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PHD THESIS

Contributions to Development of Medical Wearable-based Applications for Subjects with Neurocognitive Disorders

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Contents

Acronyms

ADL Activities of Daily Living. 8

AI Artificial Intelligence. 2

BLE Bluetooth Low Energy. 34

CNN-LSTM CNN-Long Short-Term Memory. 23

CWT Continuous Wavelet Transform. 17

DCD Developmental Co-ordination Disorder. 2

DFA Detrended Fluctuation Analysis. 15

DL Deep Learning. 4, 33

DLAs Daily living activities. 1

DLB Dementia accompained by Lewy bodies. 6

DTs Decision Trees. 30

ET Essential tremor. 2

FOG Freezing of Gait. 4

HAR Human activity recognition. 23

HD Huntington Disease. 6

IoT Internet of Things. 13

KNN K-Nearest Neighbor. 5, 30

L-dopa Levodopa. 7

MDS-UPDRS Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale. 1

MID A management, instrumentation, and discovery. 35

ML Machine Learning. 2

NCDs Neurocognitive Disorders. 1

PaaS Platform as a Service. 2

PD Parkinson's Disease. 1, 34

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses. 9

PwPD Patients with Parkinson's Disease. 2

QoL Quality of Life. 1

RF Random Forest. 5

TL Transfer Learning. 26

UE Upper extremity. 11

UI User Interface. 35

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1 Introduction

The prevalence of Neurocognitive Disorders (NCDs) in patients demands the use of wearable devices to transform the future of mental health. There are numerous applications of wearable devices in healthcare ranging from physiological diseases, i.e., cardiovascular diseases, hypertension, and muscle disorders to NCDs, in particular Parkinson's Disease (PD), Alzheimer's disease, and other movement disorders such as paraplegia.

This thesis seeks to give a broad perspective on the necessity of improving eHealth systems, personalized medicine, and frameworks that automatize the evaluation process of different neurological disease stages in the case of Parkinson's, paraplegia, or neuro-motor disabilities caused by different injuries.

1.1 Background and Motivation

NCDs are a group of conditions that frequently lead to impaired mental function. NCDs are not psychologically rooted; there foundation is by medical disease or drug usage or physical diseases or elimination which affect brain performance. A severe NCD is described as a considerable cognitive impairment that interferes with a person's Quality of Life (QoL) and Daily living activities (DLAs). The most common cause of NCDs is a neurodegenerative disease. Neurodegenerative diseases that can lead to the development of NCDs include Alzheimer's disease and PD. The main cause of PD is decreased dopamine production in the brain i.e. although the cell's death generate dopamine transmitters transcended around 60% [1].

According to National Institute of Aging, the prevalence rate of PD is 10 million of population around the globe affecting 50% more men than women [2]. In every 5 hours, 10 patients are diagnosed with PD. In United Kingdom, 60000 people yearly are diagnosed with PD cases before the age of 50 [3] The estimated PD rate is to be double by 2030 [4]. The PD is characterized by both motor and non-motor symptoms. The non-motor symptoms incorporates mental and behavioral changes, sleep disorders, hallucinations, mood changes, depression, memory difficulties, and fatigue and the best-known motor symptoms are: tremor, slowness, stiffness, and walking and balance problems. However, motor symptoms are more dominant than non-motor symptoms, which worsens with disease progression and depends from individual to every individual person. The time of progression to a PD depends on the length and stage of disease. For NCD to be attributed as PD, the motor and other symptoms of PD must be present well before cognitive decline. Presently, the PD identification is primarily based on clinical rules and neurological assessment of the suffering individuals managing them by following the Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [5]. In particular, Section III of the MDS-UPDRS is devoted to looking into and assessing the patient's motor impairment as demonstrated by the completion of standardized activities. Neurologists ask patients to carry out certain motor activities that typically use their upper and lower limbs during clinical assessments. The specialist allots a score between 0 (no motor symptoms) and 4 (severe motor symptoms) for each test, and the aggregate of all the tasks yields the patient's evaluation. A number of significant problems are associated with this type of evaluation; first and foremost, the evaluation is unavoidably affected by the patient's condition at the time of the evaluation and, second, it is subject to the subjectivity of the clinicians who evaluates the patient. As a result,high inter-rater variability may affects the assessment [6]. Technically, the main challenge is to focus more on the system's wearability and automate the processing algorithms to provide a solid framework that may be quickly applied and embraced by medical professionals as well as PD patients. In fact, the ability to use such a device at home might have a favorable effect on PD management, benefiting patients as well as healthcare systems by boosting home monitoring by empowering patients and their caretakers. In order to assign the same score to people with various issues, we would overcome with the typical MDS-UPDRS evaluation for the clinical application because it has limited granularity and only ranges from 0 to 4 for each activity. Using Artificial Intelligence (AI) and various Machine Learning (ML) techniques in healthcare applications has been actively investigated over the last few years for diagnosis and monitoring of PD patients. Smart wearables with combination of ML approach have turned the traditional healthcare into smart healthcare [7]. Some of the wearable devices are commercially present for objective assessment and monitoring of Parkinsonism symptoms such as such as DynaPort MiniMod, SwayStar, SENSE-PARK system1, Kinesia system2, Parkinson's Kinetigraph (PKG)3 and Physilog4. Despite of their reliable performance and validation these systems are limitedly adopted by medical personnel and patients. So the inconsistencies in adoption and implementation of these proposed systems possibly due to the shortfall of users' perspectives in gadgets design and its development [8]. The application of these wearable medical devices to explore clinical evaluation in people with various types of NCD and causing motor impairment, such as in gait or postural instability, to improve the assessment of differential diagnosis is another unresolved difficulty.

These prototypes and systems somehow lack a specific cloud based assessment environment, require improved security and privacy features, better communication capabilities and most importantly quick real-time monitoring capacity. By this meaning, there is a dire need of a system that also provides the quantification of the disease severity and helps in rehabilitation of Patients with Parkinson's Disease (PwPD) in a free-living environment, with patients being able to use it without any supervision in their ON/ OFF stage.

1.2 Overview of the Research

Since limb impairment or limb disability, such as muscle weakness, loss of dexterous movement, and reduced sensation, are common in NCDs or after a brain injury. For instance, the nerve condition known as Essential tremor (ET) can cause uncontrolled tremors. The upper body, including the hands and arms, is most usually affected by ET. Similar to this, youngsters who appear to have terrible coordination may really have a motor skills disorder (MSD). This lack of coordination makes it difficult to fulfill goals or carry out age-appropriate everyday tasks (e.g., walking, playing catch, etc). Furthermore, Developmental Co-ordination Disorder (DCD), also known as dyspraxia, is a typical motor disability that affects 5–6% of children, with a greater risk of up to 50% in preterm infants. Better recognition of DCD [9] accurate and early diagnosis may help doctors in deciding promising therapeutic approaches for patients. Considering all these motor impairments, the preferences, and requirements of healthcare personnel and patients can be met using wearable technology. This research aims to develop cutting-edge algorithms for use in the eHealth architecture's decision-making and data extraction; to establish a revolutionary eHealth architecture based on wireless communication modules, connections, and wearable materials; to experiment with and evaluate the suggested architecture on NCD patients. The research is done into three phases: first - the development of wearable device, the second - development of the Platform as a Service (PaaS) platform, and the last one is the cloud-based data processing tools. The workflow involves four major components- sensor devices, smartphones, cloud services, and service users. A schematic representation of the concepts, devices and techniques proposed, analyzed and used by the framework developed in this thesis is represented in Figure 1.1

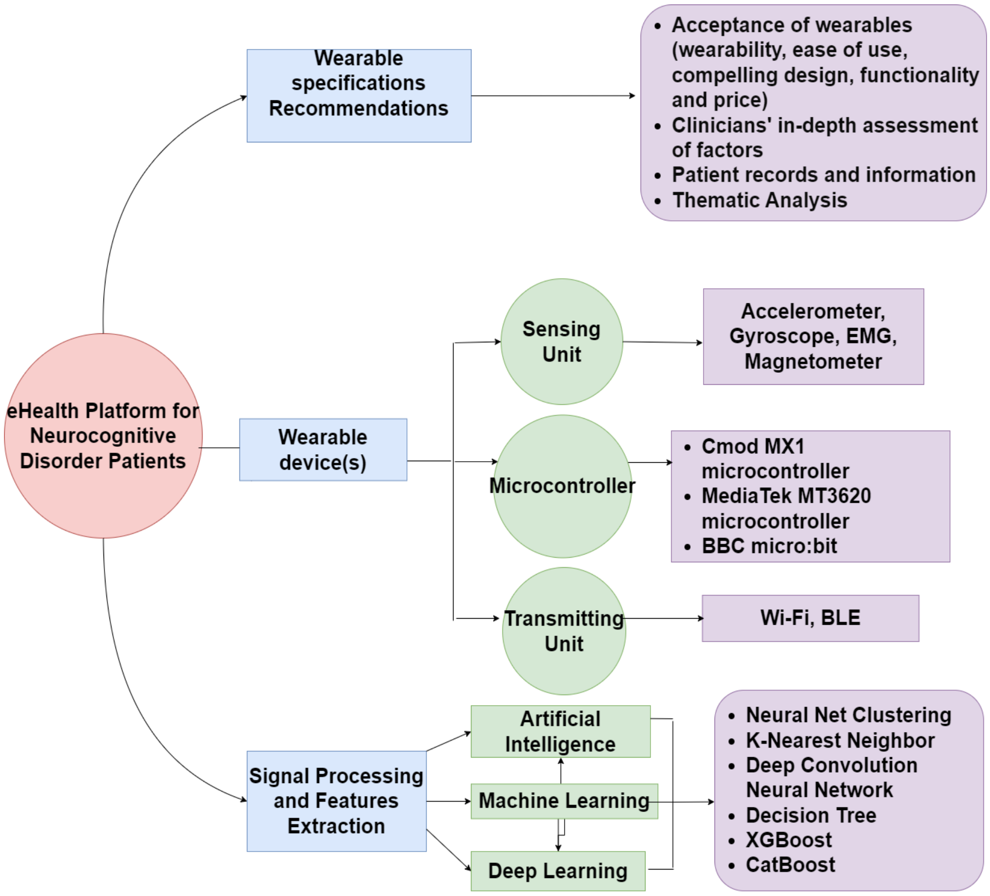


Figure 1.1: Schematic Representation of framework developed in this thesis.

1.3 Research Questions

After providing a brief study summary, this thesis focuses on how wearable medical devices might benefit those who have NCDs and PD. to integrate cutting-edge technology into clinical practice and give neurologists accurate tools for assessing motor deficits in people with PD.

This thesis specifically aims to respond to the questions below:

- How wearable devices can be useful for patients with NCDs?
- Can wearable devices help in early identification, monitoring, and rehabilitation of Parkinson's patients?
- What are the challenges in designing of wearable solution for patients with PD and NCD?
- How new classification methods perform on data acquired from medical wearable devices?
- What are the challenges in designing of wearable solution for patients with PD and NCD?
- How much improvement for imbalanced data classification can be achieved by employing resampling techniques?
- Can wearable device be used to find the effect of medication state on motor symptom severity classification?
- How to develop Smart eHealth system for PD Patients evaluation leveraging Deep Learning and cloud technology?

To address the above questions, the following section outlines the aim and objectives of the performed research reported in this thesis.

1.4 Research Aims and Objectives

The goal of this research is to create a wearable system that is dependable, responsive, and cross-platform and that can be used by patients, with or without the assistance of a caregiver, to objectively measure the degree of tremor in persons with PD. Identifying patients' and healthcare professionals' perceptions on current evaluation techniques as well as their needs and preferences for wearable technology is also important.

To achieve the above research aim, the following objectives were identified:

1. Evaluate the existing literature with reference to the use of medical wearable devices for NCD patients specifically for PD patients. The significance of wearables in improving the QoL of PD patients. What improvements are required to make these systems more robust?

2. To understand how to develop wearables that are sufficient and provide long-term benefit to doctors and patients.

3. Extract features from inertial signals to find characteristics in the data that help to find PD motor symptoms i.e. tremors, bradykinesia, Freezing of Gait (FOG).

4. Develop an A-WEAR bracelet, collect data from patients and evaluate ML methods on it for early diagnosis of PD.

5. Investigate the effectiveness of Deep Learning (DL) model on data collected from PD patients, healthy subject and elderly using smart insoles. How the gait cycle differentiate among all.

6. Modify A-WEAR bracelet in terms of wireless communication i.e Wi-Fi and long lasting battery so that data can be analyzed continuously.

7. Explore the effectiveness of various resampling techniques in combination with ML approaches to estimate tremor and bradykinesia severity of patients.

8. Investigate medication state effects on tremor severity classification.

1.5 Outline of this Thesis

This thesis comprises of seven chapters. The summary of contents of each chapter are highlighted below:

Chapter 2: A critical analyze on the design of Wearable Solutions for patients with Parkinson's Disease and Neurocognitive Disorder

This chapter presents a comprehensive review of the relevant literature under seven sections: clinical assessment methods and objective assessment methods for NCD patients. The second section provides a brief history of PD, a list of its symptoms, and information on associated NCDs. The third section addresses the existing clinical monitoring and assessment techniques and identifies their shortcomings. PD early diagnosis, treatment response, and PD rehabilitation phase, particularly automatic monitoring from data collected from insoles, are the three main areas based on application that are covered in the fourth section, which also presents and discusses the work that has been done into the use of wearable technology in PD motor symptoms assessment. The fifth section critically analyze the use of wearables for upper limb motor assessment in PwPD and NCDs. The last two sections illustrates the importance of wearables in other domains like COVID-19 detection and discuss the rise of Wearable Devices during COVID-19 Pandemic, use of sweat-glucose sensors for glucose level monitoring. Finally the last two section summarize the key challenges in wearable product development and future directs.

Chapter 3: Innovative medical wearable devices for neurocognitive disorders evaluation

This chapter explains how cutting-edge clinical technology can give neurologists trustworthy instruments for assessing motor deficits in NCD patients. Researchers have looked at the significance and potential of wearable systems, such as smart insoles and wrist wearable gadgets, as well as ML algorithms to create effective decision support systems for enhancing the evaluation of motor symptoms connected to PD.

Chapter 4: Machine Learning based methods for classifying medical data

This chapter focuses on the algorithms used to analyze the data that was collected for medical purposes. From medical images like X-rays to wearable inertial sensors that assess the motor performances of participants undertaking the motor assessment process. This chapter highlights the importance of ML and DL classification methods in various medical applications such as: for posture identification of Obstructive Sleep Apnea patients, association of smartwatches for prognosis of COVID-19, X-Ray classification of images for COVID-19 patients or influenza, finally the human action recognition by cascading pose features.

Chapter 5: Hybrid (ML based) techniques for Parkinson's Disease Severity Evaluation

This chapter offers a way to improve the categorization of tremor severity. The suggested method combines wearable devices, signal processing, and various resampling techniques, such as over-sampling, under-sampling, and a hybrid combination. Resampling techniques are integrated with well-known classifiers, such as XGboost, K-Nearest Neighbor (KNN) and Random Forest (RF). In first section of this chapter the experiment is conducted using the modified version of A-WEAR bracelet developed in Chapter 3 for classifying the severity of tremors and bradykinesia. In second section of this chapter we enhanced the overall performance of system by integrating ML with resampling methods. Through the use of sophisticated measures, the performance of the suggested technique is assessed, and the results are far better than those of past efforts.

