GAIT ANALYSIS USING SMARTWATCHES

by

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ABSTRACT

GAIT ANALYSIS USING SMARTWATCHES

Monitoring gait characteristics is an important tool used in many areas including orthopedics, sports, rehabilitation and neurology. Current methods applied to analyze the gait need clinical settings and equipments for measuring gait parameters. In this study, we propose an unobtrusive and comfortable system to perform gait analysis. Smartwatches equipped with embedded sensors including accelerometer and gyroscope are used to extract three main parameters of gait: step length, swing time and stance time.

Data is collected from 26 healthy and volunteer participants with different ages and genders in clinical settings. Subjects wore smartwatches on both wrists, data is collected from two sensors: accelerometer and gyroscope. The data is preprocessed and step features are extracted. Relevant gait parameters are estimated using various regression models and compared with the ground truth data coming from the clinician using the golden standard instrumented walkway.

Four machine learning algorithms including Linear Regression (LR), Gaussian Process Regression (GPR), Support Vector Machine (SVM) and Regression Tree, and two neural network architectures Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are used to fit data. Performance of the models is measured using a basic error metric, i.e. RMSE. The best model fitting the data is found as GPR. Its RMSE value for the step length (cm) estimation is calculated as 5.29 cm.

Besides the placement of sensors is less convenient than the state of the art studies, the gait analysis with smartwatches gives promising results and encourages for extended future studies.

ÖZET

AKILLI SAAT KULLANILARAK YÜRÜME ANALİZİ

Yürüme karakteristiklerinin takibi ortopedi, spor, rehabilitasyon ve nöroloji gibi birçok alanda kullanılan önemli bir araçtır. Mevcut yürüme analizi teknikleri klinik bir ortamı ve birçok ekipmanı gerektirmektedir. Bu çalışmada, göze batmayan ve konforlu bir yürüme analizi sistemi sunulmuştur. İvmeölçer ve jiroskop gibi gömülü sensörlere sahip olan akıllı saatler üç temel yürüme parametresinin tespiti için kullanılmıştır: adım uzunluğu, salınım süresi ve basma süresi.

Farklı yaşlardan ve cinsiyetlerden, sağlıklı ve gönüllü 26 kişiden klinik ortamda veri toplanmıştır. Katılımcıların her iki bileklerine de birer akıllı saat takılmış, ivmeölçer ve jiroskop sensörlerinden veri toplanmıştır. Toplanan veri bir ön işlemden geçirildikten sonra adım özellikleri elde edilmiştir. İlgili yürüme parametreleri çeşitli regresyon modelleri kullanılarak tahmin edilmeye çalışılmış ve klinik tedavi uzmanının altın standart yürüme yolunu kullanarak elde ettiği referans değerlerle karşılaştırılmıştır.

Lineer Regresyon (LR), Gaussian Proses Regresyonu (GPR), Destek Vektör Makinesi (SVM) ve Regresyon Ağacı makine öğrenimi algoritmaları ve Konvolüsyonel Sinir Ağı (CNN) ve Uzun Kısa Süreli Bellek (LSTM) sinir ağı mimarisini içeren teknikler veriye uygun bir model geliştirmek için kullanılmıştır. Modellerin performansı temel bir hata ölçüm parametresi olan Kök Ortalama Kare Hatası (RMSE) ile ölçülmüştür. Veriye en uygun model Gaussian Proses Regresyonu (GPR) olarak tespit edilmiştir. İlgili modelde adım uzunluğu 5.29 cm Kök Ortalama Kare Hata değeri ile hesaplanmıştır.

Sensörlerin konumunun mevcut çalışmalara göre daha az kullanışlı bir yerde, yani bileklerde olmasına karşın, akıllı saatlerle yapılan yürüme analizinde umut verici sonuçlar ortaya çıkmış ve gelecek çalışmalar için teşvik edici nitelikte olmuştur.

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LIST OF ACRONYMS/ABBREVIATIONS

3D	Recursive Least Squares
ALS	Amyotrophic Lateral Sclerosis
AD	Alzheimer's disease
GPS	Global Positioning System
IMU	Inertial Measurement Units
HD	Huntington Disease
NCA	Neighborhood Component Analysis
PD	Parkinson's Disease
PSD	Power Spectral Density
RLS	Power Spectral Density
MAE	Mean Absolute Error
MSE	Mean Squared Error
R^2	R-Squared Error
RMSE	Root Mean Squared Error

1. INTRODUCTION

Walking is one of the most important activities that people perform during daily life. The quality of gait activity has an important effect on individual's quality of life. For most of daily life activities people need to walk, therefore it is crucial to keep gait quality as high as possible.

Gait analysis is a systematic method to assess a person's body movements during walking or running and detect abnormalities in a gait cycle. The assessment is mostly held with the help of an observer or a clinician and several types of technical equipments to measure gait related parameters. Gait analysis is used in different areas including sports and healthcare. While in the field of sports, it can help to improve the performance of players for gait related activities [3, 4], in the healthcare field, it provides comprehensive analysis of the gait process and used to assess and treat patients with physical injuries, abnormalities in the legs or feet [5, 6] or neurological disorders causing gait problems [7, 8]. The process of clinical gait analysis is applied to gather quantitative information about gait to understand the abnormalities with the help of specialized technology including camera-based motion capture systems, electrodes located on the body to track muscle activity, and platforms to measure the pressure in a walkway that patient creates on the ground. The parameters measured during the gait analysis are mainly step length, stride length, cadence, speed, cycle time, stance time, swing time, stance ratio, clearance and turning rate. After the collection of these objective measurements, gait experts use these data to decide the best treatment method for each patient.

Apart from various physical ailments like injuries or problems related to leg or feet, some of the neuro-degenerative diseases including Parkinsonś Disease (PD) [9], Amyotrophic Lateral Sclerosis (ALS) [10], and Huntington Disease (HD) [11] can cause abnormality on gait e.g. slowed movement, impaired balance, taking small steps, freezing of gait. Since the effects of these diseases on gait disturbances are unpredictable in terms of progression and emergence of degeneration, following up patterns of gait may help to detect abnormality and take precautions to prevent getting worse. However, such symptoms may not occur during a short period of gait analysis in a clinic. To detect signs of abnormality in the gait of a patient with a neurological disorder, a continuous monitoring system is needed and this continuity is not possible with instrumented pathways. However, recent developments in wearable computing technologies provide a valuable opportunity to check such conditions and give a capability of remote monitoring to clinicians.

Wearable computing technologies provide many facilities in very different areas with creative applications. Healthcare monitoring is one of the popular research areas in ubiquitous computing. Rapid development in unobtrusive computing technologies leads to advanced diagnostic and therapeutic capabilities. Availability of data exchange between healthcare systems and wearable computing devices, and ability to analyze the streaming data enable continuous patient care. Wireless body area networks (WBAN), inertial measurement units (IMUs), smartphones, smartwatches, fitness bands, wearable glasses are some prominent devices used in wearable computing area for healthcare.

With the recent improvements in inertial measurement units (IMUs) and video cameras, medical professionals are given the opportunity of remote monitoring. However, video recordings have always been prone to raise privacy issues, and IMUs turned out to be not really unobtrusive sensors due to their size, maintenance and setup complications.

The smartwatch is one of the latest products in this field and a very promising mobile device which equipped with a rich set of on-board sensing capabilities in terms of healthcare monitoring. Compared to other wearable devices used in health management, smartwatches may be a step forward with very comfortable usage and friendly user interface. Using smartwatches health status metrics including activity levels [12] and heart beats, an individual's health [13] can be logged comfortably. Another health related metric which has a potential to be detected via smartwatches is walking. Thanks to the high level of comfort that smartwatches present, gait analysis can be held in both indoor and outdoor environments.

In numerous studies focusing on gait analysis, inertial measurement units (IMU) are exploited to determine the gait metrics [14–16]. An IMU include sensors of accelerometer, gyroscope and magnetometer. In most gait analysis studies, these measurement units are located on feet and gait metrics are extracted mostly analyzing foot movements. Although a smartwatch includes all sensors that an IMU contains, since it is a wrist-worn device, detecting standard metrics of gait is challenging. Moreover, using a wrist-mounted device do not allow us to use domain knowledge that may assist the inferences. For instance, determining the zero-velocity periods which are quite useful for calculating most of the gait parameters is easy with foot-mounted sensors while it is almost impossible to find with a wrist-worn device.

In this study, we aim to investigate the capability of a smartwatch for determining standard temporal gait metrics including step length, stance time, and swing time. To validate usage of a smartwatch for gait analysis, we collected data from healthy and volunteer 26 subjects with ages range from 23 to 58 in hospital settings. Subjects wore two smartwatches one for each wrist. Data is collected during the gait analysis held by a clinician. Collected data from smartwatches are used to extract the aforementioned spatio-temporal gait metrics and the results are compared with a clinician's assessment.

Contributions of the proposed system compared to the state of the art works can be summarized as follows:

- Unobtrusive and comfortable design is an important advantage of the system. By using a smartwatch for gait analysis, patients do not need to go to a hospital or a clinic, the analysis can be held during daily life settings. With the help of comfortability of the watch, people will not be disturbed during the evaluation.
- Gait analysis with a smartwatch is a more economical solution. Analyzing the gait in hospital settings needs more resources both in terms of human and physical sources. Ability to analyze the gait with a smartwatch only needs the necessary software solutions besides the smartwatch.
- Continuous monitoring opportunity is another contribution of the system. Detection of abnormality in a gait cycle has an important effect especially for people

with neurological or orthopedic disorders in terms of following up the course of their disease. It gives the clinicians a valuable chance to check the current conditions of a patient.

The rest of the thesis is organized as follows. In Chapter 2, the state of the art works are presented in the context of gait analysis domain. Technical equipments used in studies and goals reached are discussed. In Chapter 3, the data collection platform and convenience of the exploited device compared to the state of the art measurement units are explained. In Chapter 4, experimental setup, the data collection procedure and preprocessing of collected data are presented. Chapter 5 contains the overall data analysis, models used and their comparative results are explained in detail. Lastly, in Chapter 6; conclusions derived, difficulties encountered and prominence of using a smartwatch to analyze gait and directions for future research are stated.

2. LITERATURE SURVEY

In this section, we provide a brief information about human gait cycle and the standard gait parameters that are aimed to detect with a smartwatch data collection platform and related works in the literature trying to find relevant gait parameters.

2.1. Human Gait Cycle and Gait Metrics

The gait cycle is defined as repetitive gait events [17] including steps and strides. While a stride means a whole gait cycle, a step indicates one single step during the gait. The step time is calculated as the time between heel strike of one leg while the stride time is the whole gait cycle. Similarly, a step length is the distance between consecutive heel strike events while the stride length is the distance covered during the whole gait cycle.

A gait cycle involves two main phases, namely stance phase and swing phase. The stance phase begins with the initial contact of the foot and ends with when the relevant foot is off. On the other hand, the swing phase starts when the foot is off and ends when the foot initial contact occurs. The stance phase approximately occupies 60% the whole gait cycle while the swing phase constitutes only 40% of it. A single gait cycle is shown in Figure 2.1.

Another gait metric is cadence which is a rhythmic metric of a gait cycle and defined as the rate person walk, expressed in steps per minute. Speed as the name suggests indicates the velocity of a walking person. Definitions for spatio-temporal gait metrics are also listed in Table 2.1 .

In this study, we are mainly interested with the gait parameters: step length, stance time, and swing time.

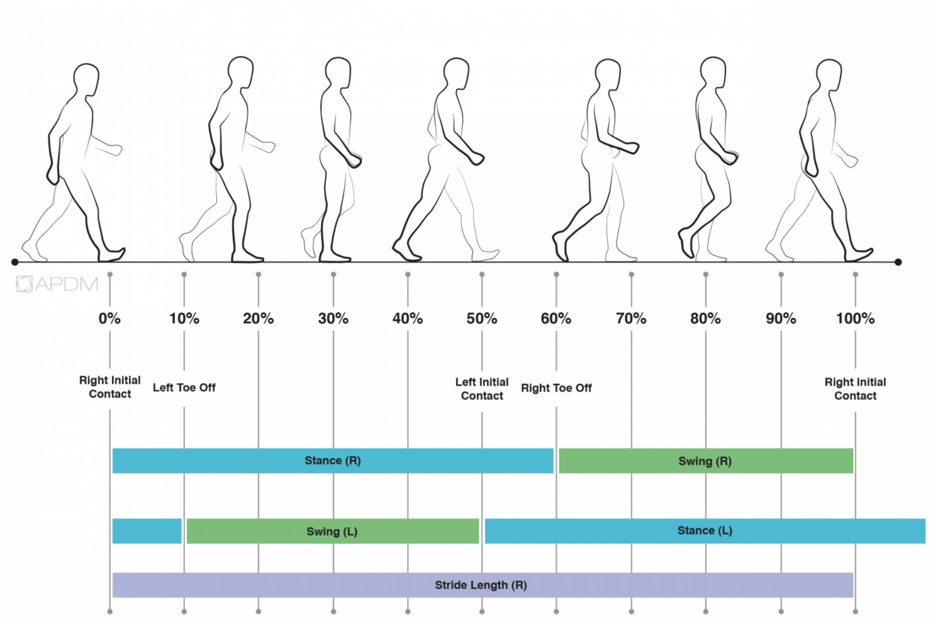


Figure 2.1: Human gait cycle [1].

