Review

Identification of Diseases Based on the Use of Inertial Sensors: A Systematic Review

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Abstract: Inertial sensors are commonly embedded in several devices, including smartphones, and other specific devices. This type of sensors may be used for different purposes, including the recognition of different diseases. Several studies are focused on the use of accelerometer signals for the automatic recognition of different diseases, and it may empower the different treatments with the use of less invasive and painful techniques for patients. This paper aims to provide a systematic review of the studies available in the literature for the automatic recognition of different diseases by exploiting accelerometer sensors. The most reliably detectable disease using accelerometer sensors, available in 54% of the analyzed studies, is the Parkinson's disease. The machine learning methods implemented for the automatic recognition of Parkinson's disease reported an accuracy of 94%. The recognition of other diseases is investigated in a few other papers, and it appears to be the target of further analysis in the future.

Keywords: accelerometer; wearable electronic devices; diseases; monitoring; ambulatory; automatic identification; parkinson's disease

1. Introduction

Ageing is presently a critical challenge worldwide, which is particularly relevant in developed countries [1–3]. In total, 9% of the population is over 64 years old worldwide, and 10% will have disabilities [4,5]. Ageing will lead to relevant impacts on the economy and society, associated with costs in healthcare [6,7]. The scenario in Portugal is not different, as it is in the top five countries with older adults worldwide [8–10]. It is relevant to mention that Portugal was the country with the highest birth rate in Europe, 45 years ago [11,12]. However, Portugal is now at the top of the list with fewer births in Europe [13,14]. Accordingly, the dependency of older adults associated with a low birth rate will lead to even more social impacts and demands for the design and development of novel and efficient strategies to promote the health and well-being of citizens [15].

The Ambient Assisted Living (AAL) concept includes multiple research domains to design improved software tools and healthcare systems for enhanced living environments [16,17]. However, different challenges still exist in the design of AAL technologies associated not only with the reception of these tools by older adults but also related to privacy and security [18–20].

Healthcare systems combine different software and hardware systems to provide multiple services not only to promote the quality of life of patients but also to support healthcare staff [21,22]. Personal healthcare devices are used for several telemedicine tasks using portable systems to monitor the patient's physical signs [23,24]. These devices can observe distinct parameters, such as blood pressure, oxygen, and medication intake, but they are also used to supervise patients' behavior and detect falls [25,26].

Presently, mobile devices such as smartphones and tablets include high power processing properties and incorporate multiple non-invasive sensors that are used to design efficient and cost-effective healthcare solutions [27,28]. Mobile healthcare applications also support patient participation in their disease prevention and management and consequently contribute to relevant cost savings [29–31]. Moreover, mobile devices incorporate multiple short-range and long-range communication protocols such as GPRS (General Packet Radio Service), 3G, HSDPA (High-Speed Downlink Packet Access), 4G, 5G, Bluetooth, NFC (Near-field communication) and Wi-Fi. These communication technologies facilitate patient monitoring in hospitals, medical facilities, and in patient's homes [32–34]. Furthermore, wearable devices currently include the same sensors as smartphones and are consequently used to supervise cardio-metabolic [35], and electroencephalogram (EEG) signals [36], in a non-invasive manner [37–39]. To summarize, mobile devices must be seen today as an essential and crucial part of personalized healthcare procedures not only for monitoring activities but also for clinical evaluation and disease detection [40–42].

The accelerometer, magnetometer, and gyroscope sensors incorporated in mobile devices or other commercial board modules are compatible with different interfaces, such as I2C, UART (Universal Asynchronous Receiver-Transmitter) and PWM (Pulse Wave Modulation). They can be applied in the context of enhanced healthcare, such as activity recognition and automatic disease detection [43–45]. The accelerometer is used in numerous clinical evaluation tasks, both incorporated in wearable-based systems or using mobile devices [46,47]. Countless people suffer from multiple diseases, causing a variety of consequences on their physical activity and mobility, such as postural instability and gait disturbances, which can lead to independence reduction and loss of movement [48–51]. Consequently, the use of automated processes for disease evaluation plays a significant role in enhanced public health.

The cross-domain knowledge sharing combining computer science and healthcare can lead to the design of effective systems for enhanced personalized healthcare assessment, which can also be supported by artificial intelligence methods to create novel techniques for automated disease recognition. On the other hand, this multidisciplinary approach can provide novel solutions to face the worldwide challenges related to ageing and the quality of personalized healthcare [52–55].

This paper presents a review of state-of-the-art accelerometry-based systems and methods for the automatic identification of various diseases. We aim to provide a comprehensive understanding of the different healthcare conditions that can be recognized, monitored, and evaluated using accelerometry devices and artificial intelligence techniques.

The main contribution of this paper is the synthesis of the existing body of knowledge, presenting the collective outcomes and limitations that must be analyzed to point out new research directions. Furthermore, we compare different methods and extract the most significant insights from the analyzed literature. As a result, this paper aims to provide a practical background not only to academics or computer science engineers but also to healthcare professionals.

The structure of this document is the following: Section 2 presented the strategy used to conduct this systematic review and describe the research questions, and the criteria for the literature section. The results are shown in Section 3, and they are later discussed in Section 4. Finally, the conclusions are presented in Section 5.

2. Materials and Methods

Systematic reviews use formal explicit methods, of what exactly was the question to be answered, how evidence was searched for and assessed, and how it was synthesized to reach the conclusion. The "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement" [56] is one of the most widely used methodologies for achieving this, therefore we have applied it in this work. For this type of studies, it is essential that they are statistical valid with enough individuals in a studied population. In continuation, the diseases that can be detected with these sensors is important to define a method for the recognition, where the recognition differs by each disease. The authors have conducted a systematic review of papers published after 2008 to provide a comprehensive, but not limited analysis considering 12 years of studies regarding the automatic detection of studies using inertial sensors. Finally, the use of artificial intelligence methods is important for the automatic recognition and measurement, and this review intends to discover which as the methods used in the literature.

2.1. Research Questions

The primary research questions of this review were as follows: (RQ1) How many people are involved in the different studies related to the use of the inertial sensors? (RQ2) Which diseases can be detected with inertial sensors? (RQ3) Which artificial intelligence methods are used for the identification or recognition of different diseases?

2.2. Inclusion Criteria

The inclusion criteria of studies and assessing methods for the automatic identification of various diseases using the accelerometer sensor were: (1) Studies that perform recognition of diseases related to the movement; (2) Studies that use at least an accelerometer sensor; (3) Studies that were published between 2008 and 2020; (4) Studies that defined the number of participants; (5) Studies written in English.

2.3. Search Strategy

The team searched for studies meeting the inclusion criteria in the following electronic databases: IEEE Xplore, ACM Digital Library, ScienceDirect, MEDLINE, and PubMed. The research terms used to identify relevant articles for this systematic review are: "diseases", "accelerometer", and "automatic identification" or "automatic recognition". Initially, we employed a tool that leverages Natural Language Processing algorithms [57] to remove duplicate articles and narrow down the potentially relevant articles. Afterwards, five reviewers independently evaluated every study, and its suitability was determined with the agreement of all parties. The studies were examined to identify the different diseases that can be identified with the use of data acquired from the accelerometer sensor.

2.4. Extraction of Study Characteristics

The following information was extracted from various articles analyzed and presented in Tables 1 and 2: year of publication, population, purpose, sensors used, diseases detected, accuracy, and outcomes of the different studies. The corresponding authors of the various papers were contacted to obtain more information about the different studies. We evaluated the identified studies based on the qualities related to the research questions, considering the number of participants (an explicit number should be stated in the study), the sensory devices (also need to be explicitly mentioned), which diseases are being automatically identified, and which artificial intelligence algorithms were applied for automatic recognition of the disease. Based on these parameters, the studies' quality was assessed. In general, the most detected disease is Parkinson's disease and other diseases related to the various walking patterns.