Chapter 6: Comprehensive framework for Parkinson's Disease Severity Estimation using Deep Learning and Cloud Technology

In order to determine a suggested technique for gauging tremor severity, this chapter introduces a revolutionary above-average rule-based methodology. It also discusses the impact of patient-related medical effects on categorization performance during data collecting. The chapter discusses the estimation of several parameters from the spatiotemporal and frequency domains, which can undoubtedly enhance the neurologist's visual examination by revealing new data that is missed by the standard motor evaluation test. The suggested system consists of a wearable wrist-based device, a mobile app, a cloud platform, a classifier, hyper-parameters, and resampling approach. The suggested method is based on a number of advanced metrics dataset results that are given in Chapter 5. Additionally, this chapter uses the ServiceNow platform to look at how medication states affect the overall eHealth system's workflflow and classification of tremor severity.

Chapter 7: Conclusions and Future Works

The outline of the research results from thesis is presented in this chapter. The major findings of this thesis are explored in relation to the Chapter 1 research questions. The chapter also outlines potential research directions for using the findings from this thesis. Additionally, some future work on this thesis has already been done in several potential areas for improvement.

2 A Critical Analyze on the Design of Wearable Solutions for Patients with Parkinson's Disease and Neurocognitive Disorder

2.1 Introduction

The history of PD spans from 1817, a renown British pharmacist James Parkinson wrote an Essay on the Shaking Palsy, to modern times [10]. Paralysis agitans (shaking palsy) was the name for PD at the time. William Sanders first used the phrase "Parkinson's disease" in 1865, and French neurologist Jean-Martin Charcot popularized it later. Although PD currently has no known cure, there are several strategies to treat its symptoms. Additionally, the therapy may differ from person to person. However, a research finds the inaccuracy of diagnoses around 25% especially when ET, atypical Parkinsonian syndromes vascular Parkinsonism are apparent. For an optimal prognosis and therapy, the proper diagnosis of PD is therefore crucial [11]. Numerous uses for wearable technology have been identified in NCDs such as PD, Alzheimer's disease, and other mental illnesses. For this reason, a variety of wearables are employed, such as skin-based wearables like smart bracelets and insoles as well as textile- and biofluidic-based wearables. Recently, wearables have performed admirably in applications related to NCDs, such as early diagnosis, body motion analysis,tremor, motor fluctuations and long-term monitoring within home settings. Before these wearables are commercialized as a completely individualized healthcare system, there are several inherent problems with them that need to be resolved. This chapter also reviews the difficulties and restrictions these wearables face in the healthcare industry as well as potential future applications.

2.1.1 Other Types of Neurocognitive disorders (NCDs)

When talking about NCDs, some specific diseases are predominant, besides PD:

- Huntington Disease (HD)
- Alzheimer Disease
- Multiple system atrophy (MSA)
- Dementia accompained by Lewy bodies (DLB)
- Frontotemporal diseases (FTD)

All these NCDs mimic PD symptoms in terms of motor impairment such as patients experiencing tremors as PD patients or stride rate variability from normal walking, rigidity in limb movement, and so on. However, some NCDs exhibit cognitive symptoms before the onset of motor symptoms. But eventually, all these NCDs affect the physical ability of patients in terms of performing their routine tasks.

2.1.2 Symptoms of Parkinson's disease

The signs and symptoms of PD vary from individual to individual. Also, early symptoms could be insignificant and unnoticed. In general, the symptoms commonly initiate on one single side of the body and typically persist severe there, even when they begin to impact the limbs on both sides. The most dominant motor symptoms are FoG, tremors, bradykinesia and posture or balance impairment.

2.2 Clinical Diagnosis and Assessment Methods

There is certainly not particular test to analyze PD. PD is a "clinical" diagnosis and Figure 2.1 illustrates the whole procedure of PD assessment. Levodopa (L-dopa) is gold standard treatment

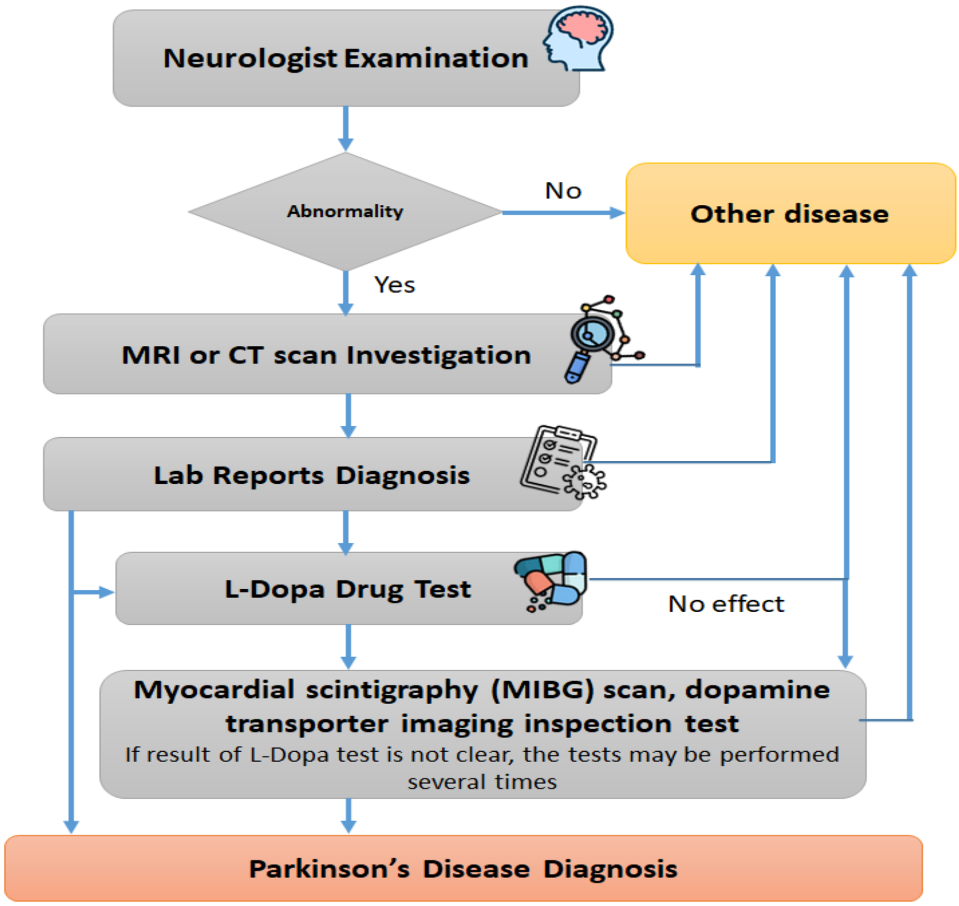


Figure 2.1: Clinical Diagnosis of PD

used to treat PD. Improvement in motor symptoms when L-dopa is given is regarded as a positive diagnosis of Parkinson's. All these tests can be performed several times to reach the conclusion that the patient is suffering from Parkinson's. Many times the doctor misdiagnoses PD and connects it with other diseases with similar symptoms. Diseases whose symptoms resemble with PD are:

1. Parkinson's misdiagnosis: Arthritis
2. Parkinson's misdiagnosis: General aging
3. Parkinson's misdiagnosis: Huntington's disease

4. Parkinson's misdiagnosis: Thyroid issues
5. Parkinson's misdiagnosis: Ankylosing spondylitis

Based on the above discussion, it is clear how PD can be severely misdiagnosed and be related to any other disease and how important is to have proper robust devices and methodologies to make the difference, avoiding misdiagnosing.

2.2.1 Parkinson's Disease Treatment

Despite knowing the fact, there is currently no cure for PD, certain symptoms may frequently be managed with medication, surgery, and other therapy.

- Drugs to treat Parkinson's disease
- Deep Brain Simulation (DBS)
- Other Therapies:Physical, occupational, and speech treatments may be used to treat tremors, stiffness, deterioration of mental abilities, and problems of the voice, gait, and speaking. Exercises that increase balance, flexibility, and coordination while also strengthening muscles.

2.2.2 Clinical Rating Scales for Neurocognitive disorder patients

- Cohen-Mansfield Agitation Inventory
- Instrumental Activities of Daily Living
- Barthel Index
- Activities of Daily Living Scale
- Functional Independence Measure (FIM)
- Activities of Daily Living (ADL) Profile
- Texas Functional Living Scale (TFLS)
- Unified Huntington's Disease Rating Scale
- Self-Assessment Parkinson's disease Disability Scale (SPDDS)
- Schwab and England Activities of Daily Living
- Hoeh & Yahr
- Unified Parkinson Disease Rating Scale

Drawback of Rating Scales

All of these rating measures are clinically based, which means the doctor provides numerical numbers based on qualitative observations of the patient in various positions, often illogical and subjective. As a consequence, the evaluation is based on the skills and expertise of the examiners, and it differs from one examiner to the next [12]. Evidence suggests that the MDS-UPDRS has significant inter- and intra-rater variability in evaluations made by nurses and neurologists [13]. As a result, a patient's tremor may be given an MDS-UPDRS score by one examiner and then examined by a second examiner and given a higher value at a subsequent consultation. It is challenging to determine whether the symptoms are becoming worse or are susceptible to subjectivity in this circumstance given the two distinct ratings Due to the lack of an objective evaluation of a patient's ability to move during a clinical examination. To provide neurologists with trustworthy wearable devices for objectively evaluating motor deficits in persons with PD and NCDs, several initiatives have been undertaken over the past 10 years to integrate emerging technology into clinical practice.. This literature apparently provides a clear picture of the work and systems proposed so far in this area.

2.3 Wearable Devices for Parkinson's and Neurocognitive Disorder Patients

Tthe purpose of this systematic review is to determine how sensor-based wearable devices can be used to diagnose and monitor PD patients, as well as to analyze how they can improve the QoL of PD patients.

2.3.1 Methodology

Elsevier, IEEE Xplorer, and PubMed/Medline databases were used to gather papers for this systematic assessment of the literature that covered the period from January 2009 to January 2020. The five steps of our search process for discovering pertinent papers is based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). In the initial step, we searched the three databases listed above using the terms "wearable sensors AND Parkinson disorder," "wearable sensors AND neurocognitive disorder," and "Parkinson patients AND rehabilitation exercises," and we found around 3158 articles. We added an additional 102 pertinent articles with these keywords that we discovered in other sources, for a total of 3260 articles.

In the second step, the first 271 duplicates are eliminated since many identical articles are discovered in many databases. We also eliminated articles based on a detailed review of their titles and abstracts. 740 records were acquired in this manner. In the third step, we eliminated the articles and only took into account those that were ISI-indexed. We obtained 639 articles using this criterion. In the fourth step, we created our own unique scoring system that was influenced by PEDro and categorized the most pertinent articles suitable for our systematic review. Five statistical indicators are predetermined in PEDro as responses to the following queries:

1. Does this paper support the use of wearable sensors to automatically measure recovery in a lab setting?
2. Were wearable sensors utilized in this piece to remotely monitor individuals at home?
3. How many participants in this study were patients or subjects?

4. Does this article contain exercise rehabilitation, which can speed up recovery and improve fitness in people with PD?

5. Is this a survey or review article?

The responses to the questions above were used to examine the articles, and we then chose the publications that scored at least four points (equivalent to "fair" or "excellent" quality), using the grading standards shown in Equations 2.1 and 2.2:

$$Qn^* = \sum_{r=1}^{n=5} Qr \tag{2.1}$$

$$Qn^* = \begin{cases} Qn^* & Qn^* < 4 \\ 4 & Qn^* \geq 4 \end{cases} \tag{2.2}$$

Q3 refers to the number of human participants who were used in the research for each publication. Review articles are an exception to this rule; for survey pieces, a separate viewpoint is determined using the same calculations. In this instance, the caliber of the references was taken into account. The maximum amount of points that could be earned for each condition was 1.

Further consideration has been given to striking a balance between recently released publications with fewer citations and older articles with more citations. A fresh, customized formula is created as a result. Its goal is to track the number of citations each work receives annually, starting with the year of publication. This is the time to highlight a few steps. Equation 2.3 provides the annual number of citations recorded for one candidate article in the first stage:

$$PYCi = \frac{TCi}{2020 - Yi} \tag{2.3}$$

PYC in the equation above stands for the number of citations per year, TC for the overall number of citations, and Y for the publication year of the article. The equation takes into consideration the fact that certain papers are published in various years, and that this element affects how many citations there are in an article. As a result, the newest items weigh more than the older ones. Equation 2.4 outlines the process for calculating the absolute value of quality Qi^* for an article from the perspective of citations in this situation:

$$Qi^* = \frac{5^* PYCi}{max_{j=1....n}(PYCj)} + \frac{6 - min(2020 - Yi, 6)}{2} \tag{2.4}$$

All of the absolute values must fall inside the range [0:5], as can be shown in Equation 2.5. Due to the fact that the overall score of each article is really the average of each statistical indicator multiplied by 2, the final number Qi has been set to range the maximum score up to 10:

$$Qi = \begin{cases} Qi^*, & Qi^* < 5 \\ 5, & Qi^* \geq 5 \end{cases} \tag{2.5}$$

According to the mentioned equations, all of these selection criteria were used, and the final number of articles that needed to be examined was 46. The examination of this smaller collection will receive more attention in the systematic review.

Approach to Analysis Selected Articles

The qualitative analysis of the remaining 46 articles comes after we compiled our selection of the most pertinent articles using quantitative analysis. We further researched them in light of the primary goal of this systematic review by addressing several recent scientific questions, such as:

1. Does a motor deficiency have an impact on the well-being of PD patients in any way?
2. Do wearable insoles aid in PD patients' diagnosis, monitoring, and rehabilitation?
3. Which workout routines or gaits affect life quality?
4. Which fitness assessments help PD patients get a thorough examination of their balance, walking, and aerobic fitness?

2.3.2 Findings of Systematic Review

Researchers have placed considerable effort into identifying the most significant gait activity parameters, such as heel off, step length, stride length, stride duration, and plantar pressure, and have offered a wide range of wearable methods for monitoring and diagnosing PD. Wearable insoles, -based monitoring systems connected at lower limbs, smart bands, -based devices, Actigraphs, GAITrite, ActivPals, and gait monitoring systems employing a smartphone equipped with inertial sensors are the most effective wearable sensor devices for identifying these qualities. The insoles stood out as the most effective and dominating among all of them, indicating that more people need to experience these wearable solutions for them to be effective. The , 6MWKT, and 10MWKT tests are the classic gold standard assessment tests for monitoring gait deflation and giving treatment analyses, including physical therapy and other activities. These tests take time and require task execution, and the results can vary depending on a number of factors, including the patient's task difficulty, the walking area, the participant's physical exertion, and their capacity to complete the task due to weariness. The TUG test is one of these, but more recent techniques are being added, and the automatic assessment system uses them to provide impressive results. These wearable technologies aid in tracking the development or involution of this condition as well as rehabilitative activities and motor skill improvement. However, there is still a lot of research and development to be done in the healthcare industry, particularly on the objectivity, accuracy, and dependability of patient and healthcare system feedback for the validation and acceptance of these wearable solutions.