Table 2.1: Definitions for spatio-temporal gait metrics.

Gait Metric	Description
Stride length	Distance between successive positions of the same foot
Step length	Distance between successive instances of foot floor contact
Stance time	The time while the foot is in contact with the floor
Swing time	The time while the foot is not in contact with the floor
Cadence	Number of steps taken per unit time
Speed	Distance / time

2.2. Related Works

Gait related analysis tools have been developed since the late 19th century. In the beginning, camera-based motion capture systems are evolved [18,19]. Applications based on multi-camera motion capture systems and platforms having a capability of measuring ground force applied by the subject are developed successfully and used in certain gait analysis laboratories [20, 21]. However, such systems require specialized laboratories, expensive devices and excessive time for the setup and processing of data.

Recently, increasing potential of wearable sensor technology provides an alternative method to develop inexpensive and effective way for gait analysis which is conducted using motion sensors including accelerometers, gyroscopes, pressure sensors, inclinometers, goniometers [22,23]. During the analysis these sensors are placed on different parts of the subject's body, such as the foot and wrist and the signals recorded by the sensors are used to perform the gait analysis.

To present the state of the art works, we especially focus on the gait analyses performed using inertial measurement units (IMUs) since these systems are closer to our work in terms of exploited sensor types, being wearable and locations placed. Also we restrict the presentation of the related works according to the targeted gait metric types, i.e., studies measure the stride length, step length, swing time, stance time, cadence.

In [24], they presented a mobile gait analysis system using the inertial sensor platform Shimmer 2R [25] consisting a 3D accelerometer and a gyroscope located on both ankle joints to measure the gait parameters stride length, stride time, swing and stance time. The data is collected from 101 elderly patients. GaitRite is used as the gold standard system [26] which is a portable pressure sensor layer. The patients performed normal walking on this electronic walkway. They do not apply manual filtering to the collected sensor data, since the Shimmer sensor units have an integrated low-pass filter. Stride events are segmented by detecting successive time warping. After this segmentation, time of gait events including toe-off (TO), heel strike (HS) and midstance (MS) are detected and using these time information, they formulate functions to get relevant parameters. The correlation between the ground truth data and their method is found as $\geq$0.94 for stride and stance time, $\geq$0.89 for swing time. The mean absolute error for stride length is calculated as 6.27 cm while the correlation is 0.93 for this parameter.

In [27], wearable sensors placed on shoes were used to get crucial information for patients with Parkinson's disease (PD) during the treatment process. Features of interest are stride velocity and stride length, turning angle, path length, and swing width. An optical motion capture system is used as a gold standard. Physilog sensor module including accelerometer and gyroscope is used for data collection. For each gait cycle, by detecting positive peaks of angular velocity mid-swing phases are extracted. After that extraction, initial and ending contacts of foot are detected with the help of zero crossing of angular velocity around mid-swing and the parameters are derived using this information for each successive foot flats. The system was tested with 10 PD patients and 10 elderly subjects with similar age. For stride velocity and stride length, they asserted that their results are better than the compared previous systems with accuracy$\pm$precision 2.8 cm/s $\pm$ 2.4 cm/s and 1.3 cm $\pm$ 3.0 cm while the compared system has the value of accuracy$\pm$precision 3 cm/s $\pm$ 7.6 cm/s for stride velocity and 3.5 cm $\pm$ 8.5 cm for stride length [28].

Another work using inertial sensors to measure gait patterns is [29]. The aim of the study is determination of mild motor impairment symptoms in PD to help early diagnosis of the disease and detecting mild and intermediate gait impairment to help therapy monitoring in PD. Sensors are placed on the shoes and 16 healthy subjects and 14 PD patients are asked to walk for 10 meters. Biometrical features are extracted from the sensor signals exploiting single steps and the whole gait sequences. For frequency based analysis, Fourier-Transform of gait sequences are used. After the feature extraction step, 290 features are gathered. Then, the Sequential Backward Selection [30] method is used to reduce the number of features. Three different classifiers are used for the classification including Boosting with Decision Stump as a weak learner, Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM) [30]. Their system has a sensitivity of 88% and a specificity of 86% in classifying patients and the control group. Additionally, in distinguishing mild and intermediate gait impairment, the system has 100% sensitivity and 100% specificity.

In [31], inertial sensor based wearable system is developed to obtain quantitative measurements to detect gait disorders and balance problems in patients with Alzheimer's disease (AD). Sensors are mounted on feet and waist. The system consists of the phases including stride detection, decomposing of gait cycles, and extracting details of the gait using these cycle information. The balance is determined by using the signal from the sensor placed on the waist of subjects. Experiments are held with 21 AD patients and 50 healthy subjects. For the gait analysis part, participants are asked to walk along the straight line of 40 m while for the balance detection part, they are asked to perform several balance ability tests. Signals are low-pass filtered and stride events are detected in two phases. Firstly, the variance of magnitudes for 0.03 s windows of the sensor signal without overlapping are evaluated, secondly according to the differences in the variances start and end points of strides are extracted. Relevant gait parameters which are number of strides, walking time, mean of stride length, stride frequency, speed and cadence are calculated by detecting the points of toe-off and heel-strike events using y-axis angular velocity of gyroscope signals as proposed in [32]. The results of the experiments show that the system is quite successful to identify whether the subject is an AD patient or not and the wearable devices can be very helpful to analyze gait and balance problems in AD patients especially for early diagnosis of AD.

The method using a body worn sensor placed on the back of a subject was proposed in [33]. The total step count and mean spatial gait characteristics are estimated. Data is collected along the way from 80 subjects: 40 young and 40 older healthy adults. Participants are asked to walk in an instrumented walkway GaitRite [26] and around a 25 m loop. Estimations for spatio-temporal gait metrics were made using the time information of initial contact (IC), final contact (FC) and step length, related algorithms are designed using the works [34] and [35] respectively. 17 different features of gait, i.e. mean, variability and asymmetry of step time, stride time, stance time, swing time, step length and step velocity for both participant groups are calculated and compared with gold standards. The system gives promising results for estimating the total step count and the mean spatio-temporal gait metrics but for variability and asymmetry, the results are poor.

Tunca et.al. proposed a mobile IMU-based gait analysis system by combining accelerometer and gyroscope sensor mounted on the foot [15]. The system aims to extract spatio-temporal gait metrics containing stride length, cycle time, stance time, swing time, cadence, speed, clearance and turning rate. An IR depth-camera-based reference system is used for the ground truth. The data is collected from 22 subjects and after the proposed model is validated to emphasize its clinical applicability, the system is tested on 17 patients with various neurological disorders. Methodologies including zero-velocity update and Kalman filtering is used for data preprocessing. By extracting IC and FC events, related gait parameters are determined. To find turning steps, foot orientation and foot ankle rotation estimations are exploited. The system provides efficient techniques to combine accelerometer and gyroscope data and more robust estimations in case of difficulties in data collection and pathological gait. Gait abnormalities resulted from various neurological disorders can be captured in non-hospital settings.

In [36], the approach to estimate a pedestrian's stride length from an inertial measurement unit mounted on foot is proposed. The data is collected from 13 subjects with different walking patterns in terms of speed of walking. The back-propagation method in artificial neural networks is used for the step length estimation. Five features extracted to train the network are the mean of stride frequencies, the maximum acceleration in a cycle, the standard deviation and the mean of acceleration, and the height of a subject. Results show that the proposed approach estimates the stride length with 2% error. Considering the number of participants, the model has a promising error value, it can be improved and be more robust when training with more subjects.

In [37], as different than the other related works presented, hand-held inertial measurement units are exploited to estimate the step length. The step frequency and the height of subjects are used to create a linear model. After steps are identified with a peak detection approach, power spectral density (PSD) analysis is applied to detect the step frequency. The Recursive least-squares (RLS) [38] method is exploited to calibrate the parameters of the model. The data is collected from 12 participants and the system is tested with 10 different subjects. The model estimates the travelling distance with an error between 2.5 and 5%.

In [39], a smartwatch and a wireless pulse oximeter were used to detect Mild Cognitive Impairment (MCI) which is defined as the stage between the normal aging and Alzheimer's disease. The acceleration and the gyroscope data are composed with the data coming from a photoplethysmography. The data is collected from 69 elderly subjects (35 healthy, 34 with MCI). Firstly, the sensor data is filtered and the peak detection algorithm is used to count the steps. A set of statistical features are extracted using the sliding window technique for each sensor data. Then a feature selection algorithm is applied to select features. Several classification algorithms are used to validate the set of features and to classify the healthy subjects and the subjects with MCI. The accuracy of the classification with the gait related feature set is found as 86%.

In [40], a smartwatch accelerometer was used to assess the association between the severity of motor fluctuations and the quantity of daily walking and also to assess the effect of levadopa intake on average daily walking quantity. The data is collected from 304 patients with Parkinson's Disease . The gait detection algorithm is developed and trained on 10 hours of the walking and non-walking data. The raw acceleration data is partitioned into 5 sec windows and the features in both the time and frequency domains. Then, a decision tree model is created to classify the walking and non-walking intervals. The accuracy of the classification is found as 98.5%. The Unified Parkinson's Disease Rating Scale (UPDRS) items related to the impact of fluctuations is used to determine the level of severity. The scores of the items are accepted as the ground truth in the analysis. Then, a linear regression algorithm is performed. In conclusion, the results of the analysis show that there is no association between the severity of fluctuations and the time spent during walking.

Musale et.al. proposed an authentication system based on a smartwatch [41]. They evaluated the capability of a smartwatch on detecting distinct patterns of the gait of the user. The data was collected from 51 participants during the 500 meters walking. The sensor data coming from the accelerometer and the gyroscope of the smartwatch was preprocessed, segmented into equal sized windows and a set of features were extracted. They trained a classifier to authenticate the users and reached an accuracy of 91.8%.

Nemati et.al. proposed a system which estimates the gait velocity using the sensors embedded in a smartwatch [42]. Peak detection algorithm is used to find walking steps and a Kalman filter is applied to recover the missing peaks due to the arm movement. Velocity of the gait is estimated using the duration of steps. A strong correlation between the walking speed and and the inverse of the square of the step time is found. The data is collected from 25 subjects. Each subject is asked to walk 50 m six times with various walking speed. The velocity of the gait is estimated with the average precision of 91.7%.

The number of inertial units used in the prominent related works, their locations in the body and the gait parameters extracted from the collected sensor data is introduced in Table 2.2. By studying the state of the art works, it is observed that recent works which exploited from the smarwatches and studied on the human gait generally focused on the classification of the subjects in terms of the health conditions or used the sensor-derived features for an authentication framework.

Table 2.2: Number of IMUs, their locations and targeted gait metrics in the related works.

Ref.	Number of IMU	Position	Gait Metrics
[24]	1	Shoe	Stride length and time, swing and stance time
[27]	1	Shoe	Stride velocity, length, turning angle, path length, and swing width
[29]	2	Shoes	Step duration and some statistical features
[31]	2	Shoes and waist	Number of strides, mean of stride length, speed and cadence
[33]	1	Back	Stance time, swing time, step length and step velocity
[15]	2	Feet	Stride length, stance time, swing time, cadence, speed, and turning rate
[36]	1	Shoe	Step length
[37]	1	Hand	Step length
[42]	1	Hand	Gait velocity

3. SMARTWATCH SENSING

In this part, we present an overview of the smartwatch used in this study, its sensing capability and briefly compare it with the wearable IMU which is the commonly used device in gait analysis. Also we give a brief information about the smartwatch application that we developed to collect the related sensor data.

A smartwatch is a wearable computing device designed to be worn on a wrist. Similar to the smartphones, smartwatches have touchscreens, the range of capabilities of these devices include mobile applications, WiFi/Bluetooth connectivity, GPS interface. Smartwatches come readily equipped with accelerometer, gyroscope, barometer, heart rate monitor, pedometer, magnetometer, light and ultraviolet sensors.