Table 1. Study analysis.

Paper	Year of Publication	Population	Purpose of the Study	Sensors	Diseases Detected	Accuracy
Viteckova et al. [58]	2020	26 healthy adults and 25 subjects with Parkinson's disease	Compare and quantify the results of repeated performance over time and the performance of healthy and sick people with Parkinson's disease	Accelerometer and Gyroscope	Parkinson	N/A
Sharif Bidabadi et al. [59]	2019	30 healthy subjects and 56 patients with Lumbar radiculopathy and related ankle dorsiflexion weakness with observable foot drop	Use of inertial measurement unit using machine learning methods to distinguish gait disturbances	Accelerometer, Gyroscope, and Magnetometer	Lumbar radiculopathy and related to ankle dorsiflexion weakness with observable foot drop	93.18%
Stamate et al. [60]	2018	22 individuals with Parkinson's disease	Develop an application to create an extensive data set of motor characteristics of individuals with Parkinson's disease	Accelerometer	Parkinson	95%
Joshi et al. [61]	2017	15 patients with Parkinson's disease and 16 healthy control subjects	Method to analyze gait variables for Parkinson's patients	Accelerometer	Parkinson	90.32%
Ribeiro et al. [62]	2016	Five volunteers with recent episodes of Epilepsy	Development of a technique using machine learning, to automatically recognize people with epilepsy	Accelerometer	Epilepsy	99%
Djuric-Jovicic et al. [63]	2014	12 patients with idiopathic Parkinson's disease	Method for the detection of walking disorders for people with Parkinson	Accelerometer and Gyroscope	Parkinson	98.55%
Gruenerbl et al. [64]	2014	12 bipolar disorder patients	Demonstrate how smartphones can be used to aid the diagnosis of people with psychiatric disorders	Accelerometer and GPS receiver	Bipolar	80%
Pendharkar et al. [65]	2014	Ten children with idiopathic toe walkers and ten children with a normal gait	Automated classification of heel accelerometer data	Accelerometer	Idiopathic Toe Walkers	97.9%
Kugler et al. [66]	2013	Five healthy adults and five subjects with Parkinson's disease	Make an automatic classification between healthy individuals and people with Parkinson's disease using walking electromyography	Accelerometer and electromyography (EMG) sensor	Parkinson	N/A
Barth et al. [67]	2012	17 healthy adults and 18 subjects with Parkinson's disease	System to analyze the motor function of the hand and to walk to differentiate healthy people and people with Parkinson's disease	Accelerometer and Gyroscope	Parkinson	97%
Alaqtash et al. [68]	2011	Ten healthy adults and four relapsing-remitting multiple sclerosis patients	Wearable system for the acquisition of gait parameters	Accelerometer	Multiple Sclerosis	N/A
Phan et al. [69]	2008	30 subjects with recent symptoms of arrhythmia or sleep apnea	Accelerometer system to compare efficiency in detecting heart disease, compared to traditionally used tools	Accelerometer and electrocardiography (ECG) sensor	Arrhythmia or sleep apnea	N/A
Garcia Ruiz et al. [70]	2008	28 patients with idiopathic Parkinson's disease	Analysis of the utility and correlation of Active Appearance Model (AAM) with timed tests and Unified Parkinson's Disease Rating Scale (UPDRS) scores with people with Parkinson's disease	Accelerometer	Parkinson	N/A

Table 2. Study outcomes.

Paper	Outcomes
Viteckova et al. [58]	The authors intended to use the instrumented Timed-Up and Go test, repeatedly in young adults and people with Parkinson's disease to make comparisons and test the efficiency of the method. Various related features were calculated, with the test time and the other parameters related to walking and angular velocity. An Xbus Mater was used for data acquisition, which includes 5 accelerometers with a sampling rate of 100 Hz.
Sharif Bidabadi et al. [59]	The study aimed to investigate disorders related to falls in people with low back problems and used machine learning algorithms. Machine learning was implemented to use an accelerometer to acquire data. The results showed that the performance was better with the use of the three classifiers Random Forest, Support Vector Machine (SVM), and Naive Bayes. In contrast, when the wrapper feature technique was used, the highest accuracy was 93.18% with the Random Forest classifier. The accelerometer used is a three-axis accelerometer to measure the different directions of movement.
Stamate et al. [60]	A cloud application called Unified Parkinson's Disease Rating Scale (UPDRS) was presented as a tool for people with Parkinson's disease. The system features a workflow compatible with various formats of audio, video, and text media. It consists of an Android application for testing, a cloud system for saving data, and a data mining tool kit for medical intelligence that incorporates quantitative data and semi-structured and longitudinal analyzes, groupings, and classifications. The data was acquired by the accelerometer embedded in 9 different phone models with a sampling rate of 50 Hz.
Joshi et al. [61]	The authors implemented a wavelet analysis method combined with the SVM method for Parkinson's patients. Various parameters related to walking were calculated, namely stride interval, swing interval, and stance interval (from both legs). The results showed an accuracy of 90.32%. The data was acquired by a three-axis accelerometer with specificity of 93.75%.
Ribeiro et al. [62]	The study used machine learning methods for the automatic recognition of people with epilepsy. Five machine learning methods were used to determine the most efficient among Naive Bayes, k-Nearest Neighbors (kNN), C4.5, Support Vector Machine (SVM), and Decision Tree-based-method (PART). The results showed that kNN had the highest computational cost, and PART and C4.5 had the lowest. Furthermore, the sensor used by the system was a three-axis accelerometer.
Djuric-Jovicic et al. [63]	The authors presented a method to identify the problem of falls in people with Parkinson's disease. Several types of stride were considered, and some features (namely Shank Movement Displacement, stride duration, and shank transversal orientation) were calculated. The results showed the highest performance of the algorithm was achieved when using a type of FOG stride with 100% accuracy. The data was acquired by a three-axis accelerometer with a minimum specificity of 87.8%.
Gruenerbl et al. [64]	The authors intended to use smartphones to help diagnose people with mental disorders such as depression and bipolar disorder. Inertial sensors and Global Positioning System (GPS) traces were used in the developed system. The results showed an accuracy level of 80%. The accelerometer used has a fixed sampling rate of 5Hz.
Pendharkar et al. [65]	The authors presented a method called Idiopathic Toe-Walking (ITW) to detect walking problems in children. The sensor used in this system was the accelerometer, with the two signals of horizontal and vertical acceleration decomposed to avoid overlap. The results showed that Blind Source Separation (BSS) techniques combined with a K-means classifier could distinguish gait from foot to normal pace in children with ITW with an accuracy of 97.9%. The sensor used is a dual-axis accelerometer.
Kugler et al. [66]	The authors presented a method of automatic recognition of people with Parkinson's disease. An accelerometer and an electromyography sensor were used to recognize and validate the walking parameters. When cross-validation to leave a subject out was used, the sensitivity and specificity values were the highest at 0.90, the best-rated features were the kurtosis and the mean frequency, and the best features had a significant difference in kurtosis of (p = 0.013). The authors used a three-axis accelerometer with a specificity of 90%.
Barth et al. [67]	The study featured a combined hand and leg analysis system for recognizing people with Parkinson's disease. Pressure sensors were used in conjunction with the accelerometer to analyze the hand. Moreover, gyroscope and accelerometer sensors were used to analyze the foot. The results were crossed between healthy individuals and people with Parkinson's disease, showing that when the AdaBoost classifier was used, the efficiency of the system reached 97%. These authors used a three-axis accelerometer, reporting a specificity between 88% and 100%.
Alaqtash et al. [68]	The authors presented a wearable sensor system for the acquisition of parameters related to walking by using a fuzzy computational algorithm, with healthy individuals and a group of patients with multiple sclerosis. The results showed that this system could be beneficial for the identification of problems related to walking showing the differences between healthy people and people with multiple sclerosis. This experiment used a dual-belt instrumented treadmill, which includes several three-axis accelerometers.
Phan et al. [69]	A system using the accelerometer was presented to detect diseases of the respiratory system and the heart. The system was positioned on the chest by using a belt. The study compared the use of traditional sensors such as an electrocardiogram (ECG) with a system implemented using an accelerometer. The results showed that the system provided identical results when the heart rate graph with the QRS complex was presented. This experiment considered the use of dual-axis accelerometer with high sensitivity.
Garcia Ruiz et al. [70]	The authors presented a method called ActiTrac for people with Parkinson's disease. The technique had the right level of efficiency in observing the motor part of the subjects participating in the study. The results showed that the mean activity significantly correlated with the total and the motor UPDRS scores. The accelerometer embedded in the ActiTrac device is a three-axis accelerometer.