2.4 Wearables for Upper Limb Motor Assessment in PD and NCD patients

NCDs and Parkinson's patients frequently have upper limb motor deficits, such as sluggish movement and trouble performing consecutive activities. PD is characterized by bradykinesia and hypokinesia, which primarily affect the dexterity and ability of Upper extremity (UE) movements.

Although most works focused on lower limbs [14], the interest in upper limb motion is growing as illustrated in Table 2.1.

However, these studies also did not take into account tremor severity distribution. Apart from this aspect, these proposed works only used a few classes or combined two different scores as one that does not represent PD progress precisely.

There is a need for an efficient solution in the form of an eHealth platform, for the assessment and monitoring of PwPD, built around a smart bracelet continuously connected to the Cloud. The bracelet would collect the motion data from the wrist or feet of the most affected

Table 2.1: Wearable technology for Upper Limb Motor Assessment

Ref	Wearable device	Experimental Protocol	Subject	Performance
[15]	GYR on the index finger's tip	FT (15s)	10 PD, 10 HC	94.4% accuracy for quadratic classifier for PD/HC classification
[16]	ACC, wrist-watches on wrists with fs=20 Hz	FT, hands opening/closing, prono-supination	12 PD, 12 HC	83.3% sensitivity, 75% specificity for SD for PD/HC classification
[17]	ACC, two touch sensors on the thumb and index finger (fs = 1/0.1 ms)	FT (60s)	16 PD, 32 HC	As the UPDRS FT score declined, the mean opening velocity and FT total distance both reduced, but the SD of FT interval rose. Results are only shown in box plots.
[18]	Mobile device in a specially constructed glove cover (fs = 20 Hz)	Resting task; Postural task (each 30 s)	23 PD, 2 De-Novo PD, 20 HC	82% sensitivity, 90% specificity, 0.94 AUC for PD/HC classification

upper/lower limb. Using Wi-Fi or , it offloads the data to the cloud-based platform where these data are automatically processed and analyzed to find the severity of motor symptoms in an ON/OFF state.

2.5 Importance of Wearables in other Healthcare Domains

2.5.1 Sweat-Glucose Sensors for Continuous Glucose Monitoring: Wearable Devices

Regular glucose monitoring is essential for managing diabetes since the prevalence of the disease is rising at an alarming rate. Currently, invasive blood sugar testing is used to determine the body's glucose levels. The blood glucose (BG) monitoring devices calculate how much sugar is present in a tiny amount of blood that is typically taken by pricking the fingertip and placed on a temporary test strip. As a result, the need for non-invasive continuous glucose monitoring makes this strategy feasible thanks to a sweat sensor-based method. Because sweat sensors have lately gained a lot of interest, there have been significant improvements in non-invasive continuous glucose monitoring utilizing sweat sensors based on a variety of approaches with a focus on the devices that may eventually be incorporated. Some wearable platforms for sweat glucose monitoring use patches.

Despite the fact that these studies produced encouraging sweat-glucose (SG) sensing accuracy results, there are still a few challenges to be solved, including real-time signal correction, long-term stability for continuous monitoring, reproducibility between sensors and different patients, and customized wireless electronics. Body fluids such as perspiration, saliva, and tears are among the potential solutions for direct glucose monitoring. In these fluids, the glucose density ranges from 1 to 10% of the blood density. The long-term goal is to create sensors that can continually sample a variety of bodily markers and be integrated into wearables like clothes, bracelets, patches, and tattoos.

2.5.2 High-Tech Consumer Wearables for COVID-19 Global Pandemic Management

On January 30, 2020, the World Health Organization (WHO) declared the epidemic a public health emergency of global concern. On March 11, 2020, the WHO labeled the outbreak a pandemic, calling for comprehensive multisectoral actions to stop further spread. A pandemic is an outbreak that affects everyone on the earth and spreads on a scale that transcends national boundaries. Wearables can serve as an important early-warning tool for the possibility of COVID-19 infection, but their application in infection surveillance has the potential to go further.

We conducted a systematic review of rising of wearable devices during COVID-19 pandemic. The most typical COVID-19 symptoms are a dry cough, fever, muscular aches, exhaustion, and shortness of breath. Along with this, less noticeable symptoms include hemoptysis, diarrhea, and headache. Wearable like smartwatch, H-watch, oura ring, wearable mask can play vital role in COVID-19 prevention, detection and tracking.

2.6 Key Challenges of Wearable Product Development

E-health wearables such as insoles, smart shoes, wristbands, rings, and so on are changing how consumers communicate, monitor, and share information and experiences. The devices are becoming smart, portable, and lightweight. In order to make their products more relevant, brands are now concentrating on fewer niches and features i.e., ergonomics, battery life, differentiating and providing value, miniaturization and integration, scaling etc.

2.7 Discussion and Future Research Possibility

Researchers have recently attempted to create methods that mirror clinical grading scales and PD tremor ratings. Several objective methods have been proposed for measuring and quantifying PD tremors from data collected during performing scripted and unscripted tasks using ML algorithms combined with signal processing techniques. Furthermore, many Internet of Things (IoT) based wearable devices for PD detection, diagnosis, and quantification are available these days, which leverage inertial sensors and computational algorithms only. Their availability has brought new challenges in terms of security, privacy, connectivity, and power efficiency. From a therapeutic point of view, it is necessary for clinicians to continuously monitor patients' motor function. Alterations in motor functions between different visits are difficult to follow and clinicians risk to take incorrect decisions. Hence there is a need to provide the medical staff with an ecosystem for a better evaluation of the Parkinson's stages and the progress of this disease in terms of tremors and bradykinesia or FOG.

In this thesis, we sought to develop a complete ecosystem in form of energy efficient wearable device, which collects PD-related motion data and sends them to the cloud in a highly secure way for storage, data processing, and severity estimation supported by ad-hoc developed learning algorithms.

3 Innovative Medical Wearable Devices for Neurological Disorders Evaluation

Considering the lack of objective assessment for NCD patients' motion capabilities while evaluating during clinical examinations, there is a dire need for an effective and innovative medical wearable system that can definitely enhance existing clinical procedures for the benefit of patients and healthcare organizations. This chapter's goal is to recommend a wearable device that combines inertial sensors for upper and lower limb motor analysis with specifically designed algorithms that can extract a wide range of metrics to objectively measure the motor performance of under investigated individuals. These wearable devices help in the early diagnosis of disease, the decision-making process for doctors in treating patients, and monitoring their performance and disease severity after rehabilitation exercises or medical doses.

3.1 Stride Rate Variability and Modified Fractal Dynamics in Relation to Age and Neurological Function

Since neurocognitive problems among the elderly are increasing. Gait cycle variability detrimentally affects QoL. The presence of stride interval variability falls in elderly people are frequent, which is considered the fifth leading cause of demise. Similarly, frequent gait alteration in form of stride interval (i.e., between successive heel strikes) causes falls in PD patients and an increased risk for injuries. According to [19], the gait variability in healthy adults is quite small, 2% around the mean, but it is drastically increased in patients with Parkinson's and HD. Over time, HD prevents certain brain regions from functioning correctly. It causes minor involuntary movements, subtle loss of coordination, and perhaps some disinhibition. It frequently becomes deadly after up to 20 years of progressively worsening symptoms. Significant research has been done in this field over the past ten years, and many authors have proposed several solutions, including wearable technology and AI algorithms for fall detection, fall risk assessment, and post-fall emergency alerts by using temporal-spatial characteristics, and concentrated on the use of linear and non-linear functions to classify PD gait patterns statistically or to extract intrinsic characteristics as the number of temporal and spatial domains.

3.1.1 Methods

The data for the walking stride interval in this study is based on time series from 15 individuals and is accessible in [20]. Of 15 subjects, 5 subjects have PD with mean and standard deviation (SD) age 70.4 ± 6.406, 5 healthy old adults with mean and SD age 74.6 ± 2.05, and 5 disease-free young participants with mean and SD age 24.4 ± 2.8. For each subject, the recordings are based on two columns. Ultra-thin force-sensitive resistors are used to capture data and are put within the participants' shoes.

Assessment of gait cycle duration using Detrended Fluctuation Analysis

Gait abnormality is observed in PD patients and older adults. According to [19], fluctuations in the stride interval show fractal dynamics and long-range correlations in disease-free young individuals. In this study, we investigated the changes in the gait cycle by changes in the neurological function of adults and aging factors using Detrended Fluctuation Analysis (DFA). It detects long-range correlation and scaling components of non-stationary signals. DFA is composed of two parts as illustrated in [21]

1. The data series B(k) is shifted by the mean and integrated (cumulatively summed),

$$x(k) = \sum_{i=1}^{k}[B(i) - \langle B \rangle] \tag{3.1}$$

   then it is segmented into a window of $\triangle n$ various sizes. In this way we have illustrated our data profile i.e. x(k). (y) is the mean of the time series. The global trend of the signal is eliminated using the subtraction of the mean. The advantage of applying scaling analysis to the signal profile instead of the signal is that it makes no prior assumptions about the stationarity of the signal. When computing the scaling of the signal profile, the resulting scaling exponent, α, is an estimation of H.

2. The integrated data is locally fitted to a polynomial in each division $xn(k)$ and the mean-squared residual F(Δn) ("fluctuations") is found:

$$F(\triangle n) = \sqrt{1/N\sum_{k-1}^{N}[x(k) - x_{\triangle n}(k)]^2} \tag{3.2}$$

In Equation 2, N represents the overall quantity of data points and $F^2(\triangle n)$ is counted as the squared sum of the residual raised in the windows, on average. Typically abbreviated as DFAn, the n-th order polynomial regressor belongs to the DFA family. This process checks for self-similarity i.e. fractal dynamics as it operates estimating (the dispersion of the residual of integrated fluctuations about a regressor) at different resolutions (window sizes). If power law scaling is present then a double logarithmic ("log-log") plot of F(Δn) versus Δn, often termed the fluctuation plot, is conventional to be linear.

$$F(\triangle n) = M(\triangle n)^{\alpha} \Rightarrow ln(F(\triangle n)) = \alpha ln(\triangle n) + ln(M) \tag{3.3}$$

In relation to 3.3, M is a constant, and a least-squares fit can be used to determine a scaling exponent α. This scaling exponent α, which is merely an approximation of the Hurst exponent H, and is a metric for signal correlation. So here we used the DFA method over the stride intervals of the young healthy adults, old healthy adults, and PD patients to find their correlation in the gait cycle and process it. Data are not correlated if $\alpha = 0.5$; they are anticorrelated if $\alpha < 0.5$; and they are long-range correlated if $\alpha > 0.5$.

3.1.2 Results and Discussion

Then the data is detrended, the scaling component is calculated and the correlations are demonstrated using the DFA approach. After calculating the α for each group, the mean absolute difference is calculated as illustrated in Table 3.1. The fluctuation component α for healthy old adults is 0.78, for PD subjects is 0.44 and for healthy young adults is 0.68. According to [22], α of PD patients is smaller than 0.5 so there is no correlation; however, α of healthy subjects

Table 3.1: Correlation difference in gait cycle of different cohorts

Subjects Group	**coefficient** α	**Fluctuations corresponding to window**	**mean absolute error**
Old	0.7821	-6.4026	Mean absolute difference between old and PD subjects = 44%
Parkinson	0.4374	-3.5858	Mean absolute difference between PD subjects and young controls =47%
Young	0.8345	-5.9349	Mean absolute difference between young and old subjects = 6.2%

is higher than 0.5 which is interpreted as a long-range correlation as illustrated Table 3.1. Automatic classification is performed on the data collected from all three groups of subjects to distinguish them into three classes. An Optimize Support Vector Machine (OSVM) classification is performed. In this study, the OSVM classifier gives an accuracy of 80%. The PD class has maximum sensitivity and specificity with 1 in contrast with the healthy cohort of young and old participants. The cohort of young subjects has 0.6 sensitivity and 0.9 specificity; in the case of old group subjects, the sensitivity and specificity both lie at 0.8. It has been determined through analysis utilizing DFA that there is no resemblance between the PD individuals and the older participants, since the value of *alpha* is larger than 0.5, despite the fact that there is a long-range connection between the two groups.

3.2 Parkinson's Disease Gait Monitoring using Wearable Insoles and Deep learning Approach

The majority of the gait analysis is done via temporal and spectral feature extraction, which has a high rate of missing crucial data. In addition, monitoring and quantifying individuals with PD provide several treatment obstacles in terms of the analysis of the severity of the motor symptoms, such as FOG, bradykinesia, and ongoing remote patient monitoring. The purpose of the present study is twofold: 1) to decide if there is any huge connection between the three groups; 2) to evaluate the severity of the disease symptoms in PD patients. In this study the dataset from smart insoles to evaluate computational methods for analyzing gait. Instead of utilizing more conventional methods for handling time series, including recurrent architectures, the goal of this research project is to apply continuous wavelet transform to convert time series signals into pictures. The results demonstrate the effectiveness of the proposed method with a 96.5% accuracy in gait variability analysis across three cohorts, including healthy adults, the elderly, and patients with PwPD, and a 91% accuracy in gait symptom analysis across different stages of PD severity.

3.2.1 Materials and Methods

The pressure sensors are used for generating the data from wearable sensors in time series form. Initially, these raw signals are pre-processed and in the next step, they are filtered. Subsequently, scalograms are created using the 3s sliding window by utilizing continuous wavelet transform which transforms time series data into a useful image. Later on, the gait abnormality is analyzed, and also the severity estimation of symptoms of PD below stratification by means of DL model CNN.

Continuous Wavelet Transform

Continuous Wavelet Transform (CWT) technique defines frequency and time domain components which have been an effective method proven multiple times. The continuous wavelet transform of a signal is expressed in Equation3.4.

$$CWT(u,v) = \langle f, \Psi_{u,v} \rangle = 1/\sqrt{u} \int_{-\infty}^{\infty} f(t).\Psi * (t - v/u)dt \tag{3.4}$$

Here wavelet mother function is denoted by ψ, it is a template basis function of variable recurrence content, zero mean, and limited length, while u and v express the dilatation and shifting moving factors (which decide how much the mother wavelet is scaled and translated), CWT (u,v) represents the coefficient of wavelet and the complex conjugate operator is $*$. 'Haar' wavelet is utilized in our research. As our dataset is labeled and already filtered out, the type of haar wavelet completely suits our requirement. Here addresses the wavelet mother function, which is a template basis function of limited length, zero mean and variable recurrence content, an and b signify the dilatation (or scale) and moving (or shifting) factors (which decide how much the mother wavelet is scaled and translated), CWT (a,b) addresses the wavelet coefficients and $*$ is the complex conjugate operator. In our case, the 'Haar' wavelet has been used.

ConvNet Deep Learning model

The purpose of this research study is to realize scalograms classification which is built using Continuous wavelet transform with huge success into different stages of PD patients and also in the gait features diagnosis in all the cohorts distinctly. In this study, the ConvNet architecture was implemented for experiments to variate in various weights and to obtain the best results. Initially, the very first step is to resize the input scalograms to $227 \times 227 \times 3$ contrasting to the breadth, height, and different three channels displaying the input image profundity. Furthermore, it is sent to the convolution layer as an input image of convolutional filters in series, each of the layers activates distinctive features from various images. With continuity, the max pooling layer and ReLu is implemented, and with repetition, convolution proceeding the max pooling layer, again with three convolution layers and proceeding with the max pooling layer, and at last fully connected layers are implemented. The training and testing of the model are carried out 70/30 respectively. The proposed research solution is mainly dedicated to gait variability in individuals for clinical assessment. The medical practitioners take aid from the proposed system when assessing NCD patients, elderly or children having motor coordination issues.