3.1. Samsung Gear Series

In the late 2014, the first smartwatch of Samsung Galaxy Gear S series is released to the market. It is a standalone wearable device providing 3G, Wi-Fi and Bluetooth connectivity aiming to replace the use of smartphones for the duration of dynamic activities, such as running and driving. After the release of Gear S, the family is expanded with Gear S2 in late 2015 and Gear S3 in late 2016. In this study, we use the second device of the series which is Samsung Galaxy Gear S2.

Gear S2 is light and easy to use, as shown in Figure 3.1. The Gear S2 is equipped with a 3-axis accelerometer and gyroscope, a magnetometer, light and ultraviolet sensors and a barometer, a pedometer and a-GPS. It runs on Tizen wearable operating system and is programmed with JavaScript. Tizen wearable applications are actually dynamic web pages and the data collection from the sensors can only be set to be event driven, in contrast to Tizen's mobile environment, where the sampling rate for each sensor can be set with predefined periods.

Figure 3.1: Samsung Gear S2 [2]

3.2. Gear S2 Application

Our Gear S application is based on Tizen version 2.3, which allows user developed Gear S applications to run only when the watch screen is on. This also means that the sensor data can only be collected when the screen is on. Gear S turns off the screen within the 'Screen timeout' period set in the system settings to conserve energy, as the screen is one of the most energy consuming components on the watch.

The documentation for Tizen 2.3 states that an application can be run as a system service, but the compiler only succeeds only when the OS flag is reduced to 2.2.

Tizen also incorporates a gesture recognition on which the screen is turned on automatically, usually with a wrist up gesture mimicking a user's arm movement with the aim of looking at a wrist worn clock. Our feasibility tests ranging over several months have shown that this feature cannot be used for reliable persistent data collection.

Accordingly, we designed our application to wake up, i.e. turn on the screen when desired and turn it off back again, in order to collect data at a desired time and duration. Our Gear S app incorporates an input screen, as shown in Figure 3.2, that aims to collect and present the current data recording. The application is furthermore configurable remotely from our data collection server. The set of active sensors, the wake-up periods, the notification types and statuses can all be set without requiring user intervention.

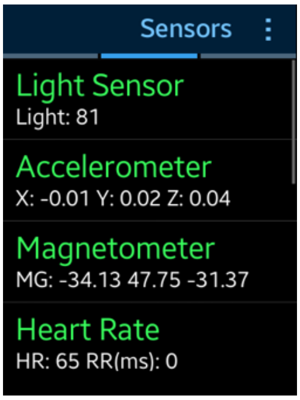


Figure 3.2: User interface of the application to observe current measures.

If the application collects data continuously, the battery runs out in approximately 3 hours. Continuous data collection is an important factor to observe and analyze everything in detail but for a full day data collection without recharging the smartwatch, we add another data collection mechanism which optimizes the battery consumption. To that end, we implemented a duty cycled data collection mechanism, where the sensors are turned on and off on a predefined schedule. The data is sampled when the sensors are tuned on for a certain period of time on regular intervals. For the remaining time, the sensors are put back into sleep in order to conserve energy. A duty-cycled recording with 1 minute and a 10 minutes of sleep prolongs the battery runtime from 3 to 12 hours.

3.3. EXL Measurement Unit

EXLs3 sensor unit in Figure 3.3 is made to be used as a wearable device to measure body movements. EXLs3 is an inertial sensor which includes 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer and a Bluetooth connection to send the collected data to a computer [43]. The adjustable sampling rate of the unit can go up to 200 Hz. The unit is also equipped with 1 GB flash memory for data storage.

Figure 3.3: EXLs3 inertial measurement unit.

3.4. Comparison of Gear S and EXL Sensor

To ensure that the usage of a smartwatch instead of an inertial measurement unit is acceptable, we carry out some experiments using both devices at the same time and analyze the collected data on the parallel. The sampling rate of Gear S2 accelerometer is 20 Hz on the average while the EXL sensor has a capability to collect data up to 200 Hz. We set the sampling rate of the EXL sensor to 100 Hz for comparison which is a typical value used in the experiments.

We perform some daily life activities while wearing Gear S and EXL sensor unit on the same wrist to see how well Gear S and EXL sensor units record acceleration data. The data recordings for the activities of raising the arm in Figure 3.4 and taking and putting an object multiple times in Figure 3.5 can be seen. As observed from the visualization of signals gathered from Gear S2 and EXL, both devices are capable of catching crucial patterns of the movements.

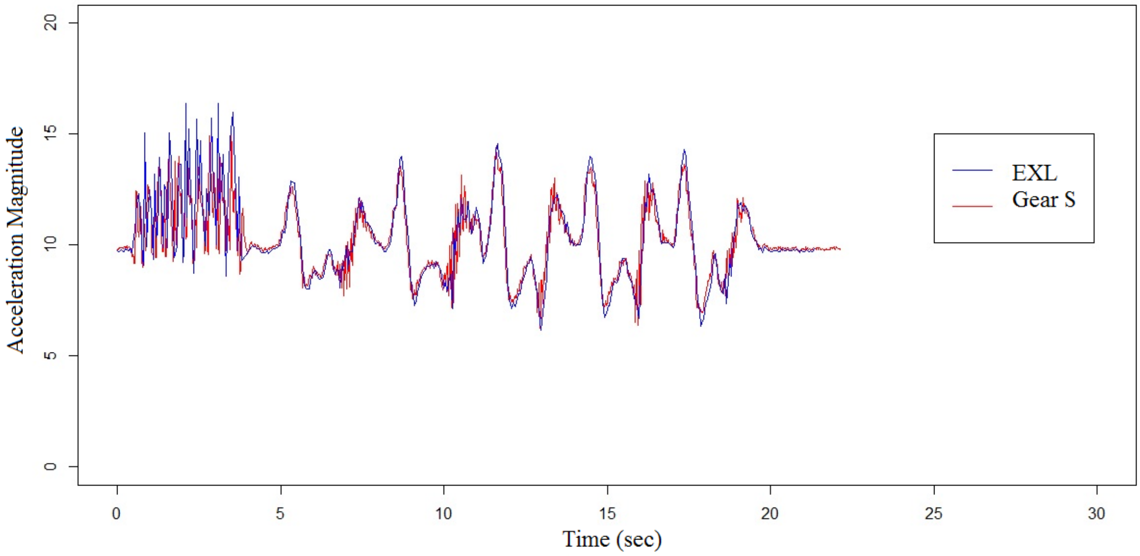


Figure 3.4: Comparison of Gear S and EXL while raising the arm multiple times.

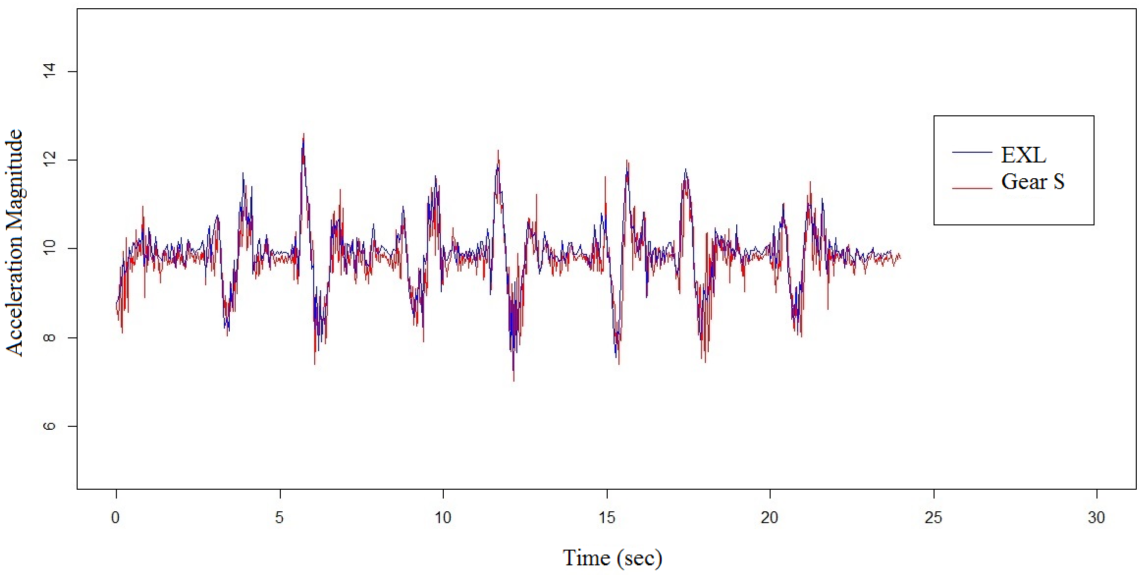


Figure 3.5: Comparison of Gear S and EXL while taking and putting an object multiple times.

4. SMARTWATCH BASED GAIT ANALYSIS SYSTEM

In this part, general information about data collection procedure, preprocessing operations including the signal filtering and determining the step windows using the peak detection algorithm is explained. After the detection of step events, feature extraction and selection procedures are applied. Then, the data is analyzed to fit a regression model. The flow chart for the system design is presented in Figure 4.1.

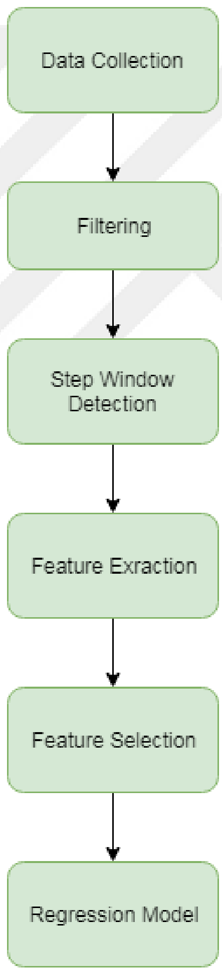


Figure 4.1: System design for gait analysis with smartwatches.

4.1. Data Collection

Patterns of acceleration signal differ according to the placements of the sensor unit. In order to improve the performance of the gait analysis system, it is usually mounted on foot or leg because these positions are directly related with the gait cycle [44]. However, since our aim is to examine the convenience of a hand-held device which is smartwatch in this work for gait analysis, we use two Samsung Gear S2 smartwatches mounted on the both wrists of subjects.

The data is collected from 26 healthy participants 11 female and 15 male ages range from 23 to 58 in hospital settings. Table 4.1 gives the general information about the all subjects who attended the experiments. The data collection is held along an instrumented pathway of 5 m during the gait analysis of a clinician. Subjects are asked to walk on this gait way and return back to the starting position, i.e., the distance covered is 10 m for each person. For the ground truth, clinician's assessment supported by a camera based reference system is used.

The sampling frequency of smartwatches is around 20 Hz. To detect the walking part easily from the raw data, subjects are asked to clap 3 times before and after the gait analysis. The data is collected from available sensors of the smartwatch which are the acceleration data with the effect of gravity removed and the gyroscope data.

4.2. Data Preprocessing

4.2.1. Filtering

The main goal of this phase is to remove the noise from the raw data to reach more accurate results in the next phases. Within this scope 1st-order low-pass Butterworth filter with a cutoff frequency of 3 Hz, which, for data sampled at 20 Hz, corresponds to 0.3π rad/sample is used to filter the raw accelerometer sensor data. In Figure 4.2 and Figure 4.3, the acceleration magnitude is shown before and after applying the low-pass filter.

Table 4.1: Information about the subjects.

ID	Gender	Age	Height (m)	Average Step Size (cm)	Dominant Hand
1	Male	54	1.81	59.9	Right
2	Female	27	1.66	61.3	Right
3	Male	23	1.67	62.5	Right
4	Female	51	1.55	57.2	Right
5	Male	58	1.71	68.1	Left
6	Female	28	1.56	52.2	Right
7	Female	32	1.64	55.4	Right
8	Male	36	1.75	62.7	Right
9	Male	51	1.79	77.9	Right
10	Male	32	1.70	53.8	Right
11	Male	43	1.82	62.3	Left
12	Male	45	1.70	59.6	Right
13	Female	53	1.75	64.3	Right
14	Female	30	1.55	63.5	Right
15	Male	25	1.80	56.9	Right
16	Female	28	1.68	70.8	Right
17	Male	33	1.71	58.6	Right
18	Male	36	1.75	62.4	Right
19	Female	28	1.56	53.3	Right
20	Female	28	1.64	50.6	Right
21	Male	55	1.75	55.2	Right
22	Female	49	1.71	68.9	Right
23	Female	43	1.74	55.7	Right
24	Male	25	1.77	57.1	Right
25	Male	24	1.87	53.8	Right
26	Male	24	1.71	60.5	Right

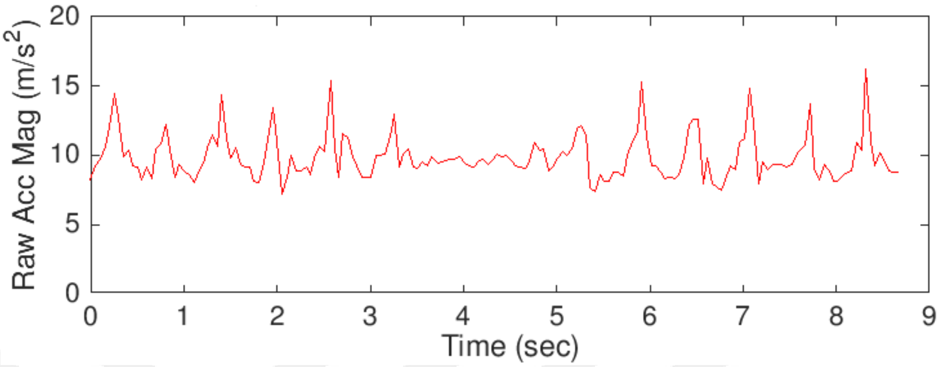


Figure 4.2: Raw acceleration magnitude data.