3. Results

As presented in Figure 1, our review identified 98 papers that included one duplicate, which was removed. The remaining 97 studies were evaluated in terms of title, abstract, and keywords, resulting in the exclusion of 50 citations. The main criteria for excluding the papers were because 50 articles were not related to automatic recognition/identification of diseases with the accelerometer sensor. The full-text evaluation of the remaining 47 papers was performed, excluding 34 items that did not match the defined inclusion criteria. The excluded articles were not focused on automatic recognition of diseases by using accelerometer sensors, or because the diseases cannot be identified only with the accelerometer. As the focus of this study consists of the recognition of diseases related to the accelerometer sensor, i.e., diseases related to the movement, these articles must be excluded. The remaining 13 studies were presented in the qualitative and quantitative synthesis. In summary, our review examined 13 research articles.
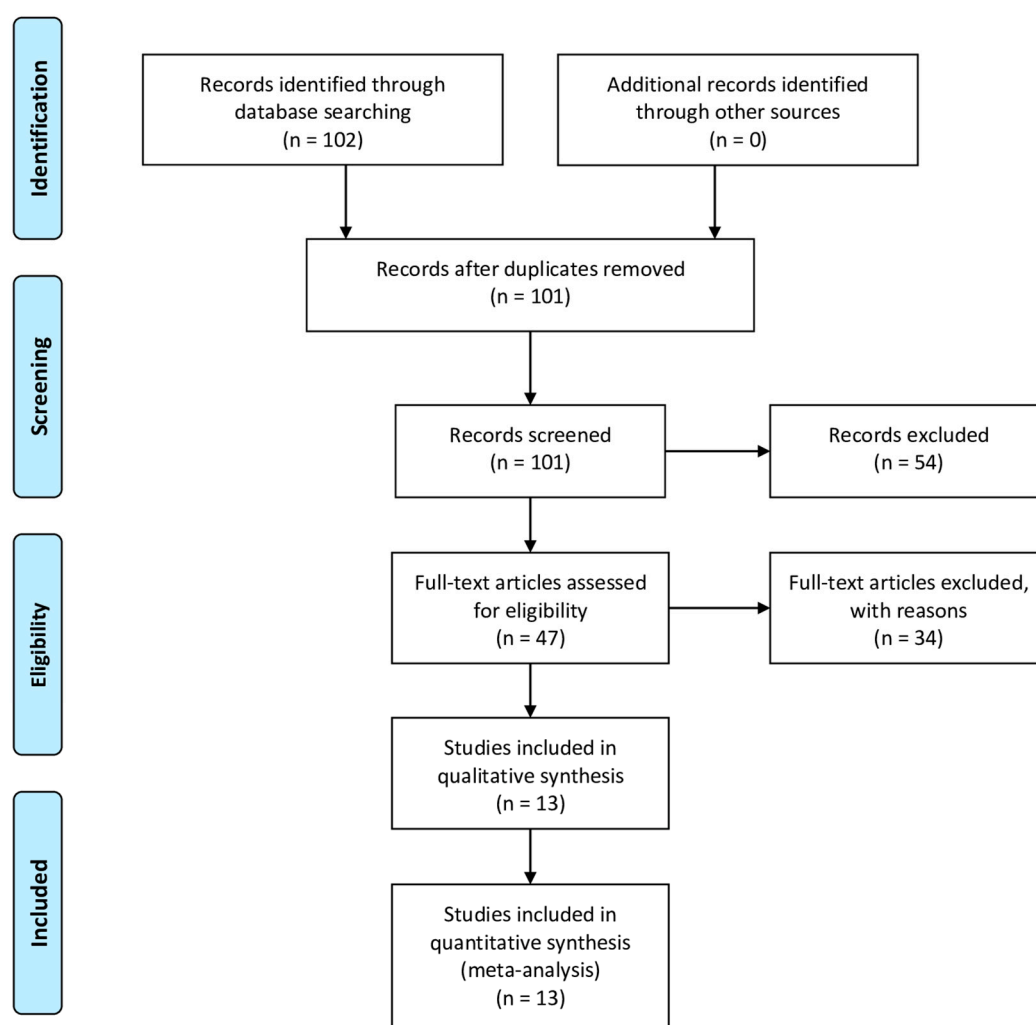

Figure 1. Flow diagram of identification and inclusion of papers.

After the analysis, the different research works are presented in Tables 1 and 2. For a more detailed analysis, the authors have also analyzed the year of each study and the location of the authors involved in the research. Also, the original studies are cited to obtain more detailed information. As shown in Tables 1 and 2, we analyzed the studies that provided an automatic recognition of the different diseases in studies that uses the accelerometer sensor. The studies analyzed were published between 2008 and

2020 with three studies in 2014 (23%), two studies (15%) in 2008 and 2018, and one study (7%) in 2011, 2012, 2013, 2016, 2017, 2019, and 2020, as presented in Figure 2.
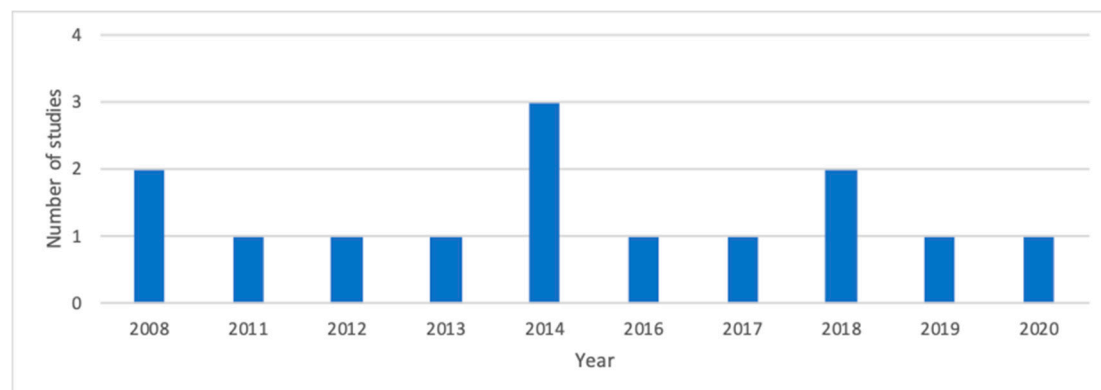

Figure 2. Distribution of the studies by different years of publication.

