School of Civil & Mechanical Engineering

Human Gait Model Development for Objective Analysis of Pre/Post Gait Characteristics Following Lumbar Spine Surgery

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This thesis is presented for the Degree of

Doctor of Philosophy
of
Curtin University

December 2019

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Human Ethics The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007) – updated March 2014. The proposed research study received human research ethics approval from the Curtin University Human Research Ethics Committee (EC00262), Approval Number HR12/2016

Signature: ....

Date: ....20/09/2019..............................

Acknowledgements

It is my great pleasure to acknowledge those who have helped make this thesis possible. First, I would like to express my gratitude to my supervision team, Professor Tele Tan, Professor Iain Murray and Professor Gabriel Lee, for their advice, constant support and comments throughout the course of this research. I also thank them for the interest they have shown in this study and in my technical development. I am proud to have had them as my supervisors. I would also like to thank Dr Gurumoorthy, Dr Susan Morris, Dr Manora Caldera, Dr Azadeh Nazemi and Dr Nimsiri Abhayasinghe for their valuable assistance and support that have made my work stronger.

I would like to acknowledge Curtin University, St John of God Subiaco Hospital and Kailas foundation as the sponsors of my research project.

I would like to deeply thank all the participants in this research—this thesis would have been impossible without their participation and patience. I am also grateful to the staff and students of the School of Civil and Mechanical Engineering and the School of Electrical and Computer Engineering for their support.

I would not have been able to complete this research without the moral support, understanding and encouragement of my dearest family, especially my parents and my dear brother, Ali. I would also like to express my appreciation to my lovely friends and colleagues at Curtin University and Siemens Company.

Last but not least, I would like to express my deepest gratitude to my beloved husband, Afshin, for his endless help, support, motivation and understanding throughout the research period.

To my dearest in the world

My precious parents

My wonderful brother, Ali

My dear Afshin

Abstract

Walking ability is a key physical behaviour that strongly influences individuals' personal functioning and independence for the successful execution of their daily activities. Gait analysis is a systematic method to analyse human walking ability, which produces indices to describe the dynamics of the walk. Such analysis is essential for a broad range of clinical applications in the areas of orthopaedics, neurosurgery, rehabilitation and sports medicine. Therefore, it is necessary to assess the gait of individuals to identify a wide range of walking disorders in an objective, repeatable and accurate manner. This assessment would lead to improvements in diagnoses, treatments and recovery of gait.

Although multiple tools and methods are available for gait analysis, these are subject to various limitations. For instance, the most common method to evaluate walking gait in the clinical environment is visual inspection. This method, which relies on the visual ability, experience and judgement of medical practitioners, is highly subjective and prone to yield inaccurate assessments.

Optical motion capture systems are the *gold standard* for gait analysis because they provide highly accurate measurements. However, these systems are complex, expensive and laboratory-based methods with high utilisation time, which make them impractical for widespread application in the clinical environment.

The purpose of this thesis is to introduce a gait analysis system that overcomes these current limitations and simultaneously addresses clinical needs. The system will be used for early identification of the foot drop gait pattern with L5 origin, which is a common gait disorder.

The proposed methodology provides a gait analysis system based on inertial measurement units (IMUs) that is specifically designed for the intended application. The design principles of the system take the following into consideration: accuracy, portability, cost-efficiency and applicability in clinical settings.

Using this system, gait data were collected from two groups of participants. The first group consisted of patients experiencing foot drop with L5 origin prior to surgical

treatment and at different recovery stages (n=56). The second group comprised adults with normal gait who performed multiple walking trials (n=30). Machine learning algorithms were then applied to this dataset to distinguish between normal gait and the foot drop gait pattern and to evaluate the severity of foot drop symptoms.

This thesis demonstrated that the combination of IMUs and machine learning algorithms provides a promising, feasible solution to differentiate foot drop gait characteristics from normal walking gait patterns as well as an objective measure to evaluate the severity of foot drop symptoms. This measure can then be used to track the recovery procedure of patients with foot drop following spinal surgery.

In conclusion, this study significantly contributes to the field of clinical gait analysis by overcoming the limitations of current gait measurement methods and analyses using a combination of IMU sensors and machine learning approaches.

Publications

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Chapter 1:

Introduction

1.1 Background

Advances in computer hardware and software technologies have significantly affected and improved all aspects of medical sciences. From imaging systems to application of artificial intelligence (AI) for identifying a wide range of diseases, the novelty of this diagnosis innovation has benefited and affected the medical discipline. In fact, owing to the increasing reliability and accuracy of medical sensors and devices, the recent trend in medical diagnostics is to move away from traditional methods towards the using of these new measurement and analysis methods.