3.3 Wrist Movement Variability Assessment using A-WEAR Bracelet in Individuals with Neurocognitive Disorders

PD patients experience a number of motor symptoms that gradually impair their quality of life from that of healthy, normal individuals. Tremor and bradykinesia are the two motor symptoms that are most common across all phases of this illness. Traditional methods are typically used to examine these symptoms, however, it is still unclear how accurate the results will be. This study suggests a method for assessing tremor and bradykinesia objectively in participants with PD (ten older people over 60 with tremor and ten older adults over 60 with bradykinesia) and 20 healthy older adults of PD patients aged-match. An A-WEAR bracelet that has been created utilizing inertial sensors, or a 3D accelerometer and gyroscope, was employed to capture physical motions. During the clinical assessment based on the UPDRS, which was employed by neurologists, participants engaged in upper extremity motor tasks. Temporal and spectral data is extracted in order to distinguish the patients from the healthy controls, and non-linear temporal and spectral features exhibit the greatest difference. ML classifiers, both supervised and unsupervised, provide accurate results. 34 of the 40 people were correctly classified by neural net clustering, whereas 91.7% of the people were correctly classified by KNN. In a medical setting, the device allows the physician to more accurately and rapidly understand the tremor and bradykinesia of patients.

3.3.1 Experimental Set-Up

Development of Wearable device

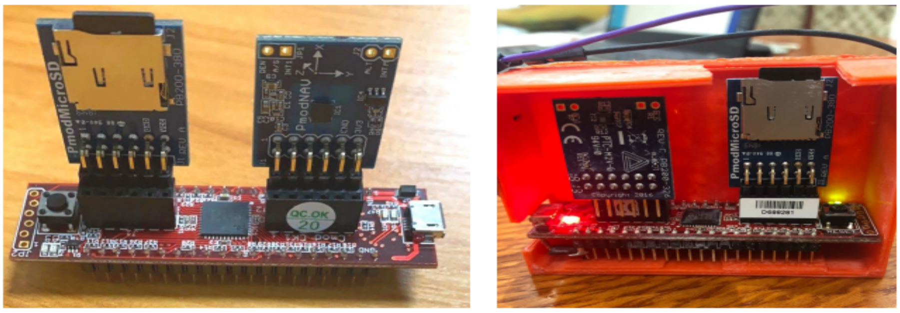
In this work, the hand bracelet is used as a measuring tool. The device gathers information about the participants' hands' motions. A specific sensor module with an accelerometer and a gyroscope is used to create the bracelet, and a small form-factor microcontroller receives real-time data from the module and transfers its output values to a micro SD card. The components used for this bracelet are:

1. The Cmod MX1 microcontroller containing a microchip PIC32MX150F128D microprocessor.

2. Pmod NAV module: 3-axis accelerometer and 3-axis gyroscope sensor.

3. Pmod micro SD module, which is used for storing data on the micro SD card.

The bracelet is made to be simple for patients to put on their wrists. Two 3 V batteries, often used in digital watches and lasting three hours, were utilized. The only purpose of this bracelet is data collection. Figure 3.1(a) depicts the bracelet's early stages of conception, and Figure 3.1(b) the bracelet's finalised prototype.



(a) Preliminary stage **(b)** Final prototype

Figure 3.1: (a) Preliminary stage design of bracelet; (b) shows final prototype of A-WEAR bracelet

Participants and Data Acquisition Procedure

The proposed system is tested on a total of 40 subjects, from which 20 subjects have PD with varying degrees of tremor and bradykinesia severity, and the rest involved age-matched healthy controls. Regarding the PD patients, 5 men and 15 women have been asked to participate in this study. Other details of them are: $meanage \pm standarddeviation$ (SD):71.65 ± 6.872 years old; average MDS/UPDRS scores $\pm SD$: 18.91 ± 7.831; average Hoehn and Yahr (H & Y) stage $\pm SD : 1.65 \pm 0.526$ with disease duration in years $\pm SD : 7.7 \pm 4.495$. The set of healthy participants consists of 16 men and 4 women, having the mean $\pm SD : 70.25 \pm 6.307$ years old. Among 20 patients, 10 patients just have tremor symptoms with no bradykinesia sign and 10

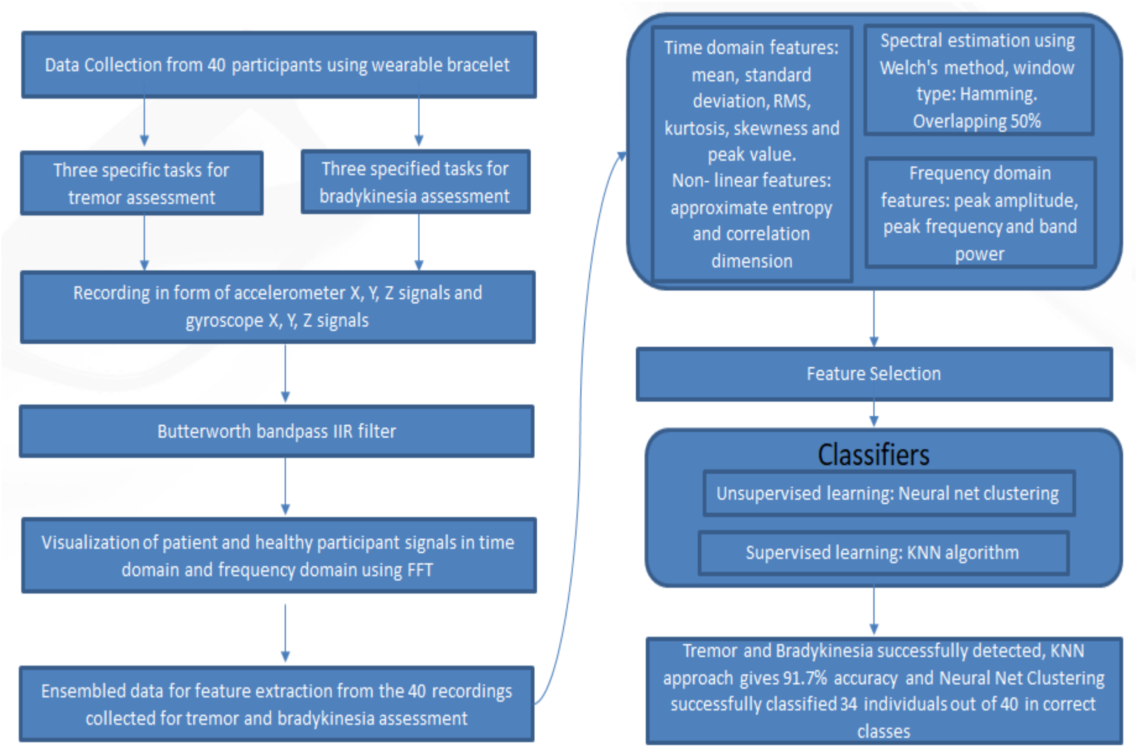


Figure 3.2: Figure illustration of the pipeline for detection of tremor and bradykinesia

patients have bradykinesia symptoms with no sign of tremor while performing the activities as in [23]. There are two sessions in the acquisition process. Only tremor detection-related tasks were carried out in the first session, while bradykinesia detection activities were carried out in the second one.

3.3.2 Methodology

Based on the analysis of prior studies describing the band in which the tremor frequency occurs, the data acquired are first processed through a filtering method to remove drift, outliers, and undesired frequency. The data is then shown to highlight the difference between individuals who are healthy and subjects who regularly suffer tremors and bradykinesia. Following feature extraction, and ML classifiers, the data is classified in order to identify tremor and bradykinesia. Figure 3.2 shows a general flow schematic of the entire operation.

Classification and Performance

An automatic classification for the detection of tremor and bradykinesia with respect to same-age elderly healthy adults based on the kinematic features as explained earlier is developed using unsupervised and supervised ML algorithms. All offline analyses were carried out using MATLAB R2016b (MATLAB, Mathworks, Natick, MA, USA). The results of this research study prove that the AWEAR bracelet can be used for acquiring the right data that can determine a robust tremor and bradykinesia diagnosis. The bracelet does not weigh much and is comfortable to wear for participants. Since this bracelet helps in PD identification, another goal is to refine the classes and use it for identifying different tremor types, tremor severity levels, and bradykinesia.

4 Machine Learning based Methods for Classifying Medical Data

In the healthcare sector, there is an unprecedented quantity of data streaming that is unlabeled, and inconsistent, and that may be evaluated using AI to derive important insights. Additionally, the technology is employed in various procedures as well as for virtual treatment. This chapter aims to provide an overview of a number of pertinent ML techniques and the range of potential applications in the field of healthcare.

4.1 Machine Learning Algorithms for Posture Identification of Obstructive Sleep Apnea Patients using an IoT Solution

Sleep apnea causes people to continuously stop and start breathing. Even after sleeping for 6 to 8 hours straight, one still feels worn out and exhausted. If the person has a history of heart problems, this disease gets significantly worse. Snoring, weariness and sleepiness are signs of sleep apnea, which has three primary types: OSA, central sleep apnea, and complicated sleep apnea. OSA is the most prevalent of them and is treatable with the right sleeping position. A shift in in-bed position has been shown to be crucial for OSA, according to research. In this study, we used data from two separate experiments from thirteen healthy subjects in different sleeping postures using two commercially available IoT-based pressure mats. We used supervised learning techniques based on ML for posture identification on this data. This monitoring system may assist in detecting each person's specific sleeping pattern and alerting caregivers and sleep apnea sufferers of improper postures in a timely way.

4.1.1 Data Setup

Data Collection Details

The data used for sleep posture monitoring is available on the Physionet website [24]. Physionet is famous for a larger collection of biomedical signals from patients and healthy subjects. As far as our research, PmatData is the first publicly available dataset of pressure sensor data which includes various sleeping postures. The data was collected under IRB approval at the University of Texas at Dallas [25] from thirteen participants in different postures. Informed consent was signed by all individuals before data collection and all agreed on the anonymous publication of their data for future research.

Materials and Experiments

With hundreds of force and pressure sensors, pressure mattresses and bedsheets come in a wide variety. Vista Medical FSA SoftFlex 2048 and Vista Medical BodiTrak BT3510, which are Force Sensitive Application (FSA) pressure mapping mattresses, were adopted to obtain the data for our study. Using Vista Medical FSA SoftFlex 2048, data from 13 people are gathered during trial 1. The mattress measures $32'' \times 64''$ and has sensors spaced one inch apart. The data is gathered at a 1 Hz sampling rate. Data is gathered in experiment II utilizing the Vista Medical BodiTrak BT3510. $27'' \times 64''$ is the size of the pressure mat that is being utilized. The data was gathered at a 1 Hz sampling rate.

4.1.2 Methodology

In this study, we focused on in-bed posture detection for sleep apnea patients using pressure sensor data signals. The block diagram of the overall methodology implemented in this research study. Initially, the data collected from pressure mats are pre-processed and the filtration is performed to only keep the data that is relevant for analysis and remove unnecessary data such as the zero-values. Later the correlation is performed between the sensors data to see the relationship between the samples that are collected. After this, we labeled the data in form of classes and performed classification using ML algorithms. The final detection and monitoring results can be directly exported to provide an alert.

Experiment I

In experiment I, the pressure mat is designed of total 2048 sensor points with a scan rate of 3072 sensors/second. These sensors are equally distributed across $32'' \times 64''$ mat with each sensor being almost 1 inch apart. The sampling frequency is 1.7 Hz and count the pressure between 0 to 100 mmHg as in [26]. In experiment I, five standard postures are collected for all 13 individuals as shown in Figure 4.1. In [27] study the most common postures in 1000 participants were recognized according to their results the right and left fetus sleeping positions are most common at around 41%. The other side lying posture or yearner position i.e. with straight legs on the left or right side account for 28% and finally the supine posture is about 8%. Therefore we labeled the collected data into five standard and common postures. First, we

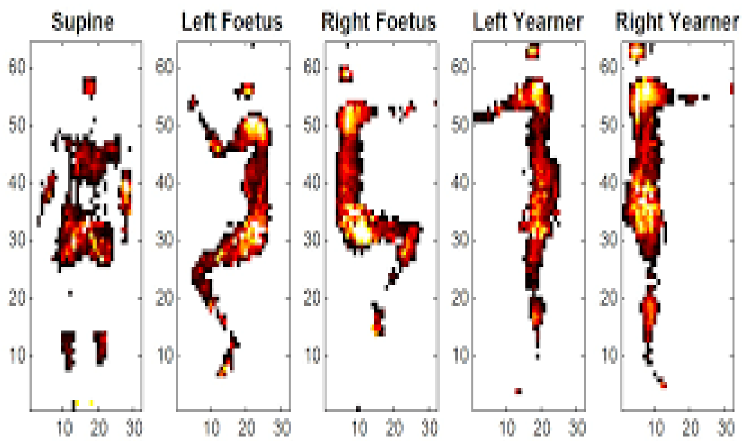


Figure 4.1: Standard postures

prepared the dataset for the first experiment by creating a separate file for each posture of the 13 participants, merging them into a single file, and then performing additional posture detection and classification. The classification learner program of the MATLAB [28] language is used to categorize the standard posture from the labeled data. For detection, we employed a variety of ML methods, and the majority of them worked quite well. With an accuracy of 98.7%, the linear classifier and weighted KNN produced good results. In the second part of the experiment I, we detected the postures of each single participant and the classifier showed promising result. This proves that we can also identify each type of posture of an individual.

Experiment II

Eight people have taken part in the second experiment. This time, the data from air mattresses were used to count various postures with varying roll angles in order to compare classification models and determine whether or not the kind of mattress affects detection accuracy.From our experiments we found the accuracy has reduced, making it impossible for an air mattress to identify postures accurately. Using the fine KNN method, the maximum accuracy was 71.1%. Based on the classifiers, we were able to distinguish between IoT-based pressure sensor mattresses and discovered that utilizing air mattresses to track sleeping positions would not yield positive results.

4.2 Robust Technique to Detect COVID-19 using Chest X-ray Images

A recently identified coronavirus is the cause of COVID-19, also known as Coronavirus disease. The patient's indications and symptoms, place of residence, past travels, and close contact with someone who has COVID-19 are now used in coronavirus identification. A healthcare professional collects a nasal sample from a COVID-19 patient in order to test them for the disease. After that, the material is examined in a lab setting. When someone coughs, saliva (also known as sputum) is released for testing. When testing resources or reagents are limited, the virus is being tracked and its severity is being assessed, and a healthcare professional comes into touch with COVID-19 positive individuals, the diagnosis becomes even more crucial. DL-based streaming diagnosis based on retroactive analysis of laboratory data in the form of chest X-rays is required in this COVID-19 scenario. In this study, a method to identify COVID-19 using DL to assemble chest X-ray (CXR) images is suggested. The trial has shown encouraging findings, with a COVID-19 diagnostic accuracy of 91.67% and a survival ratio accuracy of 100%.