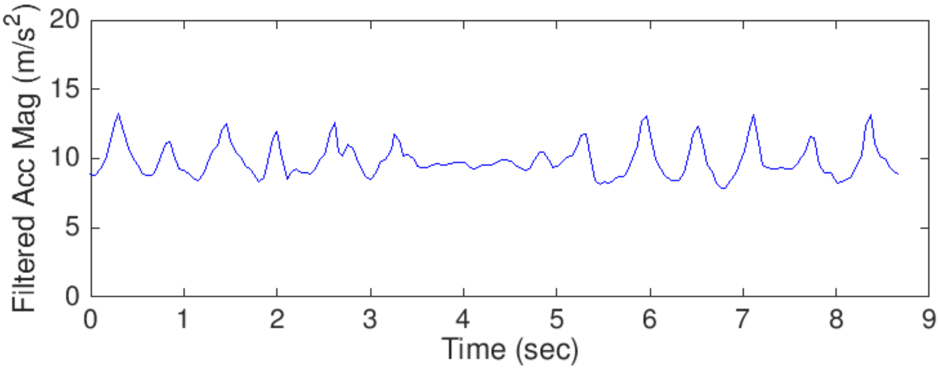


Figure 4.3: Low-pass filtered acceleration magnitude data.

4.2.2. Step Event Detection

Arm swing during the human gait produces periodic peaks in the signal recorded by the accelerometer mounted on the wrist. The analysis of the accelerometer signal in the time domain enables to capture this periodicity. By exploiting this fact, gait events is usually detected by using a peak detection algorithm [28, 45]. Hidden Markov models (HMM) are also used for this task and reach good accuracy [46].

When the sensors are mounted on the foot of a subject, the step detection is applied easily by detecting zero-velocity periods corresponding to the stance phase of the foot. Since the inertial sensors are located on the wrists in our study, zero-velocity periods cannot be observed. However, biomechanical studies have shown that foot motion and swinging of the arm have a synchronization [47]. With the help of this relation between arm and foot movements, step events are detected by analyzing periodic arm movements of subjects.

After extracting the gait analysis signals from inertial measurements and filtering, a peak detection algorithm is used to determine gait cycles, i.e., steps from the magnitude of the accelerometer signal. Since the analysis includes a turning phase, there is a part which the periodic subsequent valley appearance distorted. These parts are separated for the turning phase. Also similar to the related works, since the first and last few steps have different characteristics in terms of dynamics of the gait process, these steps are excluded for the data analysis part. As a consequence, 242 step windows are acquired to analyze in the next phases of the study. Examples for the detected step windows and the turning phase is shown in Figure 4.4

4.2.3. Feature Extraction

To perform analysis with various machine learning techniques a set of features should be extracted. The collected data includes signals from accelerometer and gyroscope sensors in three axes X, Y, and Z. Since we are interested in spatio-temporal gait parameters for each cycle one by one, the feature extraction procedure is applied

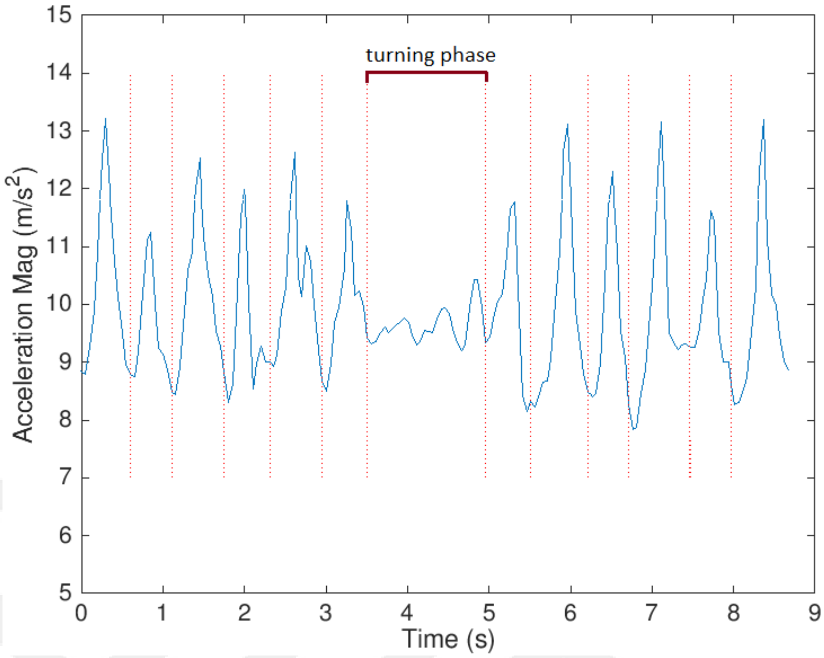


Figure 4.4: Detected step windows and turning phase in acceleration magnitude signal.

to each step window detected as explained in 4.2.2.

Since the magnitude of acceleration or gyroscope signal is a robust feature of the step and not to be affected by the orientation of the sensor unit, the magnitude is calculated as follows before starting the feature extraction.

$$magnitude = \sqrt{x^2 + y^2 + z^2}$$

The following features have been identified for the regression process:

- Minimum and maximum values for each axes X, Y, Z, and magnitude.
- Mean and variance values for each axes X, Y, Z, and magnitude.
- Energy of signal using FFT transform of the signal.
- Step frequency calculated by computing the inverse of step duration

During the data collection the subjects wore smartwatches in each wrists and we extract all features for both hands. As a result of the feature extraction process, we gather 35 features for each hand and 70 features in total.

4.2.4. Feature Selection

The feature selection has an important effect in the regression process and performance of the designed model. To improve the performance of regression models, irrelevant and redundant features have to be eliminated as much as possible. In the analysis part, since we try to fit a regression model to predict gait parameters including step length, swing time and stance time, features are separately selected for these output parameters.

4.2.4.1. Stepwise Feature Selection. In stepwise feature selection, all features extracted are consecutively added or removed during linear regression model fitting. To make a decision on adding or removing a feature, thresholds are determined by the user [48]. The process of determining the final optimal model is also called as forward and backward stepwise regression. Importance of each feature is represented by the p-values, and aforementioned thresholds used for including and excluding features are determined according to these p-values.

Average p-values for the selected features in our feature domain are presented for each parameter: step length, swing time and stance time in Tables 4.2, 4.3, and 4.4. Smaller p-value means the relevant feature is more significant. For the step length estimation, 13 features out of the 70 features are selected as shown in Table 4.2. For swing and stance times, the numbers of the selected features are six and four respectively as seen in Tables 4.3 and 4.4.

When we analyze the extracted features with the stepwise feature selection algorithm, for the step length estimation data gathered from the dominant hand which is the right one for all subjects except the two of them and their features are more significant. Also it can be asserted by analyzing gyroscope related features' p-values, this sensor data have more impact on calculating gait related metrics. The step frequency which is the inverse of the duration of step event has a significant effect on time related gait parameters including swing time and stance time.

Table 4.2: Selected features for step length estimation with stepwise feature selection and corresponding p-Values.

Feature	**p-value**
Min of Acc X for Left	2.226×10^{-2}
Max of Acc X for Left	1.2964×10^{-1}
Std of Acc X for Left	1.547×10^{-4}
Max of Gyro Z for Left	6.068×10^{-5}
Step Frequency	0.17112
Max of Acc X for Right	3.9107×10^{-2}
Mean of Acc X for Right	2.6307×10^{-2}
Max of Acc Y for Right	0.2232
Std of Acc Z for Right	5.228×10^{-5}
Mean of Gyro X for Right	8.272×10^{-3}
Min of Gyro Y for Right	3.025×10^{-10}
Mean of Gyro Y for Right	4.081×10^{-5}
Std of Gyro Mag for Right	2.226×10^{-3}

4.2.4.2. Neighborhood Component Analysis. Neighborhood Component Analysis is an algorithm which resembles the k-nearest-neighbor (KNN) technique to select features with the aim of maximizing the prediction accuracy of regression [49]. This algorithm learns a distance metric by maximizing the leave-one-out cross validation technique.

Table 4.3: Selected features for stance time estimation with stepwise feature selection and corresponding p-Values.

Feature	**p-value**
Max of Acc Y for Left	2.435×10^{-2}
Energy of Acc Mag for Left	6.422×10^{-6}
Step Frequency	5.869×10^{-11}
Min of Gyro X for Right	1.219×10^{-3}
Max of Gyro Z for Right	4.081×10^{-5}
Std of Gyro Mag for Right	1.919×10^{-8}

Table 4.4: Selected features for swing time estimation with stepwise feature selection and corresponding p-Values.

Feature	**p-value**
Max of Acc Y for Left	5.522×10^{-4}
Min of Gyro Z for Left	4.866×10^{-3}
Step Frequency	1.621×10^{-5}
Max of Gyro Z for Right	8.837×10^{-3}

Parameters of a neighborhood component analysis (NCA), i.e., feature weights to be used in the analysis calculated for the step length are presented in Table 4.5.

Table 4.5: Selected features for step length estimation with neighborhood component analysis and feature weights.

Feature	**Weight**
Max of Acc X for Left	5.88
Mean of Acc X for Left	3.14
Max of Acc Y for Left	5.89
Mean of Acc Y for Left	2.29
Mean of Gyro X for Left	4.87
Min of Gyro Y for Left	4.60
Max of Gyro Y for Left	1.04
Mean of Gyro Y for Left	5.82
Mean of Gyro Z for Left	6.96
Energy of Gyro Mag Left	3.25
Min of Gyro X for Right	4.57
Max of Gyro Y for Right	2.53
Mean of Gyro Z for Right	5.49
Energy of Acc Mag Right	5.69
Energy of Gyro Mag Right	2.89

5. ANALYSIS AND RESULTS

In this part of the thesis, various regression algorithms are tested and reported to estimate ground truth data for gait parameters mainly step length, swing time and stance time using features extracted and selected in Sections 4.2.3, 4.2.4 and raw sensor data for each step window. Since the system shows better performance with the selected feature set which is acquired by using the stepwise feature selection algorithm, we will use this set to present the results of the analyses for the selected features. Firstly, we try to fit feature data on four different regression models including Linear Regression (LR), Gaussian Process Regression (GPR), Support Vector Machine (SVM) regression and Regression Tree. Secondly, models based on a neural network architecture consisting of Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) are experimented to estimate the gait metrics.

General information about the exploited regression models, architectures, experiments held to find the three main gait parameters and their results are presented in the following sections. Overview of the analysis procedure can be seen in Figure 5.1.

5.1. Machine Learning Models

Machine learning is a set of algorithms for learning applications to make predictions more accurately without being explicitly programmed but by exploiting example data [50]. In this section, results for the regression models consisting of Linear Regression (LR), Gaussian Process Regression (GPR), Support Vector Machine (SVM) regression and Regression Tree are presented.

