifier that results from enlarging the feature space in a specific way, using kernels.

3.6.3 K-Nearest Neighbors

The textitK-Nearest Neighbors is a simple classifier that, given a positive integer K and a test observation x, first identifies the K points in the training data that are closest to x, represented by N. It then estimates the conditional probability for class j as the fraction of points in N whose response values equal j. Finally, KNN classifies the test observation x to the class with the largest probability. The choice of K has a drastic effect on the KNN classifier obtained.

3.6.4 Kernel Fisher Discriminant

The *Kernel Fisher Discriminant*, also known as Kernel Fisher's Linear Discriminant Analysis (Kernel FDA), is a nonlinear extension of the classical Fisher's Linear Discriminant Analysis (LDA). Fisher's LDA is a dimensionality reduction technique and a supervised classification method used for feature selection and data visualization. It seeks to find a linear combination of the original features that maximizes the separation between classes in the dataset.

However, when the relationship between classes in the data is not linear, Fisher's LDA may not perform optimally. This is where the Kernel Fisher Discriminant comes into play. Kernel FDA is designed to handle nonlinear relationships between classes by transforming the original data into a higher-dimensional space using a kernel function.

The kernel function maps the data into a space where the classes might become linearly separable.

The steps involved in Kernel FDA are as follows:

Choose a suitable kernel function: Common choices include the radial basis function (RBF) kernel, polynomial kernel, or sigmoid kernel.

Compute the kernel matrix: Calculate the pairwise similarities between data points using the chosen kernel function. This results in a kernel matrix, which represents the transformed data in the higher-dimensional space.

Find the eigenvectors and eigenvalues of the kernel matrix: This step is similar to the classical FDA. T he goal is to find the directions (eigenvectors) that maximize the separation between classes while minimizing the variance within each class.

Select the top eigenvectors: Choose the eigenvectors corresponding to the largest eigenvalues, which represent the directions of maximum discrimination.

Project the data: Project the data onto the selected eigenvectors to obtain a new feature space that enhances class separability.

Kernel FDA is a powerful technique for handling complex, nonlinear relationships in data, making it valuable in various applications such as pattern recognition, image analysis, and bioinformatics. It is commonly used in conjunction with support vector machines (SVMs) for nonlinear classification tasks.

Chapter 4

Experimental validation and application aspects

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Chapter 5

Conclusions

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