4.2.1 Data Collection

The data used in this study is compiled using two publicly available datasets. The first dataset we used was provided in [29]. In this database, there are a total of 320 chest X-ray images out of which 259 images are of MERS, SARS, and ARDS (pneumonia cases). These images are collected and extracted from different websites and online publications. The rest of the 3347 images we used are from [30] for better DL classifier training and performance. Hence total of 3606 images are used in this study. 80% of the images are used for training and 20% of images are used for testing the system. 3347 out of 3606 images are related to other diseases i.e MERS / SARS / ARDS / SARS-Cov-2 / without chest disease. The remaining 259 are of COVID positive patients.

4.2.2 Methodology

The goal of this study is based on four main objectives related to the answers to the following questions:

1. Is the patient infected with COVID-19 or not?
2. Is the patient infected with COVID-19 going to survive or not?
3. According to data what is the most common age ratio of COVID-19-positive patients?

4. According to data what is the ratio of males and females infected with COVID-19?

The main methodology of this study is depicted in Figure 4.2. According to this, we first collected the images of CXR and arranged the data for the detection of COVID-19 and others. In the initial stages, we converted all the images into grayscale and afterward arranged them into two classes i.e. COVID-19 and other diseases (i.e. SARS, MERS, and ARDS). If COVID-19 is detected then it is further classified to find the survival rate of patients. For this, we used DL convolution neural network (CNN) with seven layers.

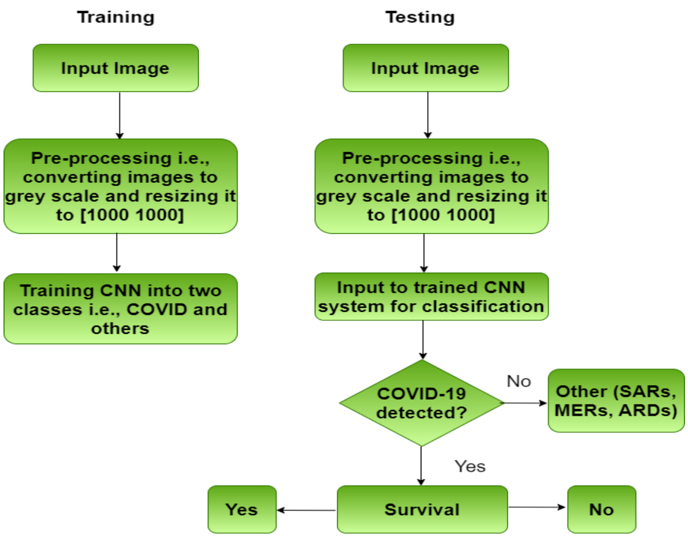


Figure 4.2: Flow chart of the system

4.2.3 Results and Discussion

The results of image processing and feature analyzing COVID-19 comes with 91.67% accuracy. Afterward, we further classified the data to find the survival ratio for which we again trained the CNN for feature extraction. The accuracy of this classifier is 100%..

4.3 Cascading Pose Features With CNN-LSTM for Multiview Human Action Recognition

Human activity recognition (HAR), utilizing computer vision, has gained significant attention from researchers all around the world in recent years because of its accurate and desired outcomes. Human-Computer Interaction (HCI), intelligent video surveillance, ambient assisted living, movement disorder patient monitoring, human-robot interaction, entertainment, and content-based video search are just a few of the numerous applications for which HAR is a useful tool. Therefore, the goal of this research is to create an effective multi-view interaction level action detection system based on DL architecture that is more accurate while utilizing less computing. Using the OpenPose method, the suggested system extracts 2D skeleton data from the dataset. The 2D skeleton characteristics are afterward directly fed to the action recognition CNN-Long Short-Term Memory (CNN-LSTM) architecture. Only the extracted features are passed to the CNN-LSTM architecture in order to decrease complexity, which eliminates the necessity for feature extraction. The results show that the suggested strategy has potential when compared to other methods already in use.

4.3.1 Methodology

The suggested technique begins with reading frames, followed by the extraction of skeleton characteristics, preprocessing, and training of the CNN-LSTM network. The proposed solution begins by reading each frame of the input video and then uses OpenPose to [31] realtime to extract skeletal characteristics. Only X, and Y coordinates are used in the proposed method, as opposed to the 25 joints' locations being supplied by OpenPose in both X, and Y coordinates and a confidence map. Finally, the CNN-LSTM method is used for classification by feeding the X, and Y coordinates of the retrieved skeletal features. The CNN-LSTM architecture, is created in a way that allows it to operate directly on skeleton features rather than producing heatmaps from skeleton features for DL architecture training.

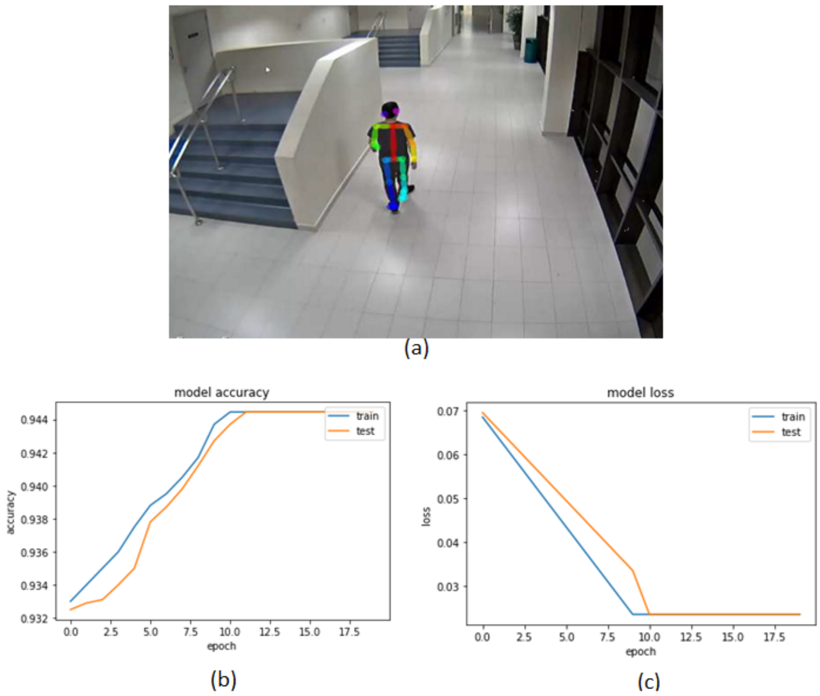


Figure 4.3: Fig (a) shows Skeleton detection from 2D image, Fig (b) explains accuracy of the proposed model during training and testing, Fig (c) illustrates the loss of the proposed model during training and testing

4.3.2 Result and Discussion

This section describes the results achieved by the proposed system. Skeleton detection from 2D image is shown in Figure 4.3. Figure 4.3 shows the training and validation accuracy of the proposed system. Training accuracy started from 93.3% on the first epoch whereas the validation accuracy started from 93.2%. As the model training process continues, after 10 epochs training and validation accuracy becomes the same around 94.4%. The model was trained on 20 number of epochs, but after 10 epochs of training and validation, accuracy was constant. Figure 4.3 shows the loss during training and validation, as the number of epochs increases model loss was decreasing, and after 10 epochs model loss becomes constant at around 0.025.

The effort of the earlier works shows that the current study in HAR has been focused on tackling complex challenges. In this research, we suggested a strategy that uses the OpenPose technology to extract the 2D skeleton data from the 2D RGB data and classifies the given action using a proposed CNN-LSTM model that is based on DL. As a result, by lowering the feature dimension, our suggested strategy greatly lowers computing complexity. The results of this comparison between the suggested method and the cutting-edge techniques support the potential of our strategy. The proposed approach can be used in different applications such as ambient assisted living, and patients with NCD i.e., PD to monitor their DLAs or predict the falls in the elderly.

One of the most efficient approaches to prevent the illness from spreading is to identify COVID-19 positive patients as early as possible. Repetitive antigen testing or reverse transcription polymerase chain reaction (RT-PCR) screening procedures are often utilized. This study suggests a strategy for analyzing biomarkers with artificial intelligence and wearable devices to identify disease non-invasively. This study reused a dataset with COVID-19, influenza, and healthy control data that is made accessible to the public. For the experiment, a total of 27 COVID-19 positive and 27 healthy controls were preselected. Several feature extraction techniques are then used on the data. In this study, several ML techniques were tested, including XGBoost, k-NN, support vector machines, logistic regression, decision trees, and random forests. The performance of these techniques is statistically assessed using a variety of metrics, including accuracy, sensitivity, and specificity. Utilizing the k-NN algorithm, the suggested experiment achieved 78% accuracy, which is much greater than that reported for state-of-the-art techniques. The accuracy for the cohort that contained influenza was 73%. The most important characteristics that might distinguish between the healthy and diseased states is also uncovered. The suggested approach can serve as a supplement to the current RT-PCR or antigen screening assays and can assist in non-invasively controlling the spread of viral infections, not just COVID-19.

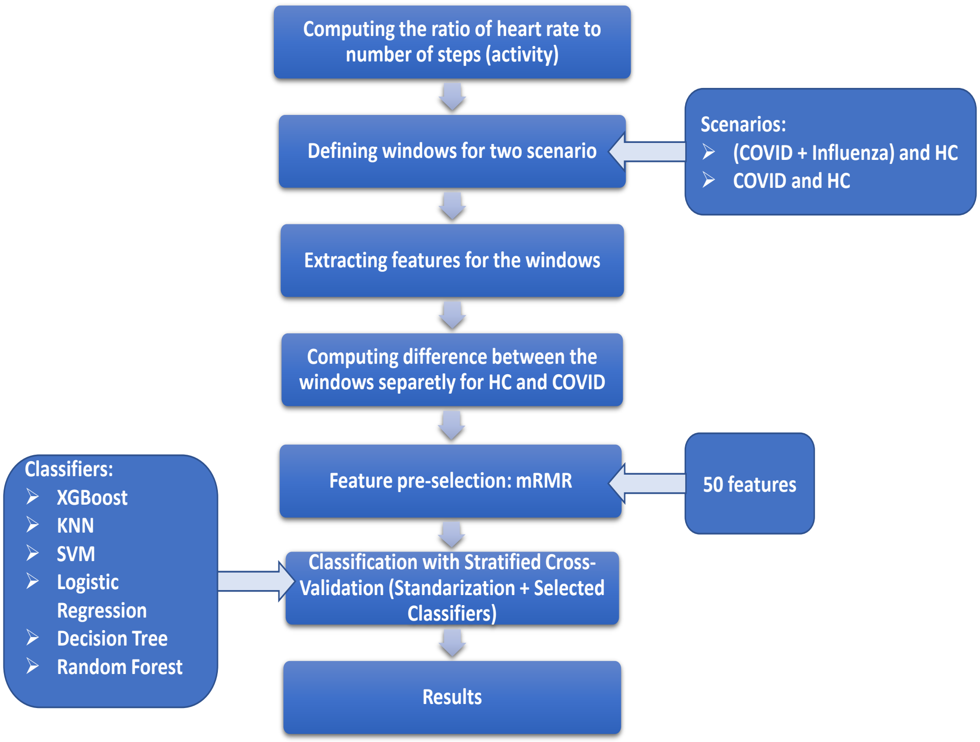


Figure 4.4: Scheme of the experiment.

4.3.3 Experiment

The research follows up mainly on paper [32] where the smartwatches were used for collecting data from 4642 volunteers in total, where 114 of them were later diagnosed as COVID-19 positive. This experiment uses the data from this paper [32]. In this paper, the experiment consisted of three steps: (a) signal pre-processing of the data, (b) ML, and (c) statistical evaluation of the accuracy. The detailed scheme of the carried-out experiment is displayed in Figure 4.4.

5 Hybrid Techniques for Parkinson's Disease Severity Evaluation

The classification of tremor severity scores by employing ML algorithms and signal processing methods has been the subject of several studies. The problem of correctly extracting features from time-series data, unbalanced data distributions, or the absence of the training data's density of a class or classes, which causes a false-negative, are well-presented obstacles to the use of ML algorithms in medical applications. This incorrect classification may result in an inaccurate assessment, resulting in an impair therapy. In this chapter, hybrid ML methods are adopted to find tremors and bradykinesia severity level in PD patients.

5.1 Tremor and Bradykinesia Severity Analysis using a Wrist-Worn Device and Deep Learning Method: A Daily Living Study in People with Parkinson's Disease

There are several wearable IoT-based devices that only use inertial sensors and computational methods for PD detection, diagnosis, and quantification. When it comes to security, privacy, connectivity, and power efficiency, they have bought new concerns. In order to adjust to the L-dopa dose induction while preventing side effects and a loss in motor activity, physicians must constantly check on patients' motor function from a therapeutic standpoint. It is challenging to monitor changes in motor function between visits, and clinicians run the risk of making bad choices. The goal is to give the medical team a paradigm for a more accurate assessment of the PD stages and their progression in terms of tremors and bradykinesia. In this study, we set out to create a complete ecosystem for the Wi-Fi-based energy-efficient wearable bracelet known as A-WEAR. A-WEAR collects motion data related to PD and securely sends it to the cloud for data processing, severity estimation, and storage using specially designed learning algorithms. The experimental results show that the robustness and effectiveness of the suggested method are demonstrated by 86.4% accuracy for bradykinesia and 90.9% accuracy for tremor estimation, with good sensitivity and specificity for each scoring class. The suggested approach will assist in the early screening of PD severity and ongoing monitoring of the patient's physical activity. When evaluating PD patients for the first time and monitoring their development and the results of any treatments, the system aids medical professionals in making decisions.

5.1.1 System Overview

The whole system design and communication flow is represented in Figure 5.1. The patient uses his most affected limb to move while wearing the A-WEAR device. The network enables wirelessly to the MS Azure cloud, which provides the ServiceNow platform as a web application and builds a database utilizing the movement information from the A-WEAR wristband. Thus, all of the information is delivered to the module designed for monitoring and analyzing PD patient symptoms. The module first uses CWT to convert the data to scalograms before sending the inertial sensor data to the Alexnet Transfer Learning (TL) module to determine the severity level. The outcomes are then updated in the ServiceNow platform, which has cloud access

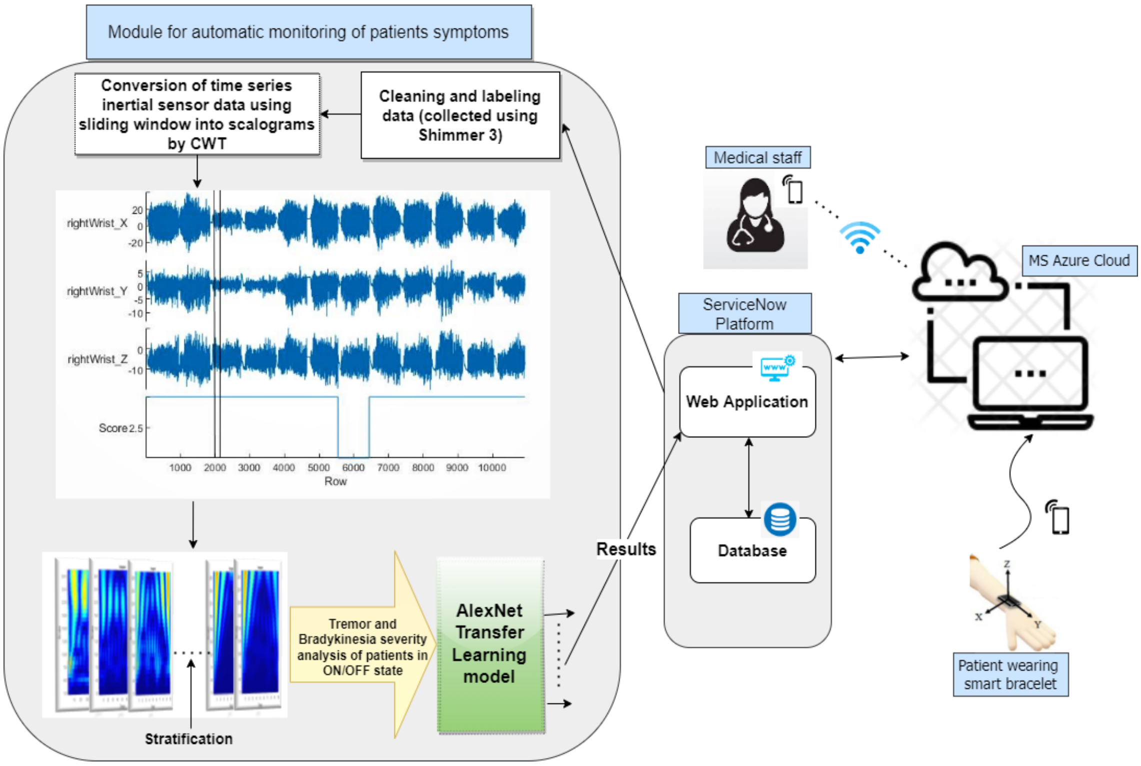


Figure 5.1: The block diagram of the proposed PD monitoring system.