We try to fit the data with selected features and also with all features to see the effect of feature selection. Since our data is limited as 242 step windows, we try to analyze the model with 5-fold-cross-validation. In 5-fold-cross-validation, the data is partitioned into five folds, and for each fold, the model is trained with the out-of-fold data. After the training, the performance of the model is assessed using the in-fold

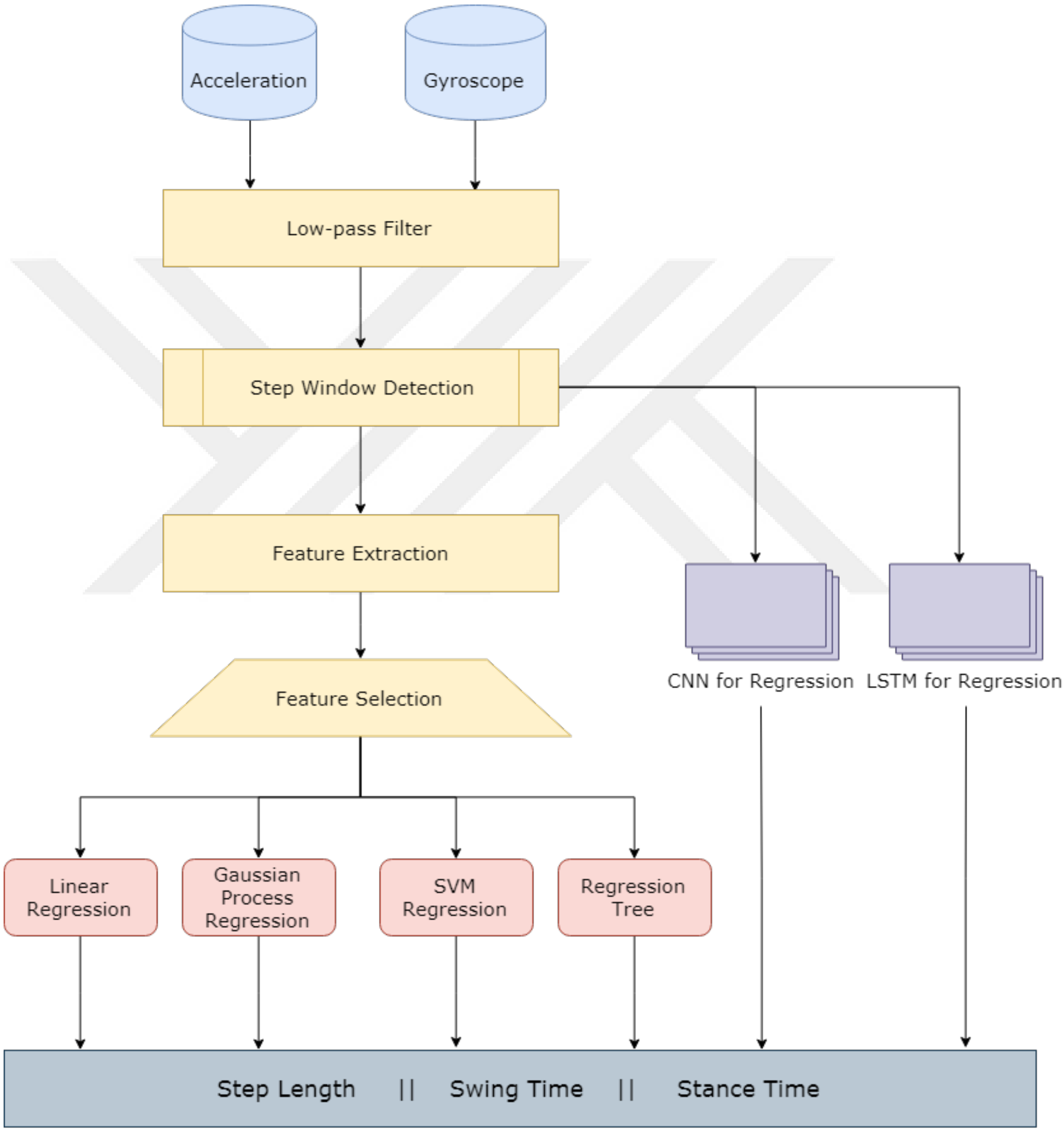


Figure 5.1: System design for gait analysis with smartwatches.

data.

Mean Squared Error (MSE), Mean Absolute Error (MAE), R-Squared Error and Root Mean Squared Error (RMSE) are the metrics used to validate and compare the models. Brief information about the used error metrics is also given in this section.

- *Mean Squared Error (MSE):* It measures the averaged squared error between the targeted value and the prediction by calculating the squared difference between them. It is defined by the following equation where $\hat{y_i}$ is the model's prediction:

$$MSE = \frac{1}{N}\Sigma_{i=1}^{N}\Big(y_i - \hat{y_i}\Big)^2$$

- *Root Mean Squared Error (RMSE):* It is the square root of MSE. The square root helps to make scale of the errors to be the same as the scale of actual values. It is calculated as:

$$RMSE = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}\Big(y_i - \hat{y_i}\Big)^2}$$

- *Mean Absolute Error (MAE):* In this metric, the error is calculated as a mean of absolute differences between the target values and the estimations. The MAE is a linear score indicating weighted average error of all the pairs of output and prediction mathematically, it is calculated using this formula:

$$MAE = \frac{1}{N}\Sigma_{i=1}^{N}|y_i - \hat{y_i}|^2$$

- *R Squared (R^2) Error:* The R^2 also known as coefficient of determination, is another metric used in evaluating a model. The main advantage of R^2 is being scale free and not depending on the range of target values, it always takes values between $-\infty$ and 1. Negative values of R^2 means the model is worse than the estimated mean. The equation of the metric is given below.

$$R^2 = \frac{MSE(model)}{MSE(baseline)}$$

The MSE of the baseline is defined as:

$$MSE(baseline) = \frac{1}{N}\Sigma_{i=1}^{N}(y_i - \bar{y_i})$$

where the $\bar{y_i}$ means the average of the observed y_i. Values close to 1 means that the model performs well and the error is close to zero.

5.1.1. Linear Regression

Linear regression is a method to find linear relationship between response and one or more predictors. Models are easy to interpret and fast in making predictions. Equations expressing the relationship between the target and a set of predictors indicate whether an empirical relationship exists between variables or not [51].

We try to fit our featured data to estimate the step length, swing and stance times determined by the clinician during the gait analysis.

- *Step Length:* The results of the LR model are presented in Table 5.1. The RMSE value is found as 7.77 cm for the step length with all features while the RMSE of the model with the selected features is calculated as 5.68 cm. R^2 value for the selected feature set is 0.28. This value is larger than the result of all feature set. It means that the model with the selected features works better for the step length estimation.
- *Swing Time:* The results of the LR model with all and the selected features set are presented in Table 5.2. The RMSE value for predicting swing time with all features is found as $8.77x10^2$ sec while it is calculated as $5.02x10^2$ sec with the selected feature set. It can be concluded that the model performs better with the

Table 5.1: Results of Linear Regression model for Step Length (cm) with all and selected features.

LR	RMSE	R-Squared	MSE	MAE
All Features	7.77	-0.35	60.41	5.85
Selected Features	5.68	0.28	32.22	4.50

selected features.

Table 5.2: Results of Linear Regression model for Swing Time (sec) with all and selected features.

LR	RMSE	R-Squared	MSE	MAE
All Features	8.77×10^{-2}	-1.15	7.70×10^{-3}	5.63×10^{-2}
Selected Features	5.02×10^{-2}	0.30	2.52×10^{-3}	4.05×10^{-2}

- *Stance Time:* For this metric, the results are shown in Table 5.3. Similar to the other two metrics, the performance of the model with the selected features is better for the stance time estimation. The RMSE value with all features is found as $12.65x10^2$ sec while it is calculated as $9.33x10^2$ sec with the selected feature set.

Table 5.3: Results of Linear Regression model for Stance Time (sec) with all and selected features.

LR	RMSE	R-Squared	MSE	MAE
All Features	12.65×10^{-2}	-0.16	15.99×10^{-3}	9.46×10^{-2}
Selected Features	9.33×10^{-2}	0.37	8.71×10^{-3}	6.78×10^{-2}

5.1.2. Gaussian Process Regression

Gaussian process regression (GPR) models are kernel based probabilistic models. They broaden multivariate Gaussian distributions to infinite dimensions. GPR is a non-parametric regression model such that the original data is used as a pier for creating a regression function as different from the parametric models in which the training data may be discarded after regression weights are obtained [52]. Estimations are held by comparing the distance between the training data points and test data point. Non-parametric models assume that data points which have the similar output values are close to each other in the data space. In this part of analysis, we create a GPR regressor with an exponential kernel function.

- *Step Length:* The results of the GPR model are presented in Table 5.4. The RMSE value is found as 5.53 cm for the step length with all features while the RMSE of the model with the selected features is calculated as 5.29 cm. The difference between the all and the selected feature sets is not that significant as in the LR model experiments. The R^2 value for the selected feature set is 0.37. This value is larger than the R^2 value of all feature set and the R^2 value of the previous model. It can be asserted that the GPR model with the selected features works better for the step length estimation.

Table 5.4: Results of Gaussian Process Regression model for Step Length with all and selected features.

GPR	RMSE	R-Squared	MSE	MAE
All Features	5.53	0.32	30.56	4.28
Selected Features	5.29	0.37	28.03	4.02

- *Swing Time:* The results of the GPR model with all and the selected features set are presented in Table 5.5. The RMSE value for predicting swing time with all features is found as $4.80x10^2$ sec while it is calculated as $4.89x10^2$ sec with the selected feature set. For the stance time estimation, the model performs slightly better with all features.

Table 5.5: Results of Gaussian Process Regression model for Swing Time (sec) with all and selected features.

GPR	RMSE	R-Squared	MSE	MAE
All Features	4.80×10^{-2}	0.36	2.31×10^{-3}	3.87×10^{-2}
Selected Features	4.89×10^{-2}	0.33	2.39×10^{-3}	3.96×10^{-2}

- *Stance Time:* For this metric, the results are shown in Table 5.6. Similar to the step length estimation results, the performance of the model with the selected features is better for the stance time estimation. The RMSE value with all features is found as $9.24x10^2$ sec while it is calculated as $8.78x10^2$ sec with the selected feature set. The GPR model shows better performance than the previous LR model for stance time prediction.

Table 5.6: Results of Gaussian Process Regression model for Stance Time (sec) with all and selected features.

GPR	RMSE	R-Squared	MSE	MAE
All Features	9.24×10^{-2}	0.38	8.54×10^{-3}	6.80×10^{-2}
Selected Features	8.78×10^{-2}	0.44	7.71×10^{-3}	6.57×10^{-2}

5.1.3. SVM Regression

Support Vector Machine (SVM) models are very popular tools in machine learning for both classification and regression. They are also non-parametric similar to the GPR mentioned in the previous subsection and depend on kernel functions. They are mainly based on trying to find hyperplanes helping to predict the continuous target value while maximizing the margin and minimizing the error [53]. We try different kernel functions and observed that the Gaussian kernel function gives the best prediction results.

- *Step Length:* The results of the SVM model are presented in Table 5.7 for the step length estimation. The RMSE value is found as 5.79 cm for the step length with all features while the RMSE of the model with the selected features is calculated as 5.46 cm. The difference between the all and the selected feature sets is not quite big similar to the GPR model but the system shows better performance with the selected features. The R^2 value for the selected feature set is 0.33. This value is found as 0.25 for the SVM model with all feature set. Depending on the R^2 values, we can say that using the selected features gives better performance for predicting the step length.

Table 5.7: Results of SVM Regression model for Step Length with all and selected features.

SVM	**RMSE**	**R-Squared**	**MSE**	**MAE**
All Features	5.79	0.25	33.56	4.55
Selected Features	5.46	0.33	29.85	4.23

- *Swing Time:* The results of the SVM model with all and the selected features set are presented in Table 5.8. The RMSE value for predicting swing time with all features is found as $4.98x10^2$ sec while it is calculated as $5.11x10^2$ sec with the selected feature set. For the stance time estimation, the model performs slightly better with using all features. Comparing the previous GPR model, the results are close to each other but the performance of the GPR model is better.
- *Stance Time:* For this metric, the results are shown in Table 5.9. Similar to the step length estimation results, the performance of the model with the selected features is better for the stance time estimation. The RMSE value with all features is found as $9.78x10^2$ sec while it is calculated as $9.18x10^2$ sec with the selected feature set. The SVM model shows similar performance with the GPR

Table 5.8: Results of SVM Regression model for Swing Time (sec) with all and selected features.

SVM	RMSE	R-Squared	MSE	MAE
All Features	4.98×10^{-2}	0.31	2.48×10^{-3}	4.01×10^{-2}
Selected Features	5.11×10^{-2}	0.27	2.60×10^{-3}	4.11×10^{-2}

model for stance time estimation but the latter one works better. The R^2 value for the selected feature set is 0.39 while it is calculated as 0.30 for all features. It also shows that the model fits the data in a better way with the selected features.

Table 5.9: Results of SVM Regression model for Stance Time (sec) with all and selected features.