On average, the different studies considered the data acquired by a different number of people between 5 and 85 persons (27 ± 22 individuals), where the higher number of individuals increases the reliability of the study. The sensors used were studied, verifying that all searched items used the accelerometer sensors. Also, other studies combined the use of the gyroscope sensor (31%), the magnetometer sensor (8%), the GPS receiver (8%), the electromyography (EMG) sensor (8%), and the electrocardiography (ECG) sensor (8%). Finally, Parkinson's disease is the most detected disease with the accelerometer sensor, which was recognized in seven studies (54%). The remaining disorders are only identified in one study each: lumbar radiculopathy and related ankle dorsiflexion weakness with observable foot drop, epilepsy disease, bipolar disorder, idiopathic toe walkers, multiple sclerosis, arrhythmia, and sleep apnea. In general, the accuracies reported are reliable, reporting 94% accuracy (on average), but four studies (31%) did not present the accuracy of the recognition. Only two studies considered the use of dual-axis accelerometer (15%), where the remaining studies are using three-axis accelerometer (85%), because this type of sensors is the most common in the different devices.

The remaining results are categorized by the recognition of the different diseases, considering the detection of Parkinson's disease (Section 3.1), and other diseases (Section 3.2), because the other healthcare diseases recognized are residual.

3.1. Parkinson's Disease

The authors [58] presented the repeated use of instrumented Timed Up and Go test in adults and patients with Parkinson's under different conditions using accelerometer data. Multiple features have been calculated over the different experiences including total time, gait sub-component, peak, the velocity of arm swing, range of motion of arm swing, arm swing asymmetry, cadence, gait cycle time, double support, stride length, stride velocity, stride time variability, stride length variability, peak trunk rotation velocity, trunk rotation, range of motion, turn sub-component, average turning velocity, peak turning velocity, sit-to-stand sub-component, average, trunk velocity, peak trunk velocity, duration, and trunk inclination.

The authors [60] developed an application for evaluating people with Parkinson's disease. The system consists of three different elements, such as an Android application for capturing sensor data, iCloud-based technologies to store the data, and data mining techniques to obtain a better analysis of the captured data. Different parameters were analyzed during the experiments, including rest tremor, postural tremor, action tremor pronation-supination movements leg agility, finger tapping, and gait.

The authors [61] proposed a non-invasive method for classifying Parkinson's disease. Using wavelet analysis combined with the Support Vector Machine (SVM), this method has a

high accuracy value. Several walking parameters were analyzed, namely stride interval, swing interval, and stance interval (from both legs). The study presents some limitations that were identified in the realization of the experiments, among which the group of people chosen did not have the same age range, the same range of weights and types, which may have influenced the results. On the other hand, as the gait rhythm was calculated based on a portable system, other parameters of walking analysis could be added, and different frequencies, which may have influenced the level of accuracy presented. Another limitation identified by the study's authors was the level of correlation between gait features, and the inertial unit of measurement (IMU) may be implemented in the future in Parkinson's or healthy individuals with the advantage of avoiding the lack of gait cycles. The Force Sensor data obtained the data in low sampling, but it did not achieve the high precision rate required in a study of this type.

The authors [63] presented an algorithm for the detection and classification of disorders during gait in people with Parkinson's disease. These types of disorders are classified as difficult to detect. The algorithm separates normal and abnormal gait using the statistical method of Pearson's correlation. The data processing features several types of stride, including normal, short minus, short plus, freezing of gait (FOG) with tremor, FOG minus, and FOG with complete block engine. In general, they were being identified in 100% of the experiences of individuals with Parkinson's disease, namely 95% in Normal FOG and a minimum of 78% in Short FOG. Different types of classifications are presented for the performance of the algorithm related to sensitivity, specificity, accuracy, and precision, with the stride of the FOG type reported the best score of 100% in all parameters. Some other features are extracted such as Shank Movement Displacement, Stride Duration, and Shank Transversal Orientation.

The authors [66] presented a method to assist in the monitoring and progression of patients with Parkinson's, using the accelerometer and electromyography as sensors for data extraction. The control group used to carry out the experiments consisted of elements with Parkinson's disease and healthy, to validate the results of the study, and prove the effectiveness in detecting the disease. The electrodes were positioned bilaterally on anterior tibialis and gastrocnemius medialis and lateralis, while accelerometers on both heels and were used to segment the steps. Features of the Statistical and frequency type were extracted and then used to train the SVM classifier and automatic recognition of the disease. The results show that the best features were kurtosis and mean frequency, with a marked difference in the case of kurtosis that sensitivity and specificity were higher up to 0.90 using leave-one-subject-out cross-validation.

The authors [67] presented a combined analysis method for people with Parkinson's disease. The accelerometer, gyroscope, and pressure sensors were positioned at the patient's hand to acquire parameters related to gait. Several features of the signal sequence type were used, including mean, variance, regression line gradient, the standard deviation of minima, maxima minima difference, autocorrelation maximum, integral, and root mean square. Also, features related to frequency analysis were used, including dominant frequency, energy ratio, energy in the frequency band, and regression line of widowed energy in the frequency band. Moreover, the features related to step features were extracted, including the falling gradient of the stance phase. The results show an accuracy level of 97% in the combined analysis. On the other hand, it shows an accuracy of 89% in isolation and 91% in the gait analysis.

The authors [70] presented a system called ActiTrac for patients with Parkinson's to validate the classification of ambulatory activity monitor. Also, devices with accelerometers were used to record the strength of the muscles and the accelerations in position changes. The results obtained show reliability when correlated with Unified Parkinson's Disease Rating Scale (UPDRS) rigidity and bradykinesia subscores. Still, it does not show reliable results with the presence of tremor subscores. The Perdue Pegboard test, finger dexterity, and walking test are correlated with the duration of illness, but it is associated not with the clinical stage.

3.2. Other Diseases

The authors [59] presented a method to classify foot drop gait characteristics using machine learning algorithms in individuals with problems with lumbar radiculopathy. Different machine learning methods were used in this study. The ones that presented the best results in terms of accuracy were Random Forest, SVM, and Naive Bayes classifiers with 88.45%, 86.87%, and 86.08%, respectively, were applying the wrapper feature selection technique, it presents the best accuracy equals to 93.18%. Three inertial units of measurement (IMU) sensors were used for the acquisition of gait data. After that, the signal is transmitted via wireless. The sensors were positioned to the segments of the foot, stem, and thigh of the affected limb for patients (leg with falling foot) and the right leg for non-patients.

The authors [62] presented a method of machine learning for people with epileptic problems. A Wearable device was used to carry out the study considering F-Score and Accuracy metrics. The system used an Arduino board, Bluetooth communication, and an accelerometer connected to the Arduino. The machine learning techniques used were k-Nearest Neighbor (kNN), Decision Tree-based method (PART), and C4.5 Decision Tree. Still, kNN has a higher computational cost when compared to PART and C4.5 Decision Tree and PART a lower computational cost than C4.5 Decision Tree. The main objective of this work is to simplify and reduce the computational cost in recognition of day-to-day activities. Thus, a method was proposed to distinguish the different events of each day.

The authors [64] presented a study to analyze the use of smartphones in the diagnosis of people with mental disorders in people with bipolar disorder. The sensors used in this study were the accelerometer and the Global Positioning System (GPS) receiver, which obtained the following conclusions: patients with depression move less often, and more slowly, on the other hand, manic patients tend to run frequently and quickly. When we talk about travel patterns, people with this type of disorder travel less and with a less constant time pattern. The results show a recognition accuracy of 80% and a precision of 96% and a recall of 94% in recognition of state changes.