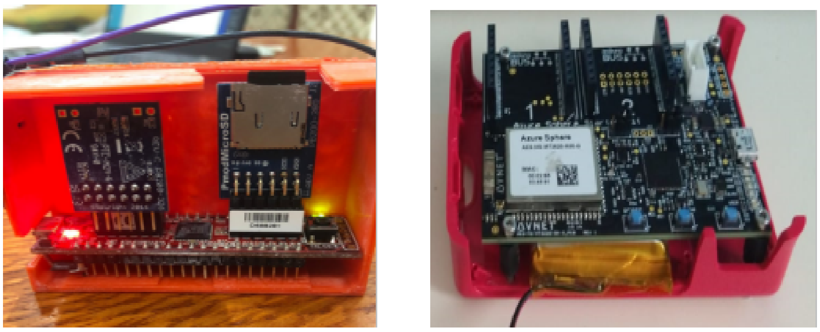
and is available to both patients and medical professionals. The system is created in three stages: first, the wristband is created, then a Platform as a Service (PaaS) platform is created, and last, the mechanisms for cloud-based data processing are designed. The workflow's four primary subsystems are service users, cloud services, sensor devices, and mobile devices. A 3D accelerometer is used in the creation of the wristband for ambulatory patient monitoring so that tremor and bradykinesia, as well as their intensity, could be anticipated as individuals engaged in various activities. The time-series data the sensor gathers is transmitted over Wi-Fi to the ServiceNow platform or cloud server. The continuous wavelet transform is used to pre-process, store, and then create images from the data (CWT). The AlexNet TL model is then used to further investigate these images for severity estimate. The clinician and PD patients receive a report containing the generated results, which are stored in a cloud database. Because only those with permission and access to the cloud platform are given access to the data, the solution preserves the patient's privacy.

5.1.2 A-WEAR PD Bracelet

The AWEAR bracelet is updated and is seen in Figure 5.2 (b). It has been improved to facilitate the uploading of the measured data from the accelerometer sensor directly to the cloud platform. This adds multiple advantages from its first version shown in Figure 5.2 (a)., which is limited to measuring only standard motor tests that last for 1 minute or 45 seconds for tremor and bradykinesia diagnosis.

5.1.3 Proposed Deep Learning Model for PD severity scoring

The data processing and analysis flowchart is displayed in Figure 5.1. In both the ON and OFF states, PwPD accelerometer data is gathered, pre-processed, and labeled in accordance with neurologists' recommendations based on UPDRS grading. CWT is used to transform the time



(a) (b)

Figure 5.2: Fig (a) AWEAR bracelet (first version) and Fig (b) depicts WEAR bracelet new version

series data into scalograms. Finally, the TL AlexNet model is used to organize and analyze this database.

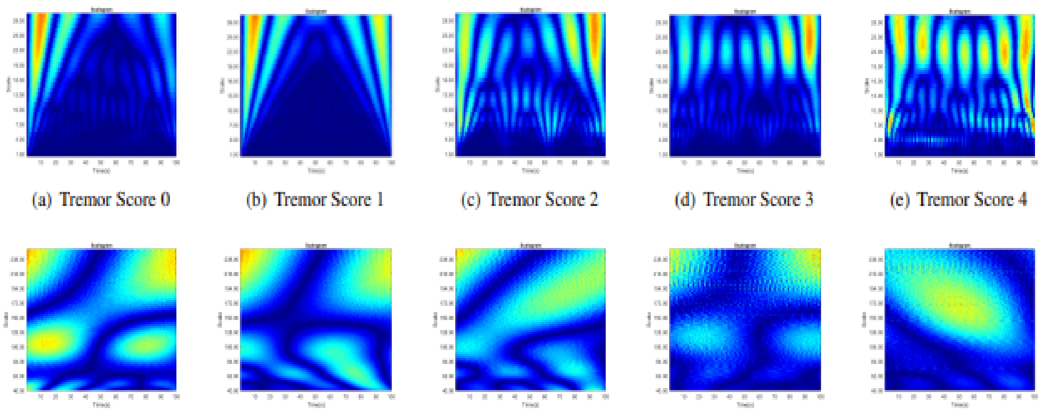
Data Description

The Michael J. Fox Foundation's Levodopa Wearable Sensors Dataset, which can be obtained at https://www.michaeljfox.org/news/levodopa-response-study, provided the data used in this study. Both at home, while performing DLAs and in-clinic using a series of routine activities, participants are observed. The cohort chosen for this research study's data collection wore Shimmer3 on both upper limbs. However, the most severely affected patient's upper limb provided the data for this study's analysis. The subjects wore these wearables for 4 days.

- On Day 1 of data collection, subjects were present in the laboratory in ON state (after taking medication(s)), answered demographic as well as medical history questions, completed sections I, II, and IV of MDS-UPDRS, and donned the wearable devices. Then, they carry out section III of the MDS-UPDRS and ADL.
- The participants engaged in their typical free-body activities while wearing all the sensors on Days 2 and 3.
- The participants arrived at the lab on Day 4 in an OFF state after being withheld for roughly 12 hours. On Day 4, the identical procedure that was followed on Day 1 was repeated.

Continuous Wavelet Transform

Scalograms are used in Figure 5.3 to illustrate an example of recorded signals with tremor and bradykinesia of varying severity. The color-coded wavelet coefficients of a certain event at a specific time and frequency are explained using these scalograms, which provide an intuitive explanation in three dimensions. For the representation of scalograms, we modified the jet colormap. Warmer tones mimic an increase in amplitude, while colder hues like navy blue mimic low amplitudes. The scalograms in Figure 5.3 depict the TF mapping of inertial signals. Motor-related disorders, such as tremors and bradykinesia, are frequently not identified with the proper severity score and the majority of the features are lost out in hand-crafted feature extraction methods, especially at such low frequency. On the other hand, this CWT approach generates the full spectrum of movement, allowing one to see the distinction between each level. Additionally, these scalograms are classified using a DL classifier after being stratified according to severity score in a different folder using a MATLAB script.



(a) Tremor Score 0 (b) Tremor Score 1 (c) Tremor Score 2 (d) Tremor Score 3 (e) Tremor Score 4

(f) Bradykinesia Score 0 (g) Bradykinesia Score 1 (h) Bradykinesia Score 2 (i) Bradykinesia Score 3 (j) Bradykinesia Score 4

Figure 5.3: Tremor and Bradykinesia scores, using CWT. Each subplot depicts the scalograms of corresponding severity score of tremor and bradykinesia. The x-axis of each represents the time whereas y-axis represents the scale. The time range adopted is 3-s temporal window preceding over the motion onset

AlexNet TL model

The AlexNet architecture is being changed in different weights in the current study to achieve the best outcomes. The updated architecture is depicted in Figure 5.4. and we have striven to increase the classification accuracy in the study of finding the severity level for better assessment by doctors. The train and test sets of the dataset are divided 70/30. This study uses a score-wise technique. Data is based on subjects who experienced varying degrees of severity, and each subject is given a severity score. As a result, we divided the severity-score-specific data into training, testing, and validation.

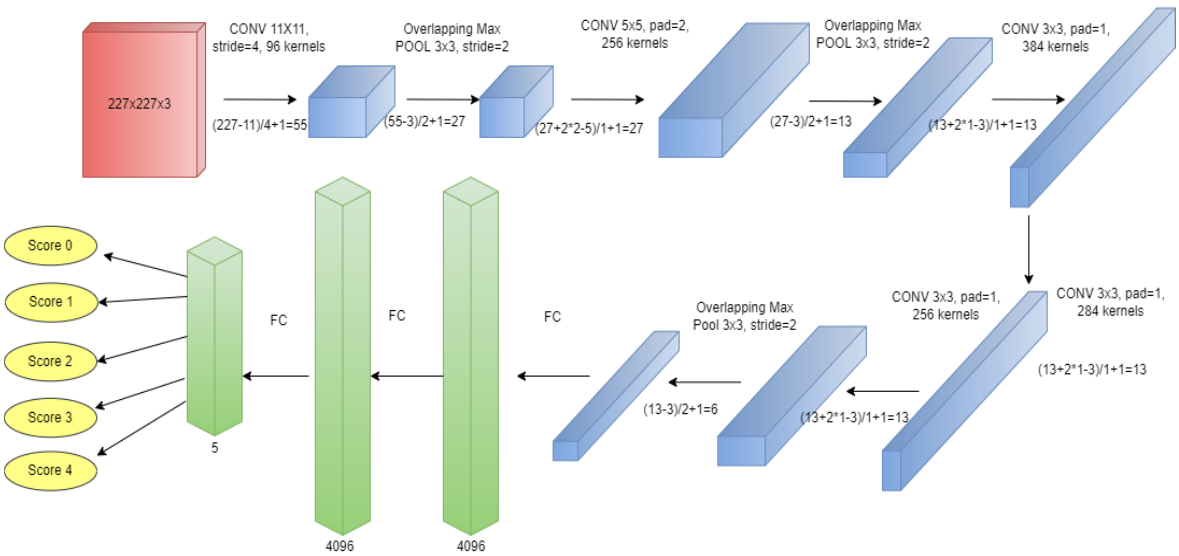


Figure 5.4: AlexNet architecture

Results

Tremor and bradykinesia severity score analysis are trained and tested separately on the model. The results from the AlexNet model are quite encouraging, with accuracy rates of 86.4%for bradykinesia estimation and 90.9% for tremor, as well as strong performance in terms of sensitivity and specificity for each scoring class as explained in Table **??**. From results of our experiments we noticed that each patient's severity in the ON/OFF state varies. The severity level has mostly increased. There may be variations in the consistency or frequency of tremors even when the severity is not increased or maintained. The professionals should alter the dosage of the levodopa shot if the level is lowered. The bradykinesia scoring level of the patients is also observed. Most of the time, its level does not vary. Considering the necessary medications and treatments, additional clinicians can offer the finest medical and neurological analyses.

5.2 Parkinson's Disease Resting Tremor Severity Classification Leveraging Machine Learning with Resampling Techniques

In this work, a dataset of PD patients with imbalances is used for a severity analysis. This is the reason that the performance of several common classification learning algorithms has endured a notable drawback while trying to classify different data that has an unbalanced class distribution. In this study, different types of resampling methods including under- and over-sampling as well as a hybrid combination are applied and evaluation metrics are found for each severity score. Renowned classifiers like XGBoost, decision trees, and KNN are used with resampling approaches. According to the findings, the oversampling strategy outperformed the undersampling and hybrid sampling techniques by a wide margin. Among the over-sampling techniques, random sampling has obtained 99% accuracy using the XGBoost classifier and 98% accuracy using a decision tree. Additionally, it is shown that various classifiers responded to different resampling techniques in different ways.

5.2.1 Methodology

Figure 5.5 shows the suggested method for categorizing an unbalanced RT severity dataset using resampling approaches. The raw inertial signals are first preprocessed to get rid of artifacts, non-tremor data, and sensor orientation dependencies. The annotated and prepossessed signals are then processed to obtain the time and frequency domain features. Data is split in training and test subgroups in the third stage. The data is also resampled in order to prevent classifier bias during training. The 10-fold cross-validation is the foundation of the data distribution. Finally, by feeding training and test data into a classifier, tremor severity levels (0–4) are predicted. Additionally, the outcomes are projected for adoption in the final step.

Classifiers

In this work, three classifiers are considered for classification: XGBoost, KNN and Decision Trees (DTs). The following classifiers were chosen based on the previous work as discussed in Chapter 3 Section 3.3 that attained good accuracy in PD classification and its severity diagnosis with balanced and imbalanced datasets. The primary advantage of XGBoost includes various hyperparameters which can be tuned and it has a built-in feature to adjust the missing values. Also, it provides distributed computing, parallelism, and cache optimization.

Adopted Resampling Methods

When a dataset is unbalanced, the resampling process is used to increase accuracy and quantify uncertainty. The creation of a training dataset for a quest for unbalanced classification is altered

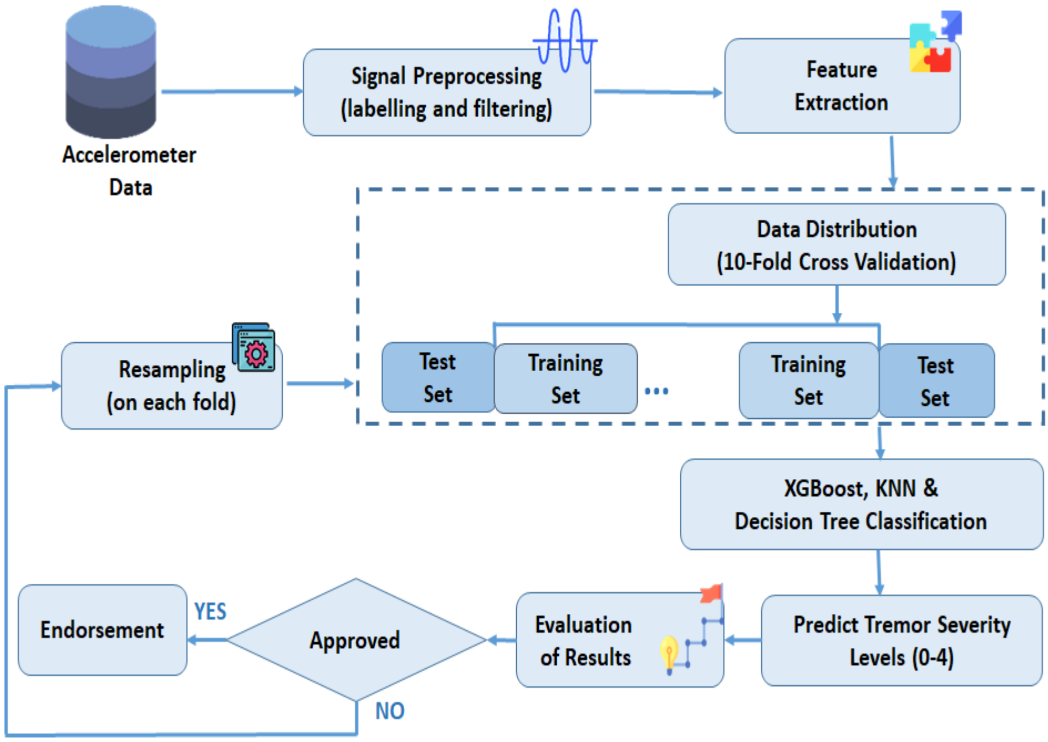


Figure 5.5: The proposed framework for tremor severity classification.

by resampling approaches. The resampling techniques used in this work are briefly described in this section. The three categories of resampling techniques are under-sampling, over-sampling, and hybrid (merging over and under-sampling).