SVM	RMSE	R-Squared	MSE	MAE
All Features	9.78×10^{-2}	0.30	9.57×10^{-3}	6.82×10^{-2}
Selected Features	9.18×10^{-2}	0.39	8.42×10^{-3}	6.61×10^{-2}

5.1.4. Tree Regression

The tree is the kind of a nonlinear predictive model in machine learning with two varieties which are regression tree and classification tree. Prediction trees basically create a tree structure to make use of recursive partitions to represent data partitions. In this technique, leaf nodes contain the actual data points and internal nodes represent the decision architecture. Since the mechanism is convenient to understand and interpret, the structure is widespread in the machine learning field [54].

We create a coarse tree with the minimum leaf size 36 to fit our featured data to estimate step length, swing time and stance time metrics.

- *Step Length:* The results of the Tree Regression model are presented in Table 5.10 for the step length estimation. The RMSE value is found as 6.23 cm for the step length with all features while the RMSE of the model with the selected features is calculated as 6.58 cm. As different to the previous models' performance on step length prediction, tree model shows better performance with all features. The R^2 value also shows the tree regression model works better with the all feature set. It is calculated as 0.13 for all features while it is 0.03 for the selected feature set.

Table 5.10: Results of Tree Regression model for Step Length with all and selected features.

Tree Regression	RMSE	R-Squared	MSE	MAE
All Features	6.23	0.13	38.91	4.92
Selected Features	6.58	0.03	43.27	5.19

- *Swing Time:* The results of the TR model with all and the selected features set are presented in Table 5.11. The RMSE value for predicting swing time with all features is found as $5.71x10^2$ sec while it is calculated as $5.56x10^2$ sec with the selected feature set. For the stance time estimation, the model performs slightly better with using the selected features.

Table 5.11: Results of Tree Regression model for Swing Time (sec) with all and selected features.

Tree Regression	RMSE	R-Squared	MSE	MAE
All Features	5.71×10^{-2}	0.09	3.26×10^{-3}	4.72×10^{-2}
Selected Features	5.56×10^{-2}	0.14	3.09×10^{-3}	4.62×10^{-2}

- *Stance Time:* For this metric, the results are shown in Table 5.12. Similar to the swing time estimation results, the performance of the model with the selected features is better for the stance time estimation. The RMSE value with all features is found as $11.52x10^2$ sec while it is calculated as $10.69x10^2$ sec with the selected feature set. The R^2 value for the selected feature set is 0.17 while it is calculated as 0.03 for all features. It also shows that the model fits the data better with the selected features. However, TR model shows the worst performance when we compare it with previous three models for all metrics.

Table 5.12: Results of Tree Regression model for Stance Time (sec) with all and selected features.

Tree Regression	RMSE	R-Squared	MSE	MAE
All Features	11.52×10^{-2}	0.03	13.27×10^{-3}	8.87×10^{-2}
Selected Features	10.69×10^{-2}	0.17	11.42×10^{-3}	8.09×10^{-2}

5.1.5. Discussion

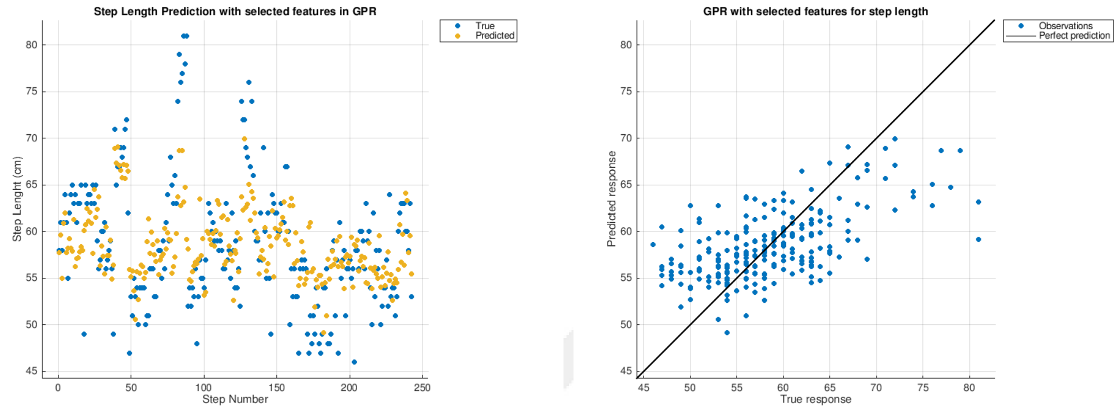
All models are tested to fit the extracted features with ground truth data. We use two different feature sets during experiments including all features and selected features. Comparing all regression models experimented, it is observed that the Gaussian Process Regression (GPR) model gives the best results for all three gait parameters step length, swing time and stance time. For all three metrics, response plots including predicted and true data points, and plots of predicted vs. actual data points for the GPR model is presented in Figures 5.2,5.3, and 5.4. In these figures, it can be seen that the system has difficulty on predicting the high value outlier data points. Generally for each of the three metrics, the model predict lower values for these high value outliers. Another critic observation is that models give better results with selected features meaning that the feature selection algorithm improves the performance.

Since the RMSE metric has the same scale as true values, we first examine its values. For the step length, as it can be seen from Table 5.13 GPR model's RMSE value is calculated as 5.29 cm, it means that we can estimate the step length of subjects with approximately 5.29 cm error. The highest value for R^2 metric which is 0.37 belongs to the GPR model reminding that R^2 values close to 1 means more success in prediction. In MSE and MAE metrics, similar to the RMSE, the minimum error values belong to the GPR model. The second most successful model is SVM and its error values are closer to the GPR values when compared with the other two models. Tree model performs worse than the other models. According to our tests, we say that the tree model is not appropriate to estimate the step length gait parameter with the selected feature set.

Table 5.13: Results of All Regression models for Step Length (cm) with selected features.

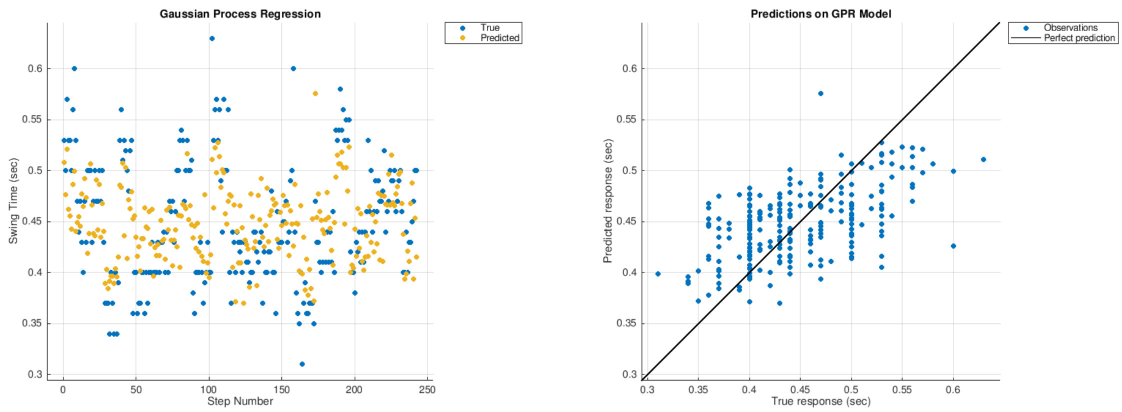
Model	**RMSE**	**R-Squared**	**MSE**	**MAE**
LR	5.68	0.28	32.22	4.50
GPR	5.29	0.37	28.03	4.02
SVM	5.46	0.33	29.85	4.23
TR	6.58	0.03	43.27	5.19

Other gait parameters which are swing time and stance time, we get very similar results to the step length metric as presented in Table 5.14 and Table 5.15. GPR is the most successful model for both gait metrics with minimum RMSE scores which are 4.89×10^{-2} and 8.78×10^{-3} respectively. The system explicitly estimates swing time better, by analyzing this consequence it can be asserted that the hand-held device is more convenient to measure the swing time than the stance time. Regression tree again has the worst performance for predicting both gait parameters.



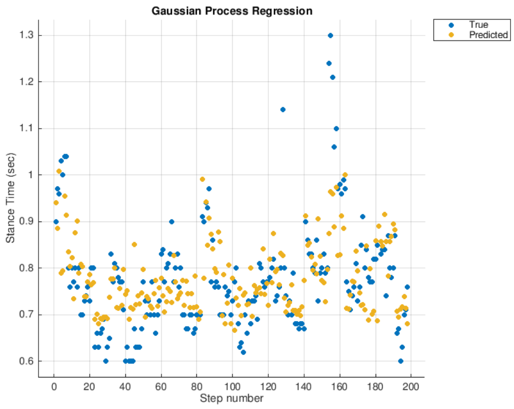
(a) Response plot for step lengths. (b) Predicted vs. Actual step lengths.

Figure 5.2: Response and Correlation plots of the GPR model for step length estimation with selected features.

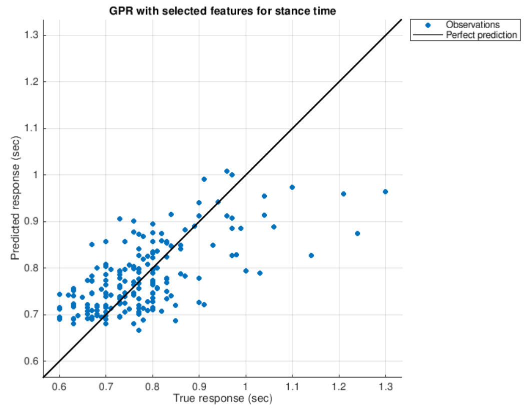


(a) Response plot for swing time. (b) Predicted vs. Actual swing time.

Figure 5.3: Response and Correlation plots of the GPR model for swing time estimation with selected features.



(a) Response plot for stance time.



(b) Predicted vs. Actual stance time.

Figure 5.4: Response and Correlation plots of the GPR model for stance time estimation with selected features.

Table 5.14: Results of All Regression models for Swing Time (sec) with selected features.

Model	**RMSE**	**R-Squared**	**MSE**	**MAE**
LR	5.02×10^{-2}	0.30	2.52×10^{-3}	4.05×10^{-2}
GPR	4.89×10^{-2}	0.33	2.39×10^{-3}	3.96×10^{-2}
SVM	5.11×10^{-2}	0.27	2.60×10^{-3}	4.11×10^{-2}
TR	5.56×10^{-2}	0.14	3.09×10^{-3}	4.62×10^{-2}

Table 5.15: Results of All Regression models for Stance Time (sec) with selected features.

Model	RMSE	R-Squared	MSE	MAE
LR	9.33×10^{-2}	0.37	8.71×10^{-3}	6.78×10^{-2}
GPR	8.78×10^{-2}	0.44	7.71×10^{-3}	6.57×10^{-2}
SVM	9.18×10^{-2}	0.39	8.42×10^{-3}	6.61×10^{-2}
TR	10.69×10^{-2}	0.17	11.42×10^{-3}	8.09×10^{-2}

5.2. Artificial Neural Network Models

In today's world, neural networks become one of the most popular machine learning algorithms. Artificial Neural Networks (ANN) are the systems inspired by the biological neural networks that enable computational devices to learn from observational data [55]. ANN systems work without being programmed explicitly with any condition specific to the task, they learn to perform assignments based on examples.

ANN consists of input and output layers, and hidden layers between them. Units in the hidden layer transform the data coming from the input layer into a specific data format depending on the application that the output layer can use. In this way, the system learns the complex patterns of the input and will be able to solve similar transforming problems without knowing the target.

Neural networks have various types of algorithms. In this study, we exploit from two different versions of ANN which are Convolutional Neural Networks (CNN) and Long Short-Term Memory Network (LSTM).

Input data format is the same for both CNN and LSTM models. Raw input data from smartwatch sensors located on both wrists is used as a matrix. For each step window extracted, acceleration and gyroscope sensor data is available for all three axes X, Y, and Z. Content for the rows of input matrix is as given below.

- Acceleration data in X, Y, Z axes from left hand.
- Gyroscope data in X, Y, Z axes from left hand.
- Acceleration data in X, Y, Z axes from right hand.
- Gyroscope data in X, Y, Z axes from right hand.

Since the sampling frequency of the watch is 20 Hz, these 12 input features are measured 20 times in a second. We create an input matrix for each and every step window. It means that the number of columns depends on the length or duration of a step and change from step to step. The variance in the column dimension of the input reveals some problems in training and testing mentioned models. However, useful techniques from the literature are exploited to overcome such difficulties.

Moreover, we separate the data into three parts 60% for training, 20% for validation and 20% for testing. Since our data is limited, we run the algorithm and train systems five times and each time data is separated randomly into three parts. Results are reported as the average of five trials and tests.