The authors [65] presented a method for analyzing gait in children. A technique called Blind Source Separation is used with Idiopathic Toe Walkers (ITW) children to identify gait parameters and detect walking problems in children. The sensor used in this system was the accelerometer having decomposed the two signals of horizontal and vertical acceleration so that there was no overlap. The results show that Blind Source Separation (BSS) techniques together with a K-means classifier can distinguish gait from foot to normal pace in children with ITW. The results show an average accuracy of 97.9%.

The authors [68] proposed an application with wearable sensors to analyze the walking parameters of healthy individuals with multiple sclerosis. An artificial intelligence algorithm called the fuzzy computational algorithm was applied. This algorithm was classified as being very promising for the health areas in helping to detect disorders related to the gait of individuals. The presented results did not report the classification accuracy, which is a limitation. On the other hand, the presented graphs allow us to perceive its efficiency as it is easily understood as the different results between healthy people and individuals with sclerosis. As future work, the authors present the possibility of developing methods that make it possible to make a quick analysis of disorders related to gait in individuals, efficient, low cost with more types of approaches. The accelerometer is the sensor used in this study, demonstrating once again the capabilities to analyze parameters related to acceleration force during gait.

The authors [69] presented a system for analyzing cardiorespiratory function using the accelerometer coupled to the chest using a belt. The authors state that this method may be useful to identify some diseases. The sensor detects the acquisition of data in different states (Normal, Apnea, and Deep Breathing) and vertical (sitting, standing) or horizontal (lying) postures, being the signal compared to frequency measurements performed by the electrocardiogram. The results show the efficiency of using the accelerometer in the detection of respiratory waves and heart rates. Presenting itself as an effective method in the discovery of some heart diseases such as arrhythmia or sleep apprehension.

4. Discussion

The data acquired from the accelerometer sensors allow the development of methods for the identification of different healthcare conditions, namely the diseases related to movement. Based on the various analyzed studies, we conclude that Parkinson's disease is the most identified disease with the accelerometer sensors. Some other disorders are marginally researched: lumbar radiculopathy and related ankle dorsiflexion weakness with observable foot drop, epilepsy disease, bipolar disorder, idiopathic toe walkers, multiple sclerosis, arrhythmia, and sleep apnea. The accelerometer acquires different data related to the acceleration of the movement that allows the identification of abnormalities during walking activity.

However, the accelerometer is available on different devices, including mobile devices and other specific types of equipment, such as the Bitalino device [71]. There are various problems related to the data acquisition that is mainly associated with the synchronism of the data transmission, the failures in the data acquisition, the sensitivity of the accelerometer used, positioning of the mobile device during the data acquisition, and other different hardware and software problems related to the devices used [72,73].

The accelerometer presents itself as a sensor with a multitude of uses in the acquisition of data related to the force and angular speed exercised by people during gait. It opens several opportunities for the automatic recognition of different diseases, and, consequently, the creation of disease patterns [74].

The acquisition of data from the accelerometer sensor combined with artificial intelligence methods allows for the recognition of different diseases, and the work of the healthcare professionals will be improved. Various machine learning techniques can be used, including k-Nearest Neighbor (kNN), Decision Tree-based method (PART), C4.5 Decision Tree, and kNN. However, these techniques need high processing capabilities, and, in most of the cases, the authors only compared the different features extracted from the accelerometer signal without the implementation of artificial intelligence techniques.

The different studies are dispersed by different countries with more incidence in Germany, the United Kingdom, the United States, Brazil, and Australia that concentrated more than five authors of the various studies (see Figure 3).
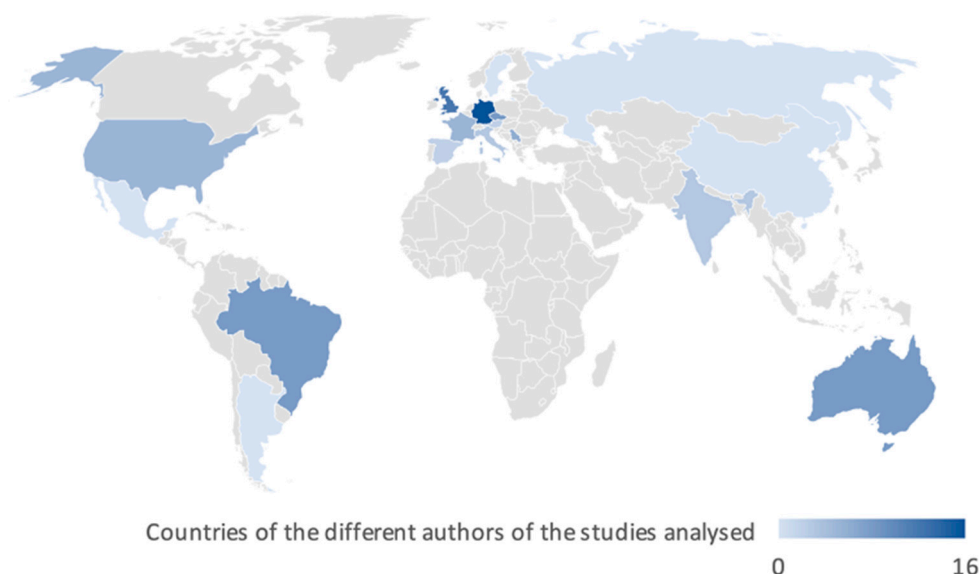

Countries of the different authors of the studies analysed

0   16

Figure 3. Geographical distribution of the different studies analyzed.

Numerous opportunities in this area have arisen, namely the detection of diseases, where the use of artificial intelligence methods facilitates its recognition. The use of automatic methods increases and speeds up the discovery of all parameters that may indicate the presence of specific disease and the individual's condition [55].

The increase in the percentage of older adults mainly in the western world and some standard protocols between research centers and those responsible for nursing homes has resulted in an increase in the number of studies to people where diseases, such as Parkinson's disease. Consequently, in the short term, this improves the speed of detecting this type of disorder and speeding up treatments.

As future work, we intend to identify different diseases based on the performance of the Timed-Up and Go test as the continuation of the work presented at [75,76]. The recognized disorders will be mainly related to the different abnormalities of movement, and other healthcare problems related to the lower limbs.

5. Conclusions

This systematic review paper presented a state-of-the-art analysis of the use of accelerometry-based systems that have emerged for the automatic recognition of multiple diseases. The authors aimed to provide a comprehensive understanding of the different healthcare conditions that can be evaluated using accelerometry devices. Moreover, we presented an analysis of the artificial intelligence techniques applied and their accuracy. The analyzed articles were published between 2008 and 2020. Most of the analyzed studies were conducted in 2014 (23%) and 2018 (15%). These studies were carried out by scholars from different countries with more incidence in Germany, the United Kingdom, the United States of America, Brazil, and Australia.

We analyzed 13 studies and obtained the following answers to the research questions considered:

- (RQ1) *How many people are involved in the different studies related to the use of the inertial sensors?* The number of volunteers involved in the studies analyzed ranged from 5 to 85 (27 ± 22 individuals), where the increasing number of individuals increase the reliability of the study.
- (RQ2) *Which diseases can be detected with inertial sensors?* Several diseases could be detected using accelerometer sensors such as Parkinson's, lumbar radiculopathy, and the related ankle dorsiflexion weakness with a noticeable foot drop, epilepsy, bipolar disorder, idiopathic toe walkers, multiple sclerosis, arrhythmia, and sleep apnea.
- (RQ3) *Which artificial intelligence methods are used for the identification or recognition of different diseases?* The artificial intelligence methods used for disease identification are Random Forest, SVM, Naive Bayes, kNN, C4.5, PART, and BSS, and K-means.