Under-Sampling Techniques

The samples from the vast majority of classes are reduced with undersampling strategies. Seven under-sampling approaches are examined in this suggested framework. Figure **??** shows how they differ from one another.

- Random undersampling
- Condensed Nearest Neighbor
- Tomek Links
- NearMiss
- Edited Nearest Neighbour
- One Sided Selection
- Neighbourhood Cleaning Rule

Over-Sampling Techniques

The samples of the minority of classes are expanded in oversampling approaches. Three over-sampling approaches are examined in this research study. Since oversampling proved to be the best strategy for our problem, oversampling is conducted during cross-validation, i.e., before training, and this process is repeated for each fold. This prevents overfitting or doing resampling incorrectly.

Random Oversampling

Synthetic Minority Oversampling Technique (SMOTE0

Borderline SMOTE

Combine Resampling Techniques or Hybrid Resampling Methods

There are various combinations of under and oversampling techniques that have proven to be more effective and together may be expressed as the resampling method.

- SMOTE with Tomek link (SMOTETomek)
- SMOTE combined with ENN (SMOTEENN)

Performance metrics When the resampling techniques were combined, XGBoost with random oversampling method performed well, achieving accuracy rates of 99%, 98% for decision trees, and 87% for KNN. This demonstrates unequivocally that balanced data in each class outperformed an imbalanced number of samples in each class in terms of how well the classifiers performed.

Table 5.1: Performance metrics of XGBoost classifier with Random over-sampling technique

	Accuracy	Precision	Sensitivity	Specificity	F1-Score	Gmean	IBA_α
Class 0	0.99	0.98	0.99	0.99	0.98	0.99	1.0
Class 1	0.98	0.99	0.99	0.95	0.99	0.96	1.0
Class 2	0.99	1	0.97	1	0.98	0.98	0.98
Class 3	1	1	1	1	1	1	1.0
Class 4	1	1	1	1	1	1	1.0

Table 5.1 explains the performance metrics of XGBoost classifier with random oversampling method.

6 Comprehensive Framework for Parkinson's Disease Severity Estimation using Deep Learning and Cloud Technology

In order to deal with the challenges for automatic quantification of tremors in PwPD and following the work present in Chapter 3 and 5 we designed and developed the final version of A-WEAR bracelet and whole eHealth platform for PD patients continuous and remote monitoring.

6.1 Methods and Materials

The suggested architecture had a number of units, including a smart device with a sensor, a mobile app, a cloud platform, and a DL method that operated inside the cloud.

6.1.1 Framework for Predicting Parkinson's Disease Tremor Severity in the Cloud

Hardware and software are both integrated via the cloud. The software is mostly on the client side, whereas the hardware is primarily on the side of the service provider. Design, modeling, programming, testing, databases, and web servers are all included in the PaaS. The task flow of the system inside the cloud structure is depicted in Figure 6.1.

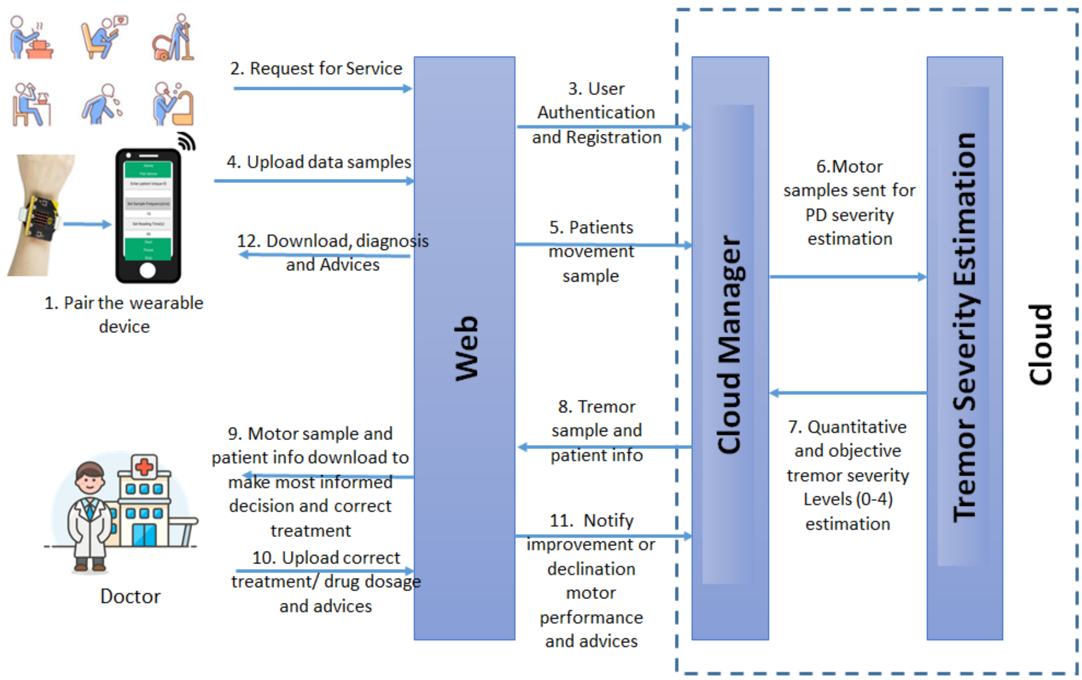


Figure 6.1: The proposed framework for tremor severity classification.

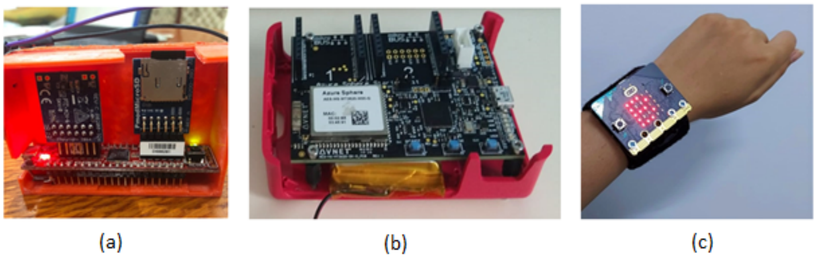


Figure 6.2: A-WEAR bracelets Fig.(a) shows First version Fig.(b) shows second version and Fig.(c) shows Final version of bracelet

6.1.2 Development of A-WEAR Bracelet

The prototype for this kind of wearable technology was created for the objective assessment of PD motor symptoms and published in [33]. That device has a few limitations, including the inability to wirelessly send data for signal analysis and the fact that it only assists in the collecting of motor signals. It also utilizes a 3V battery that only lasts for 6 hours. In light of these difficulties, we created a new model of this device, as seen in Figure 6.2 (b), utilizing a MediaTek 3620 microcontroller that has been improved to facilitate uploading measured data from the accelerometer sensor directly to a cloud platform. This has several benefits over the previous version, which is shown in Figure 6.2 (a), and is only capable of assessing conventional motor tests lasting 45 seconds or 1 minute for the diagnosis of bradykinesia and tremor.

The BBC micro: bit, a development board that employs a microcontroller, was used to create our most recent version of the A-WEAR bracelet, which is seen in Figure 6.2 (c). We took these concerns into consideration and made them more feasible for patients and medical professionals. The micro: bit microcontroller was selected as an update because it guarantees low power consumption, a compact form size that is ideal for wearable designs, and out-of-the-box peripherals like an accelerometer, Bluetooth Low Energy (BLE), and a matrix display. The whole micro: bit device has an operating voltage range of 1.7V minimum to 3.6V maximum. The CPU, BLE, Matrix Lex, and accelerometer are the controller's key components, and Figure

Figure 6.3: Power consumption of CPU, BLE, Matrix Lex and Accelerometer

6.3 illustrates their respective power usage. Maximum employment of all the aforementioned components would result in a worst-case scenario power consumption of 97mW. The expected battery life for the microcontroller and its peripherals at maximum use, when using a CR2032 battery with a voltage of 3 volts and a capacity of up to 240mAh, is roughly 5 to 6 hours. Of course, this would be the worst-case situation, in which the microcontroller would continually be employed for the activities that required the most power. According to our trials, the battery lasted more than two weeks before it needed to be changed. Normal usage is defined as performing 10 to 20 readings of one minute each day.

6.1.3 ServiceNow Platform: Cloud based Monitoring Platform

The unique A-WEAR User Interface (UI) component, which provides a user-friendly interface for accessing the A-WEAR bracelet, is first hosted on the ServiceNow platform. It includes capabilities like patient registration, obtaining fresh readings from them and managing the DL model's training and prediction results. It is now possible to create a fully customized web application with all the features and functionalities that a web application may provide thanks to the new UI Components from ServiceNow. As demonstrated by the aforementioned procedure,

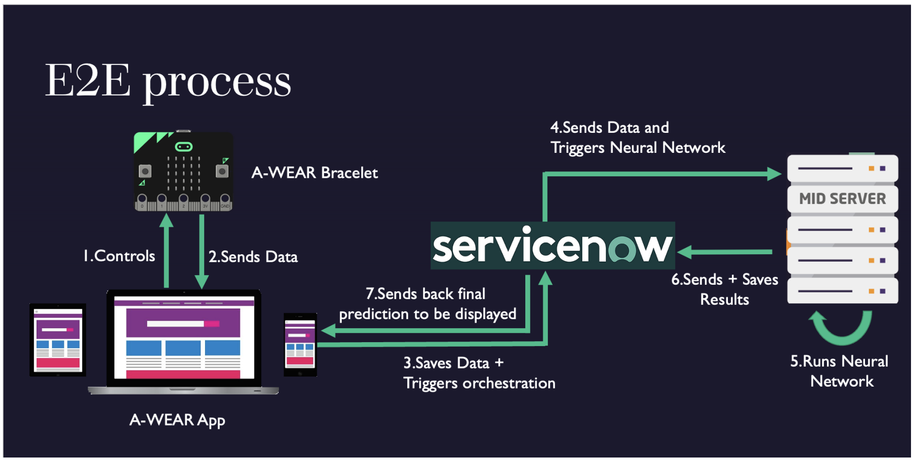


Figure 6.4: End to End process flow between A-WEAR Bracelet (micro:bit controller), A-WEAR Application (ServiceNow UI Component), and MID Server which runs the DL

training the DL model may also be initiated straight from the A-WEAR app. Once the collected data has been tagged, a new training set record may be formed in ServiceNow to store the data and retrieve the training results. Figure 6.4 depicts end to end process flow between bracelet, A-WEAR Application and A management, instrumentation, and discovery (MID)Server. The training tests were run on a Supermicro server having two Intel(R) Xeon(R) CPU X5690 at 3.47GHz with a total of 24 Logical Cores, a total of approximately 30 GB of RAM, and running a Debian distribution.

The aforementioned execution times are measured for the following datasets, which have an average size of 10 to 11 MB (from the training session start in the A-WEAR application until the final results were uploaded back to the ServiceNow platform). The mean execution time of each step is described in Table 6.1. The retrieval and upload actions are carried out via REST API, and the total time also includes the ServiceNow platform-specific operation regarding database reading and update. In this case, the execution time also includes retrieving a CSV dataset file from the ServiceNow platform (for the filter step) and uploading the output training graphs back to the ServiceNow platform (for the classification step).

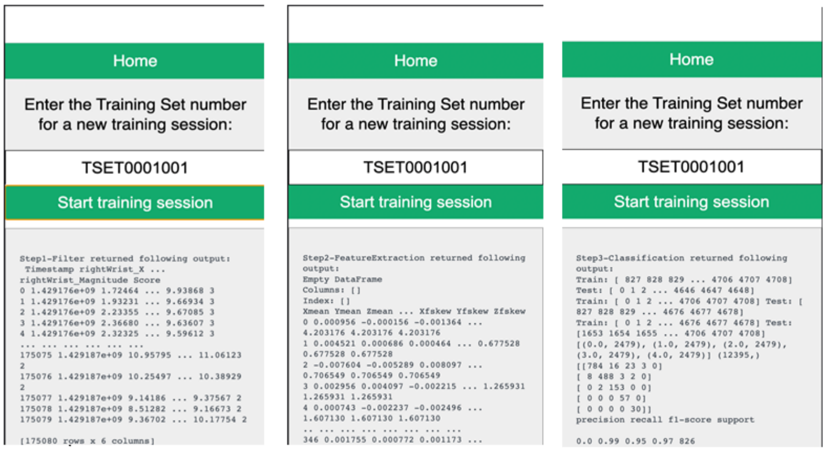


Figure 6.5: Training Session application screen Fig.(a) shows Filter Step of training executed and logged into the application, Fig(b) shows Feature Extraction Step of training executed and logged into the application and Fig(c) depicts Classification Step of training executed and logged into the application

Table 6.1: Mean execution times for datasets of size 10-11MB

Class (Training Steps)	**Execution time (ms)**
Filter	14338*
Feature Extraction	6408
Classification	26573*
Total time	*49011***

6.1.4 Cloud Service: Data Processing and Decision Making

We have adopted same dataset as used in Chapter 5. The data processing pipeline in the cloud is shown in Figure 6.6.

Signal Processing

As previously covered in Section **??**, the experimental procedure called for two visits to the research location. At each visit, the individuals were given a list of activities to perform (i.e. in ON and OFF state). First, a JAVA script was used to trim the raw signal into separate procession events using the 3-s temporal window before motion commencement. Given that the fundamental frequency of tremors frequently ranges between 3 and 12 Hz, a 3-s window length should be enough for recording signal characteristics related to high-frequency movements. After that, any frequency components that do not fall within the tremor frame are attenuated by using a second-order Butterworth IIR filter to band-pass filter the raw sensor data with cutoff frequencies of 3 to 12 Hz.