5.2.1. Convolutional Neural Networks

A convolutional neural network (CNN) is a type of artificial neural network to learn a task from data. CNN is used mostly in the areas including image processing and natural language processing. A CNN also consists of input, output layers, and one or multiple hidden layers between them. The hidden layers generally include a convolutional layer, an activation function layer, i.e., ReLU, a pooling layer, a normalization layer and a fully connected layer [56]. In this part of the experiments, we create a CNN for regression of gait parameters step length, swing time and stance time by using the raw sensor data coming from accelerometer and gyroscope of the smartwatches mounted on both hands. As mentioned in the introduction of this section, our input data consists of the matrix including raw sensor data for each step. A CNN takes inputs in which all have the same dimensions both vertically and horizontally. However, the length of each step or the number of columns in our input matrices is not the same for all of them. Therefore, we apply zero-padding to the inputs which have less than 18 columns. Padding is performed as adding zero-valued columns to both right and left side of the input matrix to reach 18 columns as in Figure 5.5. As a result of this operation, each input matrix has dimensions of [12 18].

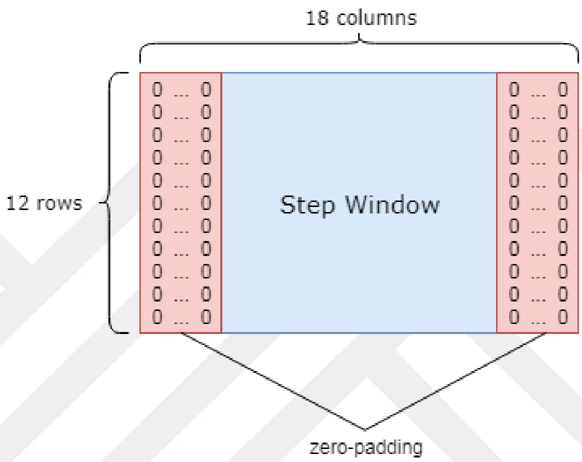


Figure 5.5: Applying zero-padding to the input matrix.

The general architecture of the created CNN can be seen in Figure 5.6. The number of the layers including the hidden layers which are convolution, batch normalization and activation and also the flow of the CNN architecture is shown in Figure 5.7 while the details for the layers of the network are presented in Figure 5.16.

We normalize each input column to a length of 1 to improve the performance of the network for estimation of the gait parameters. To give information about the training progress of the CNN regression model, we plot one run of training process for the step length as an example in Figure 5.8. Each run has 30 epochs, the initial learning rate is 0.001 and it drops to 0.0001 after the 20th epoch. After the 10th epoch, the model almost converges to minimum RMSE value and it starts to decrease slower until the end of training process. The final RMSE value is found as 7.46×10^{-2} m which equals to 7.46 cm for this run.

ANALYSIS RESULT

↑	Name	Type	Activations
1	SensorInput 12x18x1 images with 'zerocenter' normalization	Image Input	12×18×1
2	conv_1 8 3x3x1 convolutions with stride [1 1] and padding 'same'	Convolution	12×18×8
3	batchnorm_1 Batch normalization with 8 channels	Batch Normalization	12×18×8
4	relu_1 ReLU	ReLU	12×18×8
5	conv_2 16 3x3x8 convolutions with stride [1 1] and padding 'same'	Convolution	12×18×16
6	batchnorm_2 Batch normalization with 16 channels	Batch Normalization	12×18×16
7	relu_2 ReLU	ReLU	12×18×16
8	avgpool2d 2x2 average pooling with stride [2 2] and padding [0 0 0 0]	Average Pooling	6×9×16
9	conv_3 32 3x3x16 convolutions with stride [1 1] and padding 'same'	Convolution	6×9×32
10	batchnorm_3 Batch normalization with 32 channels	Batch Normalization	6×9×32
11	relu_3 ReLU	ReLU	6×9×32
12	conv_4 32 3x3x32 convolutions with stride [1 1] and padding 'same'	Convolution	6×9×32
13	batchnorm_4 Batch normalization with 32 channels	Batch Normalization	6×9×32
14	relu_4 ReLU	ReLU	6×9×32
15	fc 1 fully connected layer	Fully Connected	1×1×1
16	GaitParameter mean-squared-error	Regression Output	–

Table 5.16: Details for the layers of CNN architecture used in training to estimate gait parameters.

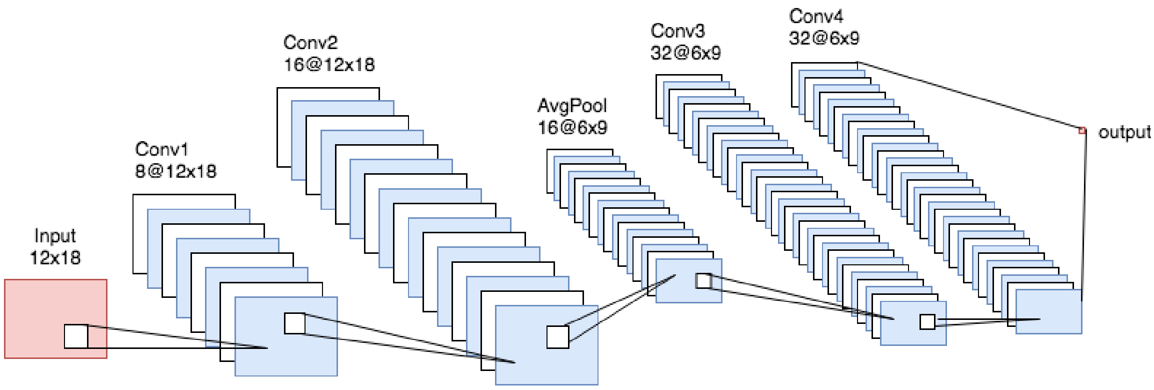


Figure 5.6: CNN architecture for regression used in training to estimate gait parameters.

Metrics used to validate the model consist of Mean Squared Error (MSE), Mean Absolute Error (MAE), R-Squared Error and Root Mean Squared Error (RMSE) similar to the previous analysis in Section 5.1. Average values of the error metrics calculated by five runs of the algorithm with randomly partitioned data are presented in Table 5.17.

Table 5.17: CNN regression model results on estimating Step Length (cm), Swing Time (sec), and Stance Time (sec).

Gait Metric	**RMSE**	**R-Squared**	**MSE**	**MAE**
Step Length	7.25	-0.19	52.56	7.28
Swing Time	7.34×10^{-2}	-0.77	5.8×10^{-3}	7.62×10^{-2}
Stance Time	11.5×10^{-2}	0.02	14.8×10^{-3}	12.17×10^{-2}

5.2.2. Long Short-Term Memory Network

Long short-term memory (LSTM) is another popular neural network type, it is based on the Recursive Neural Network architecture [57]. Different from the other types of neural networks, this architecture has feedback connections which enable to

Figure 5.7: Number of layers and the flow of the CNN architecture for regression used in training to estimate gait parameters.

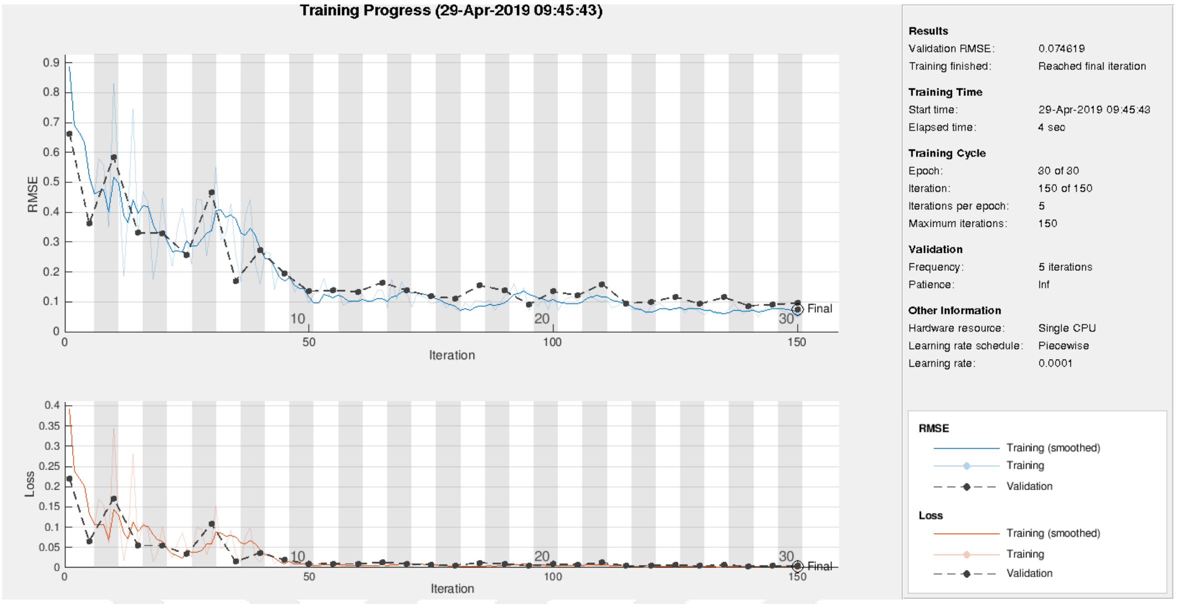


Figure 5.8: Training progress for step length estimation with CNN regression model.

learn the data consist of sequences in an efficient way. Since we have time series data, we decided to train an LSTM model to estimate the relevant gait parameters using raw sensor data.

Our input consists of 242 sequences/step windows of dimension 12 of varying length. During training, the data should be split into mini batches and the length of each sequence in the batch should be the same. Similar to the preprocessing phase of the CNN model to prepare the input data, we applied padding to improve the network performance. However, this time, we sort the data according to the lengths of sequences as in Figure 5.9 and apply padding such that mini batches have the same sequence length.

During training, by default, the software splits the training data into mini-batches and pads the sequences so that they have the same length. Too much padding can have a negative impact on the network performance. To prevent the training process from adding too much padding, the training data can be sorted according to the sequence length, and a mini-batch size can be chosen so that sequences in a mini-batch have a similar length. Figure 5.9 shows the sorted sequences before applying padding.

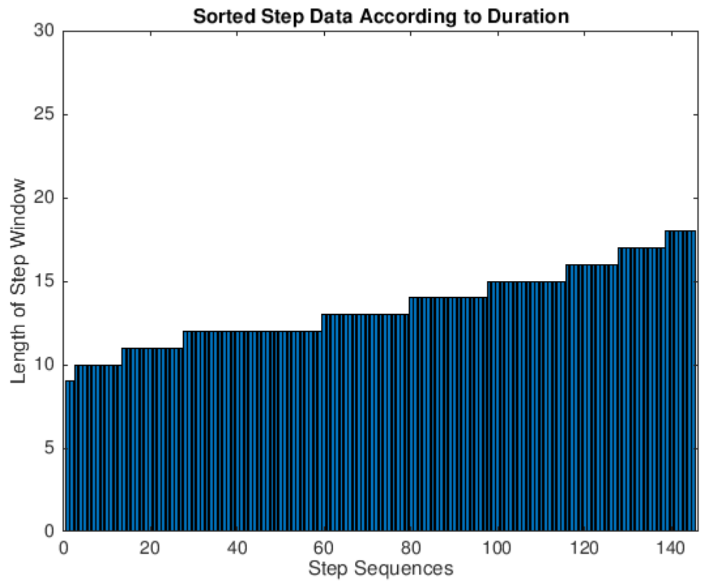


Figure 5.9: Sorted step sequences according to the length of step window.

The general architecture of the LSTM model can be seen in Figure 5.10. There is one hidden layer consists of 20 LSTM units while the input dimension is 12. The number of the layers in the network and the details of them are presented in Table 5.18.

	Name	Type	Activations
1	SensorInput Sequence input with 12 dimensions	Sequence Input	12
2	lstm LSTM with 20 hidden units	LSTM	20
3	fc 1 fully connected layer	Fully Connected	1
4	GaitParameter mean-squared-error	Regression Output	-

Table 5.18: Details for the layers of LSTM architecture used in training to estimate gait parameters.