Furthermore, we concluded that the data from other sensors such as gyroscope, magnetometers, GPS receivers, EMG, and ECG were combined with the accelerometer data to identify multiple diseases. Parkinson's disease was the most studied disease using accelerometer sensors, representing 54% of the analyzed papers. Additionally, the average accuracy reported by the studies using artificial intelligence methods was 94% (on average).

In conclusion, multidisciplinary approaches creating a synergy between computer science and medical sciences can lead to the design of effective architectures that improve the processes related to the identification of different diseases. These architectures can incorporate artificial intelligence methods to create novel techniques for automated disease recognition and provide enhanced personalized health solutions to face the overall concern of healthcare in older adults and address the global ageing challenge.

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References

1. Teixeira, A.A.C.; Nagarajan, N.R.; Silva, S.T. The Impact of Ageing and the Speed of Ageing on the Economic Growth of Least Developed, Emerging and Developed Countries, 1990–2013. *Rev. Dev. Econ.* **2017**, *21*, 909–934. [CrossRef]

2. Nagarajan, N.R.; Teixeira, A.A.C.; Silva, S.T. Ageing Population: Identifying the Determinants of Ageing in the Least Developed Countries. *Popul. Res. Policy Rev.* **2020**, 1–24. [CrossRef]

3. Tsoi, K.K.F.; Hirai, H.W.; Chan, F.C.H.; Griffiths, S.; Sung, J.J.Y. Predicted Increases in Incidence of Colorectal Cancer in Developed and Developing Regions, in Association with Ageing Populations. *Clin. Gastroenterol. Hepatol.* **2017**, *15*, 892–900. [CrossRef] [PubMed]

4. WORLD FACTS AND STATISTICS ON DISABILITIES AND DISABILITY ISSUES. Available online: www.cdc.gov/ncbddd/disabilityandhealth/dhds.html (accessed on 17 December 2018).

5. Population Ages 65 and above (% of Total) Data. Available online: https://data.worldbank.org/indicator/SP.POP.65UP.TO.ZS#fromHistory (accessed on 24 November 2018).

6. Office of Disease Prevention and Health Promotion. *2020 Topics & Objectives: Older Adults*; ODPHP: Washington, DC, USA, 2020.

7. World Health Organization. Ageing and Health. Available online: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health (accessed on 27 December 2019).

8. Euromonitor International. The Top 5 Oldest Countries in the World. Available online: https://blog.euromonitor.com/the-top-5-oldest-countries-in-the-world/ (accessed on 30 April 2019).

9. Paulo, A.C.; Sampaio, A.; Santos, N.C.; Costa, P.S.; Cunha, P.; Zihl, J.; Cerqueira, J.; Palha, J.A.; Sousa, N. Patterns of Cognitive Performance in Healthy Ageing in Northern Portugal: A Cross-Sectional Analysis. *PLoS ONE* **2011**, *6*, e24553. [CrossRef]

10. Lopes, M.C.; Liberato, D.; Alén, E.; Liberato, P. Social Tourism Development and the Population Ageing: Case Study in Portugal and Spain. In *Advances in Tourism, Technology and Smart Systems, Proceedings of the ICOTTS 2019, Buenos Aires, Argentina, 5–7 December 2019*; Rocha, Á., Abreu, A., de Carvalho, J.V., Liberato, D., González, E.A., Liberato, P., Eds.; Springer: Singapore, 2020; pp. 527–536.

11. Kana, M.A.; Correia, S.; Peleteiro, B.; Severo, M.; Barros, H. Impact of the global financial crisis on low birth weight in Portugal: A time-trend analysis. *BMJ Glob. Health* **2017**, *2*, e000147. [CrossRef]

12. Correia, S.; Rodrigues, T.; Montenegro, N.; Barros, H. Critical evaluation of national vital statistics: The case of preterm birth trends in Portugal. *Acta Obstet. Gynecol. Scand.* **2015**, *94*, 1215–1222. [CrossRef]

13. PORDATA, Índice de Dependência de Idosos: Que Países Têm Mais e Menos Idosos por 100 Pessoas em Idade Activa? 2018. Available online: https://www.pordata.pt/Europa/%C3%8Dndice+de+depend%C3%AAncia+de+idosos-1929 (accessed on 31 October 2018).

14. Guimarães, H.; Boix, H.; Rodrigues, C.; Tomé, T.; Rocha, G.; Vento, M. Impact of the global financial crisis on newborn care in Portugal and Spain: Perception of health professionals. *Acta Paediatr.* **2020**, *109*, 625–627. [CrossRef]

15. Marques, G.; Pitarma, R.; Garcia, N.M.; Pombo, N. Internet of Things Architectures, Technologies, Applications, Challenges, and Future Directions for Enhanced Living Environments and Healthcare Systems: A Review. *Electronics* **2019**, *8*, 1081. [CrossRef]

16. Colantonio, S.; Coppini, G.; Giorgi, D.; Morales, M.-A.; Pascali, M.A. Computer Vision for Ambient Assisted Living. In *Computer Vision for Assistive Healthcare*; Elsevier: Amsterdam, The Netherlands, 2018; pp. 147–182. ISBN 978-0-12-813445-0.

17. Ganchev, I.; Garcia, N.M.; Dobre, C.; Mavromoustakis, C.X.; Goleva, R. *Enhanced Living Environments: Algorithms, Architectures, Platforms, and Systems*; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2019; Volume 11369, ISBN 978-3-030-10751-2.

18. Dobre, C.; Mavromoustakis, C.X.; Garcia, N.M.; Mastorakis, G.; Goleva, R.I. Introduction to the AAL and ELE Systems. In *Ambient Assisted Living and Enhanced Living Environments*; Elsevier: Amsterdam, The Netherlands, 2017; pp. 1–16. ISBN 978-0-12-805195-5.

19. Botia, J.A.; Villa, A.; Palma, J. Ambient Assisted Living system for in-home monitoring of healthy independent elders. *Expert Syst. Appl.* **2012**, *39*, 8136–8148. [CrossRef]

20. Costa, S.E.P.; Rodrigues, J.J.P.C.; Silva, B.M.C.; Isento, J.N.; Corchado, J.M. Integration of Wearable Solutions in AAL Environments with Mobility Support. *J. Med. Syst.* **2015**, *39*, 184. [CrossRef]

21. Azimi, I.; Rahmani, A.M.; Liljeberg, P.; Tenhunen, H. Internet of things for remote elderly monitoring: A study from user-centered perspective. *J. Ambient Intell. Humaniz. Comput.* **2016**, *8*, 273–289. [CrossRef]

22. Biagetti, G.; Crippa, P.; Curzi, A.; Orcioni, S.; Turchetti, C. Analysis of the EMG Signal During Cyclic Movements Using Multicomponent AM–FM Decomposition. *IEEE J. Biomed. Health Inform.* **2015**, *19*, 1672–1681. [CrossRef] [PubMed]

23. Park, K.; Lim, S. A Multilayer Secure Biomedical Data Management System for Remotely Managing a Very Large Number of Diverse Personal Healthcare Devices. *BioMed Res. Int.* **2015**, *2015*, 1–17. [CrossRef] [PubMed]

24. Park, K.; Pak, J. An Integrated Gateway for Various PHDs in U-Healthcare Environments. *J. Biomed. Biotechnol.* **2012**, *2012*, 1–7. [CrossRef]