6.1.5 Features Extraction and Selection

A set of characteristics necessary for interpreting tremors were extracted from the filtered signals using prior research as a reference. First, we divide the signal into 3s windows and extract the respective features for each window. However the frequency domain features are extracted after converting the raw signal from the time domain to the frequency domain using the FFT,

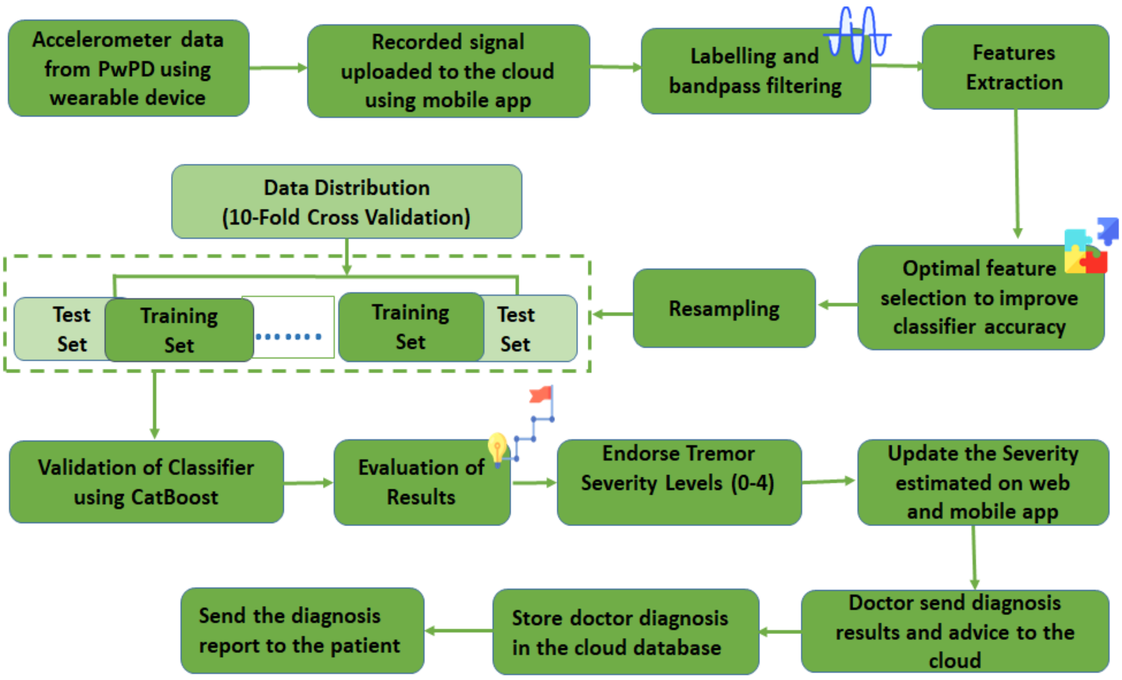


Figure 6.6: Pipeline of data processing inside cloud

according to Expression 6.1 below.

$$F(y) = \sum_{t=0}^{W_l-1} x_t e \frac{-j2\lambda yt}{W_l} \tag{6.1}$$

for y = 0....W_l-1. F(y) is a complex series which has the identical dimensions as the input sequence $(x_t)_{t=0}^{W_l}$ and $e\frac{-j2\lambda yt}{W_l}$ is a primitive Nth root of unity. The extracted features were acquired by processing the acceleration values of X-, Y-, and Z-axis.

Following feature extraction, we carried out feature selection, which is crucial for model construction. Using the Python module **FeatureWiz**, features are chosen. The greatest features of any size dataset may be quickly determined using the featurewiz package in Python.

Resampling method

In this study, we examined an unbalanced dataset. When samples are distributed unevenly among class labels, the resulting data is deemed to be unbalanced. According to the findings of our prior research study, [34] oversampling techniques performed better than undersampling and hybrid sampling in terms of accuracy and $IBA\alpha$. Therefore, we used oversampling methods in this research.

Oversampling is the practice of reproducing or synthesizing extra examples of the minority classes in order to make the number of instances in the minority class more closely resemble or match the number of examples in the majority classes. The dataset is first segregated into k stratified divisions, and only the training set (corresponding to the first k divisions) is oversampled i.e. SMOTE and Borderline SMOTE, during cross-validation. In order to estimate the model's generalization capability from the training data objectively, this condition excludes oversampling the model or exposing it to patterns present in the test set during the training phase.

Table 6.2: Performance metrics of CatBoost classifier with SMOTE technique

SMOTE	Score 0	Score 1	Score 2	Score 3	Score 4	Overall
Accuracy	0.96	0.98	0.98	0.99	1	0.96
Precision	0.99	0.96	0.85	0.92	21.00	0.96
F1-score	0.97	0.97	0.92	0.96	1.00	0.97
Sensitivity	0.94	0.97	0.98	1	1	0.96
Specificity	0.98	0.98	0.98	0.99	1	0.99
IBA_α	1.0	0.99	1.0	1.0	1.0	0.97
Gmean	0.95	0.97	0.98	0.99	1.0	0.97

Classifier

The term "CatBoost" is a combination of the phrases "Category" and "Boosting. The distinguishing characteristic of CatBoost is that, in contrast to XGBoost and LightGBM, it builds balanced (symmetric) trees. At each step, the leaves from the previous tree are divided under the same conditions. The feature-split pair that accounts for the least loss is selected for each of the level's nodes. Because the topology serves as regularization, the balanced tree architecture facilitates efficient CPU implementation, decreases prediction time, produces rapid model implementers, and lowers overfitting. Cross-validation is a popular method to increase a model's accuracy rather than simply employing a train/test split. In fact, CatBoost with k=10 folds provides the greatest accuracy, at about 96%.

6.2 Results and Discussions

To assess the system performance of the classifier, the ROC parameter is computed. Macro-averaging, which equally weighs the categorization of each label, is another assessment metric for multi-label classification. Since the CatBoost classifier in a combination of SMOTE resampling technique gives better results i.e. 96% accuracy as illustrated in Figure 6.2. The extended metrics one-vs-one ROC AUC scores are 0.99 (macro) and 0.98 (weighted by prevalence). While, one-vs-rest ROC AUC scores are 0.998 (macro) and 0.996 (weighted by prevalence).

Based on a smart bracelet continuously connected to the cloud, this study proposes an efficient eHealth platform for the assessment and monitoring of PwPD. The results of this study indicate that the CatBoost classifier in combination with the SMOTE over-sampling approach is the best system. A-WEAR bracelet assessment data were used to evaluate the suggested recommended method, which obtained accuracy=96%, IBA=97%, F1-score=97%, G-mean=97%, and AUC=99%. Additionally, it has been demonstrated to accurately estimate the degree of tremor in test data from our A-WEAR bracelet as well as wearable devices Shimmer. The XGBoost and CatBoost classifiers provide the best way to evaluate tremor severity while patients are on or off medication, according to a performance comparison of several classifiers.

7 Conclusions and Future Work

7.1 Personal Considerations and Conclusions

For more than two centuries, medical research has been aware of PD. Therapeutic developments during that time have changed it from a lethal condition to a disease that can be managed with varying degrees of long-term effectiveness. For instance, a variety of pharmacological and nonpharmacological approaches, such as surgical procedures and multidisciplinary care, are now available. However, the progression of this extremely complicated and uniquely variable disease cannot be stopped by the treatments that are currently available, ultimately leading to a marked decline in QoL. I claim that medical research has so far failed to give PD patients practical tools for managing the whole complexity of their condition on a daily basis and customized to each person's specific needs, i.e., to give PD patients the tools they need to engage in efficient self-care.

In this thesis, I have demonstrated that the use of wearable technology in the form of an eHealth system can contribute to improving self-care in PD, assessing motor activities, and suggesting the right treatment at right time. For this system, each component is developed considering all the limitations and possibilities, from prototype to cloud platform and working of DL approach running inside the cloud.

7.2 Contribution of Thesis

The work in this thesis gave a new paradigm for monitoring and assessment of PD and NCD patients. This thesis demonstrates the importance of using a robust framework based on wearable computing and a cloud-based approach. The recommended system is developed by working on each subsystem in chronological order. The major contributions are listed as follows:

- Chapter 2 provides a critical analysis of wearable devices in NCD patients and PD patients. The analysis is based on both qualitative and quantitative analysis. The findings reveal that wearables can be very useful in terms of diagnosis, monitoring, quantification, and rehabilitation evaluation of motor disability in patients with NCD. Among different types of wearables, wrist-based devices and insoles gave better results and were accepted by NCD patients and clinicians.

- Chapter 3 illustrates the use of innovative medical wearable devices i.e. insoles and bracelets for NCD patients. This chapter starts with the use of insoles on elderly, PD, and healthy subjects to evaluate how their stride variability differentiates and at what level using fractal dynamics applied to data from insoles. I also adopted insoles data and instead of using conventional methods for handling time series data I employed CNN architecture to evaluate the gait functioning in three groups of subjects i.e. PwPD, old-aged subjects, and healthy participants. For wrist movement variability assessment I developed an A-WEAR bracelet for acquiring data for robust tremor and bradykinesia identification.

- Chapter 4 demonstrate the importance of ML and DL algorithms with the combination of wearable technology. With the help of ML and DL approaches wearable solutions become easier to use, provide very concise information, and have ease of interpretation. This chapter provides how ML-supervised algorithms can help OSA patients in their posture identification and alert them if they are sleeping with the wrong posture. Similarly, the DL method helped in COVID-19 detection using chest X-ray images and not just the diagnosis with computer vision technology I found the severity as well. The use of ML is not just there but I was also able to investigate how human actions can be recognized by cascading pose features with CNN-LSTM. Keeping in mind the repetitive antigen testing for COVID-19, I proposed a system to diagnose COVID-19 based on data from smartwatches and ML techniques.

- In Chapter 5 I proposed a hybrid technique for PD severity estimation. I modified the A-WEAR bracelet as discussed in Chapter 3 so it just not collects data for a few hours but also works for around 14-20 hours, second step was to build an algorithm that runs on a cloud database and quantify the severity level of patients tremor and bradykinesia. Further in this chapter, I analyzed the evaluation metric not just on the accuracy, sensitivity or specificity, but I also recombined ML methods with resampling techniques to balance the number of samples collected from wearable devices.

- In Chapter 6 a complex recommended system based on the requirements of patients and clinicians is built. The system is developed in three stages: the construction of the wristband, the mobile interface, the Platform as a Service (PaaS) platform, and finally the implementation of the cloud-based data processing tools.

7.3 Future Work

This section discusses the main directions for future research after the work done in this thesis.

1. Design and test a prototype wearable device based on the findings discussed in Chapter 6 while taking into account the real-world experience of PD patients and medical professionals to ensure widespread acceptance and implementation. This could result in enhancements to the smart eHealth system for PwPD monitoring and assessment's functionality, comfort, and aesthetics.

2. In this study, the data is offline processed to assess the PD tremor severity. Therefore, it would be intriguing to involve PD patients in the data collection and interpretation process while having them wear our A-WEAR wristband for continuous remote monitoring.

3. It would be useful to update and change the user-friendly interface that we have created for patients and physicians to make the tremor severity estimate method easier to use. As an illustration, one might use voice-overs and videos to demonstrate how to train patients on obtaining data and other activities. Additionally, to evaluate and convey the data analysis findings to physicians in a way comparable to current grading systems.

4. In Chapter 6 the framework we proposed involves the analysis of tremor from accelerometer signals in future exploring of other cardinal symptoms such as FoG, bradykinesia or gait variability will be investigated by exploring different DL techniques with different windows sizes and different overlaps effects.

5. Only accelerometer and gyroscope signals have been used in this thesis. To evaluate tremor direction in addition to its magnitude, future research might explore EMG signals or the combination of all signals.

6. Considering the finding of this thesis we can investigate the use of wearables and smart monitoring system on other types of NCD patients.

7.4 Publications

Journal Papers:

Channa, A., Popescu, N. & Ciobanu, V. Wearable solutions for patients with Parkinson's disease and neurocognitive disorder: a systematic review. *Sensors.* **20**, 2713 (2020), (IF=3.275, Q1), WOS:000537106200277

Channa, A., Ifrim, R., Popescu, D. & Popescu, N. A-WEAR bracelet for detection of hand tremor and bradykinesia in Parkinson's patients. *Sensors.* **21**, 981 (2021), (IF=3.576, Q1), : WOS:000615495300001

Channa, A., Popescu, N., Skibinska, J. & Burget, R. The rise of wearable devices during the COVID-19 pandemic: A systematic review. *Sensors.* **21**, 5787 (2021), (IF=3.576, Q1), WOS:000694550300001

Channa, A., Memon, M., Cramariuc, O., Popescu, N., Mammone, N. & Ruggeri, G. Parkinson's Disease Resting Tremor Severity Classification using Machine Learning with Resampling Techniques. *Frontiers In Neuroscience.* pp. 1664, (IF=5.152, Q2), DOI: 10.3389/fnins.2022.955464

Skibinska, J., Burget, R., Channa, A., Popescu, N. & Koucheryavy, Y. COVID-19 Diagnosis at Early Stage Based on Smartwatches and Machine Learning Techniques. *IEEE Access.* **9** pp. 119476-119491 (2021), (IF=3.367, Q2), WOS:000692228400001

Zafar, H., Channa, A., Jeoti, V. & Stojanović, G. Comprehensive review on wearable sweat-glucose sensors for continuous glucose monitoring. *Sensors.* **22**, 638 (2022), (IF=3.576, Q1), WOS:000747700500001

Malik, NUR., Abu-Bakar, SAR., Sheikh., UU., A., Channa, A.& Popescu, N. Cascading Pose Features With CNN-LSTM for Multiview Human Action Recognition. *Signals, MDPI*, **Under review**

Ifrim, R., Channa, A., Popescu, N., Popescu, D., Ruggeri, G., Iera, A. & Skibinska, J. A Wearable Computing and Cloud-based Monitoring System for Parkinson's Disease. *IEEE Sensors*, (IF=3.301, Q1), **Under review**

Channa, A., Ruggeri, G., Ifrim, R., Mammone, N., Iera, A. & Popescu, N. Smart eHealth System for Parkinson's Disease Patients Evaluation Leveraging Deep Learning and IoT Wearable Device. *IEEE Access*, (IF=3.367, Q1) **Under review**

Conference Papers:

Channa, A., Yousuf, M. & Popescu, N. Machine Learning Algorithms for Posture Identification of Obstructive Sleep Apnea Patients using IoT Solutions. *2020 International Conference On E-Health And Bioengineering (EHB).* pp. 1-6 (2020), WOS:000646194100005

Channa, A., Popescu, N. & Others Robust technique to detect COVID-19 using chest X-ray images. *2020 International Conference On E-Health And Bioengineering (EHB).* pp. 1-6 (2020), WOS:000646194100088

Channa, A., Popescu, N. & Others Association of Stride Rate Variability and Altered Fractal Dynamics with Ageing and Neurological Functioning. *2021 23rd International Conference On Control Systems And Computer Science (CSCS)*. pp. 509-514 (2021), DOI: 10.1109/CSCS52396.2021.00089

Channa, A., Popescu, N. & Others Managing COVID-19 Global Pandemic with High-Tech Consumer Wearables: A Comprehensive Review. *2020 12th International Congress On Ultra Modern Telecommunications And Control Systems And Workshops (ICUMT)*. pp. 222-228 (2020), WOS:000627398300039

Channa, A., Popescu, N. & Faisal, M. Parkinson's Disease Gait Evaluation Leveraging Wearable Insoles and Deep Learning Approach. *2022 8th International Conference On Control, Decision And Information Technologies (CoDIT)*. **1** pp. 543-549 (2022), WOS:000846862800090

Channa, A., Ruggeri, G., Mammone, N., Ifrim, R., Iera, A. & Popescu, N. Parkinson's Disease Severity Estimation using Deep Learning and Cloud Technology. *2022 IEEE International Conference On Omni-layer Intelligent Systems (COINS)*. pp. 1-7 (2022), WOS:000859114600060

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