We again split the data into three parts 60% for training, 20% for validation and 20% for testing and try to create a model and test it five times with randomly selected partitions. Similar to the CNN model, each input column is normalized to a length of 1 to improve the performance of the network for estimation of the gait metrics. One

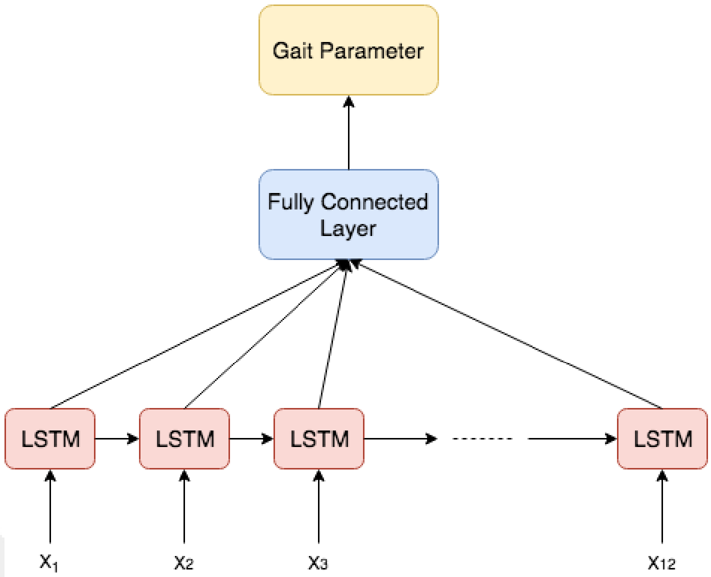


Figure 5.10: LSTM architecture for regression used in training to estimate gait parameters.

of the five runs of the training is plotted for the step length metric in Figure 5.11. Each run has 30 epochs, the learning rate is 0.001. After the 10th epoch, the model converges to minimum RMSE value and it starts to decrease slower until the end of training process.

To give information about the training progress of the LSTM regression model, we plot one run of training process for the step length as an example in Figure 5.11. Each run has 20 epochs, the learning rate is 0.001. After the 10th epoch, the model almost converges to minimum RMSE value and it starts to decrease slower until the end of training process, for this run it is calculated as 5.63×10^{-2} m which is 5.63 cm.

Average values of the error metrics used to validate the model including MSE, MAE, R^2 error and RMSE calculated from five times running of the algorithm with randomly partitioned data is presented in Table 5.19.

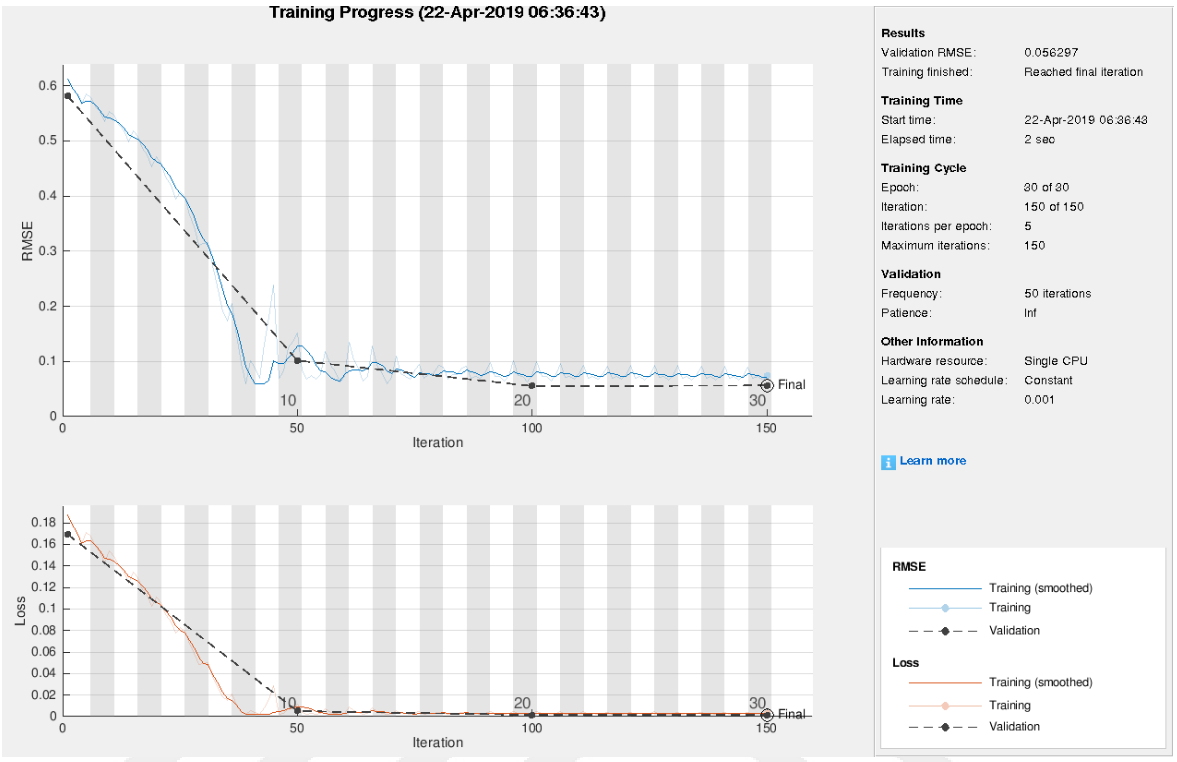


Figure 5.11: Training progress for step length estimation with LSTM regression model.

Table 5.19: LSTM regression model results on estimating Step Length (cm), Swing Time (sec), and Stance Time (sec).

Gait Metric	RMSE	R-Squared	MSE	MAE
Step Length	6.87	-0.11	47.19	7.0
Swing Time	6.56×10^{-2}	-0.21	4.3×10^{-3}	6.56×10^{-2}
Stance Time	15.16×10^{-2}	-0.58	24.5×10^{-3}	15.65×10^{-2}

5.2.3. Discussion

We experimented two neural network models CNN and LSTM to train a system able to predict the gait parameters. Input of the networks contains raw sensor data with 12 rows of features.

For the gait metrics including the step length and the swing time, the LSTM architecture gives better results by evaluating RMSE values as seen in Tables 5.20 and 5.21, i.e., LSTM can predict a step length with error 6.87 cm. Similarly other three metrics R^2, MSE and MAE also show that the performance of LSTM is more preferable.

However, when we evaluate the models in terms of the stance time estimation, the CNN has better performance. In Table 5.22, it can be observed that the CNN have the minimum value of error in all error metrics.

On the other hand, comparing the performance of the experimented machine learning (ML) algorithms for regression in Section 5.1 and neural network architectures CNN and LSTM, it can be asserted that all regression models LR, GPR, SVM and TR performs better in estimating all relevant gait parameters. The GPR model is almost twice as successful as ANN models for all gait metrics prediction. However, such a difference may result from the different measurement and evaluation techniques. In ML models, 5-fold-cross validation is used to measure the success of the system, on the other hand, we randomly shuffle the dataset and split it into three parts five times and take average of these five runs. Another reason for the variation of success in ML models and NN models can be the input set. Remembering Section 5.1 we exploited the feature set extracted and selected from raw data of each step window for ML models. However, in NN models input data consists of raw sensor data itself. Using the selected feature set may be more advantageous in terms of predicting gait metrics from hand-held sensor data. On the other hand, using the raw data needs fewer operations for preprocessing and may be advantageous in terms of the time spent. Moreover, the neural network architectures generally require a large amount of data for training but we have limited data. The performance of the networks can be improved by collecting more data in terms of the number of subjects and the duration of the gait analysis.

Table 5.20: Results for both CNN and LSTM regression models on estimating Step Length (cm).

Model	**RMSE**	**R-Squared**	**MSE**	**MAE**
CNN	7.25	-0.19	52.56	7.28
LSTM	6.87	-0.11	47.19	7.0

Table 5.21: Results for both CNN and LSTM regression models on estimating Swing Time (sec).

Model	**RMSE**	**R-Squared**	**MSE**	**MAE**
CNN	7.34×10^{-2}	-0.77	5.8×10^{-3}	7.62×10^{-2}
LSTM	6.56×10^{-2}	-0.21	4.3×10^{-3}	6.56×10^{-2}

To compare all the traditional regression models and the neural network models, in Table 5.23, the results for the RMSE values are presented for each gait parameter: step length, swing time and stance time. As seen from the table, the GPR model gives the best results for the estimation of all metrics. It is also observed that the traditional regression models performs better than the neural network models. Probably, the main reason for this situation is that the amount of data is not sufficient to train a deep learning model.

Table 5.22: Results for both CNN and LSTM regression models on estimating Stance Time (sec).

Model	RMSE	R-Squared	MSE	MAE
CNN	11.5×10^{-2}	0.02	14.8×10^{-3}	12.17×10^{-2}
LSTM	15.16×10^{-2}	-0.58	24.5×10^{-3}	15.65×10^{-2}

Table 5.23: Comparison of all regression models depending on RMSE value for estimating Step Length (cm), Swing Time (sec), and Stance Time (sec).

Model	Step Length (cm)	Swing Time (sec)	Stance Time (sec)
LR	5.68	5.02×10^{-2}	9.33×10^{-2}
GPR	5.29	4.89×10^{-2}	8.78×10^{-2}
SVM	5.46	5.11×10^{-2}	9.18×10^{-2}
TR	6.58	5.56×10^{-2}	10.69×10^{-2}
CNN	7.25	7.34×10^{-2}	11.5×10^{-2}
LSTM	6.87	6.56×10^{-2}	15.16×10^{-2}

5.3. Comparative Evaluation of Single and Double Smartwatch Based Systems

In this study, we use two smartwatches, one for each hand, during the data collection. However, in terms of the unobtrusiveness of the proposed system, using the two watches may be disadvantageous. To test the capability of the system with one smartwatch, we try to estimate the gait parameters with using the sensor data only coming from the smartwatch worn on the dominant hand of the subjects. We use the extracted and selected features belong to the dominant hand of each participant and evaluate the performance of the system.

The GPR model which gives the best results for the estimation of each gait parameter is used to compare the single and double smartwatch usages and the performance of these configurations are experimented for the three gait parameters. The results of the comparison is presented in Table 5.24. When we evaluate the outputs of the comparison, it can be said that the double smartwatch system is more successful than the single smartwatch based system in predicting the three gait parameters: step length, swing and stance times. However, the difference between the performances of the two systems is not quite big. Therefore, depending on the purpose of the application, the single smartwatch based system may be preferred and the higher error rate of the system can be tolerated for the sake of unobtrusiveness.

Table 5.24: Comparative evaluation of single and double smartwatch based systems on the GPR model.

Single or Double	Gait Metric	RMSE
Single	Step Length	6.11 cm
Double	Step Length	5.29 cm
Single	Swing Time	5.44×10^{-2} s
Double	Swing Time	4.89×10^{-2} s
Single	Stance Time	13.10×10^{-2} s
Double	Stance Time	8.78×10^{-2} s

6. CONCLUSION

In this study, different from the most of related works on focusing gait analysis, we examine the convenience of using a wrist-worn device which is smartwatch to perform gait analysis. Basic gait metrics including step length, swing time and stance time which enable to analyze main characteristics of the gait are tried to be extracted from the data collected using a smartwatch.

The data is collected from 26 healthy participants from different ages and gender in clinical settings. Subjects wore smartwatches on both hands during the analysis, the data is collected from two sensors embedded in the smartwatch accelerometer and gyroscope. The data is preprocessed and by detecting step windows, we try to extract relevant gait parameters for each step and compare them with our ground truth data coming from clinician's assessment.

In the vast majority of the gait analysis studies, sensor measurement units are located on the foot or leg, since the lower body placement is more sensitive to gait phases. However, we use a wrist-mounted device which is a smartwatch and it restricts us to use domain knowledge that may assist the inferences. Therefore, the main challenge of the study is the sensor placement. However, despite we have limited resources on collecting data in terms of the amount of data and number of the subjects, our gait analysis with a smartwatch gives promising results. Even if the results cannot reach the accuracy of the state of the art works using foot mounted sensors, for a wrist-worn device, they are encouraging for the extended future studies.

Unobtrusiveness and comfortability are the main advantages of the proposed gait analysis system. Thanks to these important features, gait analysis can be held in both indoor and outdoor environments conveniently. The proposed system gives a valuable opportunity to monitor the gait of subjects continuously without needing any clinical equipments and hospital settings. This convenience is quite critical especially for the people with neurological or orthopedic disorders in terms of the diagnosis of abnormality in a gait cycle which is a very important factor to check their course of disease.

In summary, smartwatches are quite promising devices for gait analysis and extracting main gait related parameters. Thanks to the high level of comfort they present, smartwatches can be used conveniently for gait analysis during the daily life. The proposed system can be improved in terms of the accuracy and the number of the gait metrics evaluated by collecting more data. The number of participants and the total distance walked on the instrumented pathway for each subject may be increased during the gait analysis. This will provide more data to train the existing models better. Especially for the neural network models, increasing the amount of data may have a significant improvement on estimation of the gait parameters. In this study, we tried to predict the three main gait parameters: step length, swing and stance times. In the future, further metrics also can be added to the gait analysis with a smartwatch, i.e., number of turning steps, duration of the turning phase, cadence, gait asymmetry, and velocity.

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