25. Evans, J.; Papadopoulos, A.; Silvers, C.T.; Charness, N.; Boot, W.R.; Schlachta-Fairchild, L.; Crump, C.; Martinez, M.; Ent, C.B. Remote Health Monitoring for Older Adults and Those with Heart Failure: Adherence and System Usability. *Telemed. E-Health* **2016**, *22*, 480–488. [CrossRef]

26. Liu, L.; Stroulia, E.; Nikolaidis, I.; Miguel-Cruz, A.; Rios Rincon, A. Smart homes and home health monitoring technologies for older adults: A systematic review. *Int. J. Med. Inf.* **2016**, *91*, 44–59. [CrossRef]

27. Luxton, D.D.; McCann, R.A.; Bush, N.E.; Mishkind, M.C.; Reger, G.M. mHealth for mental health: Integrating smartphone technology in behavioral healthcare. *Prof. Psychol. Res. Pract.* **2011**, *42*, 505–512. [CrossRef]

28. Charani, E.; Castro-Sánchez, E.; Moore, L.S.; Holmes, A. Do smartphone applications in healthcare require a governance and legal framework? It depends on the application! *BMC Med.* **2014**, *12*, 29. [CrossRef]

29. Lloret, J.; Canovas, A.; Sendra, S.; Parra, L. A smart communication architecture for ambient assisted living. *Commun. Mag. IEEE* **2015**, *53*, 26–33. [CrossRef]

30. Parra, L.; Sendra, S.; Jiménez, J.; Lloret, J. Multimedia sensors embedded in smartphones for ambient assisted living and e-health. *Multimed. Tools Appl.* **2015**, *75*, 1–27. [CrossRef]

31. Pires, I.M.; Marques, G.; Garcia, N.M.; Flórez-Revuelta, F.; Ponciano, V.; Oniani, S. A Research on the Classification and Applicability of the Mobile Health Applications. *J. Pers. Med.* **2020**, *10*, 11. [CrossRef] [PubMed]

32. Bisio, I.; Lavagetto, F.; Marchese, M.; Sciarrone, A. Smartphone-centric ambient assisted living platform for patients suffering from co-morbidities monitoring. *Commun. Mag. IEEE* **2015**, *53*, 34–41. [CrossRef]

33. Iglesias, R.; Parra, J.; Cruces, C.; de Segura, N.G. Experiencing NFC-based touch for home healthcare. *ACM Press* **2009**, 1–4. [CrossRef]

34. Kakria, P.; Tripathi, N.K.; Kitipawang, P. A Real-Time Health Monitoring System for Remote Cardiac Patients Using Smartphone and Wearable Sensors. *Int. J. Telemed. Appl.* **2015**, *2015*, 1–11. [CrossRef] [PubMed]

35. Yan, K.; Tracie, B.; Marie-Ève, M.; Jean-Luc, B.; Benoit, T.; St-Onge, M.; Marie, L. Innovation through Wearable Sensors to Collect Real-Life Data among Pediatric Patients with Cardiometabolic Risk Factors. *Int. J. Pediatr.* **2014**, *2014*, 9. [CrossRef] [PubMed]

36. Matiko, J.W.; Wei, Y.; Torah, R.; Grabham, N.; Paul, G.; Beeby, S.; Tudor, J. Wearable EEG headband using printed electrodes and powered by energy harvesting for emotion monitoring in ambient assisted living. *Smart Mater. Struct.* **2015**, *24*, 125028. [CrossRef]

37. Zhu, C.; Sheng, W.; Liu, M. Wearable Sensor-Based Behavioral Anomaly Detection in Smart Assisted Living Systems. *IEEE Trans. Autom. Sci. Eng.* **2015**, *12*, 1225–1234. [CrossRef]

38. Aced López, S.; Corno, F.; De Russis, L. Supporting caregivers in assisted living facilities for persons with disabilities: A user study. *Univers. Access Inf. Soc.* **2015**, *14*, 133–144. [CrossRef]

39. Zainal, A.; Razak, F.H.A.; Ahmad, N.A. Older People and the Use of Mobile Phones: An Interview Study. In Proceedings of the 2013 International Conference on Advanced Computer Science Applications and Technologies, Kuching, Malaysia, 22–24 December 2013; pp. 390–395.

40. Majumder, S.; Deen, M.J. Smartphone Sensors for Health Monitoring and Diagnosis. *Sensors* **2019**, *19*, 2164. [CrossRef]

41. Haghi, M.; Thurow, K.; Stoll, R. Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices. *Healthc. Inform. Res.* **2017**, *23*, 4. [CrossRef]

42. Guo, J.; Zhou, X.; Sun, Y.; Ping, G.; Zhao, G.; Li, Z. Smartphone-Based Patients' Activity Recognition by Using a Self-Learning Scheme for Medical Monitoring. *J. Med. Syst.* **2016**, *40*, 140. [CrossRef] [PubMed]

43. Chung, P.-C.; Hsu, Y.-L.; Wang, C.-Y.; Lin, C.-W.; Wang, J.-S.; Pai, M.-C. Gait analysis for patients with Alzheimer's disease using a triaxial accelerometer. In Proceedings of the IEEE International Symposium on Circuits and Systems (ISCAS) 2012, Seoul, Korea, 20–23 May 2012; pp. 1323–1326.

44. Ibrahim, A.; Eltawil, A.; Na, Y.; El-Tawil, S. Accuracy Limits of Embedded Smart Device Accelerometer Sensors. *IEEE Trans. Instrum. Meas.* **2020**. [CrossRef]

45. Trisno, R.; Nair, P.; Martin, D.; Baghini, M.S.; Chung, H.; Pendharkar, G.; Kulkarni, J. Using accelerometer as a diagnostic tool to detect drug-induced parkinsonism (DIP) secondary to first-generation anti-psychotic medications. *Australas. Psychiatry* **2020**. [CrossRef] [PubMed]

46. Biagetti, G.; Crippa, P.; Falaschetti, L.; Orcioni, S.; Turchetti, C. Human activity monitoring system based on wearable sEMG and accelerometer wireless sensor nodes. *Biomed. Eng. OnLine* **2018**, *17*, 132. [CrossRef] [PubMed]

47. Miao, F.; He, Y.; Liu, J.; Li, Y.; Ayoola, I. Identifying typical physical activity on smartphone with varying positions and orientations. *Biomed. Eng. Online* **2015**, *14*, 32. [CrossRef]

48. Weiss, A.; Sharifi, S.; Plotnik, M.; van Vugt, J.P.P.; Giladi, N.; Hausdorff, J.M. Toward Automated, At-Home Assessment of Mobility Among Patients with Parkinson Disease, Using a Body-Worn Accelerometer. *Neurorehabil. Neural Repair* **2011**, *25*, 810–818. [CrossRef]

49. Poewe, W.; Seppi, K.; Tanner, C.M.; Halliday, G.M.; Brundin, P.; Volkmann, J.; Schrag, A.-E.; Lang, A.E. Parkinson disease. *Nat. Rev. Dis. Primer* **2017**, *3*, 1–21. [CrossRef]

50. Deng, H.; Wang, P.; Jankovic, J. The genetics of Parkinson disease. *Ageing Res. Rev.* **2018**, *42*, 72–85. [CrossRef]

51. Learmonth, Y.C.; Ensari, I.; Motl, R.W. Cognitive Motor Interference in Multiple Sclerosis: Insights from a Systematic Quantitative Review. *Arch. Phys. Med. Rehabil.* **2017**, *98*, 1229–1240. [CrossRef]

52. Kunkle, S.; Christie, G.; Yach, D.; El-Sayed, A.M. The Importance of Computer Science for Public Health Training: An Opportunity and Call to Action. *JMIR Public Health Surveill.* **2016**, *2*, e10. [CrossRef]