Among measurements sensors, inertial measurement units (IMU) have been proved to have considerable potential in sensing and measuring the kinetics and kinematics of human body movements. An IMU is a device that consists of one set of accelerometers, gyroscopes and magnetometers in each axis (x, y and z), which are integrated into a single unit. The combination of these three types of sensors in a single device can provide portable recordings of ambulatory measurements. IMUs have significantly affected gait analysis, which is the systematic study of human motion by using equipment to measure body movements. Gait analysis has received high attention from practitioners in various areas, including rehabilitation, sports science and the defence sector.

A key application of gait analysis is within the clinical environment, in which it is used to capture, measure and assess the walking gait pattern. However, despite the importance of this task, currently the most common clinical method for gait abnormality detection is visual inspection by trained clinicians, which can be subjective and inaccurate. Therefore, a major aim of this project is to assist medical practitioners in their daily assessments of gait by providing an accessible, objective gait analysis method using IMU sensors.

A common walking abnormity in adults is referred to as ‘foot drop’.(1) This term refers to the paralysis or weakness associated with ankle joints, which can have a profound effect on the walking gait cycle. Foot drop can occur owing to several reasons, such as spinal cord injuries, sports injuries and stroke. It occurs in about half of the stroke survivors and negatively affects their walking ability.(2) In general, it leads to slower walking speed; increased risk of falls, thus increasing the necessity to use walking aids; and reduced feeling of safety.(3) Moreover, forecasts indicate that the global foot drop treatment market will grow at a compound annual growth rate of 9.57% during 2016–2020.(4)

Identifying the foot drop disorder at the early stages to enable application of the correct treatment is critical.(5) In addition, it is important to be able to track the recovery procedure of the patients with foot drop after spinal surgery. Based on these two requirements, developing a gait index that can objectively classify the severity of foot drop symptoms would benefit the recovery process. However, to estimate such an index, it is necessary to model and analyse data from datasets recorded by the IMU system on both groups of patients and healthy individuals. In this regard, machine learning (ML) provides the means to deal with a large volume of data and is considered a suitable analytic method to process data.

1.2 Scope and objectives

This interdisciplinary research aims to assist clinicians by providing an engineering solution. Therefore, the scope of the study involves capturing gait data in the clinical environment from patients with foot drop, as well as using signal-processing methods and ML techniques to analyse the noisy, interconnected and large amount of IMU data.

The main objectives of the project are as follows:

- To design an IMU-based gait analysis system to capture the gait event in clinics; the system must be low cost, portable, accurate and applicable in the clinical environment.
- To study the gait characteristics of patients with foot drop and compare with the healthy and normal gait model in an objective manner.
- To evaluate treatment effectiveness as well as improvements after surgical treatment and during the recovery procedure objectively.

1.3 Thesis outline

This thesis is organised into seven chapters and each chapter explains a key step of the project. The thesis is structured as follows.

- **Chapter 2** provides a brief introduction to gait analysis and the anatomical aspects of the human gait. An overview of the gait measurement systems and gait disorder assessment-related studies is presented. It provides a scoping review on the gait evaluation techniques used previously in clinical applications to quantify and assess gait disorders.
- **Chapter 3** provides the details of the designed gait analysis system that is proposed for clinical gait evaluation of foot drop.
- **Chapter 4** explains the validation task to examine the measurement accuracy of the proposed system.
- **Chapter 5** introduces the ML model and quantifiable features from the gait event measurements utilizing the proposed system. Further, it presents a comparison of various ML algorithms that best distinguish the foot drop gait pattern from the normal style.
- **Chapter 6** presents a comparison of various ML algorithms in classification and regression analysis at different stages of foot drop recovery following the lumbar spine surgery.
- **Chapter 7** concludes the thesis and summarises the chapters, results and findings of this thesis. It also suggests future research directions.