53. Molina Recio, G.; García-Hernández, L.; Molina Luque, R.; Salas-Morera, L. The role of interdisciplinary research team in the impact of health apps in health and computer science publications: A systematic review. *Biomed. Eng. OnLine* **2016**, *15*, 77. [CrossRef] [PubMed]

54. Free, C.; Phillips, G.; Galli, L.; Watson, L.; Felix, L.; Edwards, P.; Patel, V.; Haines, A. The Effectiveness of Mobile-Health Technology-Based Health Behaviour Change or Disease Management Interventions for Health Care Consumers: A Systematic Review. *PLoS Med.* **2013**, *10*, e1001362. [CrossRef] [PubMed]

55. Davenport, T.; Kalakota, R. The potential for artificial intelligence in healthcare. *Future Healthc. J.* **2019**, *6*, 94–98. [CrossRef] [PubMed]

56. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; The PRISMA Group. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Med.* **2009**, *6*, e1000097. [CrossRef]

57. Zdravevski, E.; Lameski, P.; Trajkovik, V.; Chorbev, I.; Goleva, R.; Pombo, N.; Garcia, N.M. Automation in Systematic, Scoping and Rapid Reviews by an NLP Toolkit: A Case Study in Enhanced Living Environments. In *Enhanced Living Environments*; Ganchev, I., Garcia, N.M., Dobre, C., Mavromoustakis, C.X., Goleva, R., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2019; Volume 11369, pp. 1–18. ISBN 978-3-030-10751-2.

58. Viteckova, S.; Krupicka, R.; Dusek, P.; Cejka, V.; Kutilek, P.; Novak, J.; Szabo, Z.; Růžička, E. The repeatability of the instrumented timed Up & Go test: The performance of older adults and parkinson's disease patients under different conditions. *Biocybern. Biomed. Eng.* **2020**, *40*, 363–377.

59. Sharif Bidabadi, S.; Murray, I.; Lee, G.Y.F.; Morris, S.; Tan, T. Classification of foot drop gait characteristic due to lumbar radiculopathy using machine learning algorithms. *Gait Posture* **2019**, *71*, 234–240. [CrossRef]

60. Stamate, C.; Magoulas, G.D.; Kueppers, S.; Nomikou, E.; Daskalopoulos, I.; Jha, A.; Pons, J.S.; Rothwell, J.; Luchini, M.U.; Moussouri, T.; et al. The cloudUPDRS app: A medical device for the clinical assessment of Parkinson's Disease. *Pervasive Mob. Comput.* **2018**, *43*, 146–166. [CrossRef]

61. Joshi, D.; Khajuria, A.; Joshi, P. An automatic non-invasive method for Parkinson's disease classification. *Comput. Methods Programs Biomed.* **2017**, *145*, 135–145. [CrossRef]

62. Ribeiro, E.; Bentes, L.; Cruz, A.; Leitão, G.; Barreto, R.; Silva, V.; Primo, T.; Koch, F. On the use of inertial sensors and machine learning for automatic recognition of fainting and epileptic seizure. In Proceedings of the 18th International Conference on e-Health Networking, Applications and Services, Healthcom, Munich, Germany, 14–17 September 2016.

63. Djuric-Jovicic, M.D.; Jovicic, N.S.; Radovanovic, S.M.; Stankovic, I.D.; Popovic, M.B.; Kostic, V.S. Automatic identification and classification of freezing of gait episodes in Parkinson's disease patients. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2014**, *22*, 685–694. [CrossRef]

64. Gruenerbl, A.; Osmani, V.; Bahle, G.; Carrasco, J.C.; Oehler, S.; Mayora, O.; Haring, C.; Lukowicz, P. Using smart phone mobility traces for the diagnosis of depressive and manic episodes in bipolar patients. In *ACM International Conference Proceeding Series*; Association for Computing Machinery: New York, NY, USA, 2014; pp. 1–8.

65. Pendharkar, G.; Naik, G.R.; Nguyen, H.T. Using Blind Source Separation on accelerometry data to analyze and distinguish the toe walking gait from normal gait in ITW children. *Biomed. Signal Process. Control* **2014**, *13*, 41–49. [CrossRef]

66. Kugler, P.; Jaremenko, C.; Schlachetzki, J.; Winkler, J.; Klucken, J.; Eskofier, B. Automatic recognition of Parkinson's disease using surface electromyography during standardized gait tests. In Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, Osaka, Japan, 3–7 July 2013; pp. 5781–5784.

67. Barth, J.; Sünkel, M.; Bergner, K.; Schickhuber, G.; Winkler, J.; Klucken, J.; Eskofier, B. Combined analysis of sensor data from hand and gait motor function improves automatic recognition of Parkinson's disease. In Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2012, San Diego, CA, USA, 28 August–1 September 2012; pp. 5122–5125.

68. Alaqtash, M.; Yu, H.; Brower, R.; Abdelgawad, A.; Sarkodie-Gyan, T. Application of wearable sensors for human gait analysis using fuzzy computational algorithm. *Eng. Appl. Artif. Intell.* **2011**, *24*, 1018–1025. [CrossRef]

69. Phan, D.H.; Bonnet, S.; Guillemaud, R.; Castelli, E.; Thi, N.Y.P. Estimation of respiratory waveform and heart rate using an accelerometer. In Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS'08—"Personalized Healthcare through Technology", Vancouver, BC, Canada, 20–25 August 2008; pp. 4916–4919.

70. Garcia Ruiz, P.J.; Sanchez Bernardos, V. Evaluation of ActiTrac® (ambulatory activity monitor) in Parkinson's Disease. *J. Neurol. Sci.* **2008**, *270*, 67–69. [CrossRef] [PubMed]

71. Batista, D.; Silva, H.; Fred, A. Experimental characterization and analysis of the BITalino platforms against a reference device. In Proceedings of the 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Seogwipo, Korea, 11–15 July 2017; pp. 2418–2421.

72. Pires, I.; Felizardo, V.; Pombo, N.; Garcia, N.M. Limitations of energy expenditure calculation based on a mobile phone accelerometer. In Proceedings of the 2017 International Conference on High Performance Computing & Simulation (HPCS), Genoa, Italy, 17–21 July 2017; pp. 124–127.

73. Pires, I.M.; Garcia, N.M.; Pombo, N.; Flórez-Revuelta, F. Limitations of the Use of Mobile Devices and Smart Environments for the Monitoring of Ageing People. In Proceedings of the 4th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2018), Madeira, Portugal, 22–23 March 2018.

74. Cancela, J.; Pastorino, M.; Arredondo, M.T.; Pansera, M.; Pastor-Sanz, L.; Villagra, F.; Pastor, M.A.; Gonzalez, A.P. Gait assessment in Parkinson's disease patients through a network of wearable accelerometers in unsupervised environments. In Proceedings of the 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Boston, MA, USA, 30 August–3 September 2011; pp. 2233–2236.

75. Ponciano, V.; Pires, I.M.; Ribeiro, F.R.; Garcia, N.M.; Pombo, N.; Spinsante, S.; Crisóstomo, R. Smartphone-based automatic measurement of the results of the Timed-Up and Go test. In Proceedings of the 5th EAI International Conference on Smart Objects and Technologies for Social Good, Valencia, Spain, 25–27 September 2019; pp. 239–242.

76. Ponciano, V.; Pires, I.M.; Ribeiro, F.R.; Garcia, N.M.; Pombo, N. Non-invasive measurement of results of timed-up and go test: Preliminary results. In Proceedings of the Ageing Congress 2019, Coimbra, Portugal, 25–28 May 2019.