1.4 References

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Chapter 2:

Literature Review

2.1 Background

2.1.1 Gait

Walking is one of the most important functions among human activities. It is the combination of repetitious actions of various body parts that move the body forward and at the same time maintain the stance ability. The shortest nonrepetitive movement in walking is termed the gait cycle. Each gait cycle starts with a heel contact to the floor and finishes with the same posture. A gait cycle consists of swing and stance phases. In the stance phase, the reference foot is in contact with the floor and during the swing phase, the reference foot is swinging forward [Figure 2-1].(1)

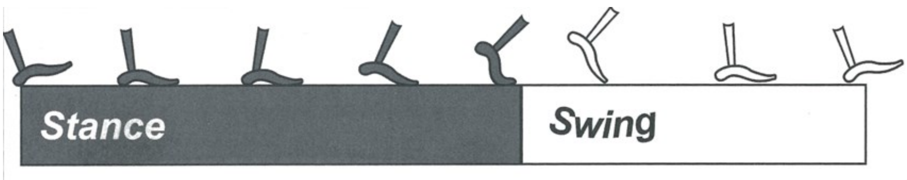

Figure 2-1 Gait cycle phases.(1)

The swing and stance phase can also be divided into individual movements (i.e. sub-phases). Figure 2-2 illustrates the movements and transitions between them. Table 2-1 shows the interval of each sub-phase.

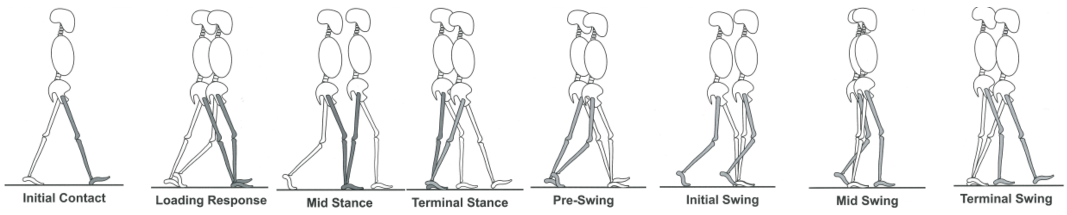

Figure 2-2 Gait cycle sub-phases.(1)

Table 2-1 Sub-phase duration during a complete gait cycle.(1)

Sub-Phase	Interval of Gait Cycle (%)
Initial Contact	0–2
Loading Response	2–12
Mid Stance	12–31
Terminal Stance	31–50
Pre-Swing	50–62
Initial Swing	62–75
Mid Swing	75–87
Terminal Swing	87–100

2.1.2 Gait analysis

Gait analysis is defined as a systematic method used to study animal locomotion.(2) More specifically, it is the study of gait cycles by measuring body movements and muscle activities during the walk.(3) Various kinetic and kinematic body parameters are measured for gait analysis, including relative angles and positions of body limbs, walking velocity and step length.(1) These measures provide invaluable information for assessing, treating and rehabilitation planning of individuals with conditions affecting their ability to walk.(4) In addition to its application in the field of medicine, gait analysis has attracted significant attention in other areas, such as sports training, human–machine interaction, military and the movie industry.(5)

In fact, gait analysis, which involves assessing and evaluating the gait, is highly important in clinical application for diagnosis and tracking the recovery procedure of patients through their treatment journey. Despite technological improvements, reporting individuals' gait status remains a challenging task, because various gait parameters need to be compared for generating such reports.(6)

Moreover, a widely accepted assessment method is unavailable until date for evaluating gait events in the clinical environment. The most popular procedures are based on visual inspection of various walking activities.(7) During these activities, the practitioner will assess different aspects of the walking ability. Since the evaluation of the tasks is based on visual inspection, the evaluation result is subjective and may be inaccurate.(8) Examples of these evaluation methods are goniometry,(9) Functional Ambulation Categories,(10) Berg Balance Scale,(11) 6-Min Walk Test,(12) dynamic gait index,(13) and 10-Meter Walk Test.(14)

A wide range of studies have been conducted to overcome the subjective nature of the visual gait analysis approaches. Consequently, many measures and devices have been introduced. Walking velocity is suggested to be a good indicator of gait health.(15-16) Moreover, muscle strength, which is measured by manual muscle testers, also provides indications of the overall gait health.(17)

Recently, the application of various sensors in gait analysis has been investigated. For instance, optical motion capture systems have been receiving extensive attention since these systems provide data on the accurate position of human limbs during the activity of walking.(18) GAITRite is another system that provides walking gait timing and information, and it is used in the clinical environment. It is a walking platform that consists of a matrix of pressure sensors and a software system to track gait events.(19) In addition, the prosthetic activity monitor system is a useful measurement tool for evaluating walking parameters and is based on acceleration measurements.(20) Moreover, IMU sensors have been proved to be practical in assessing gait events particularly because of characteristics such as portable recording of ambulatory measurements and long-term monitoring.(21-22)

2.1.3 Gait disorders

A variety of walking gait abnormalities can have a substantial negative impact on a patient's quality of life, such as those owing to knee injuries, stroke, Parkinson's disease, foot drop and cerebral palsy. Since the characterisation and evaluation of gait abnormalities can assist in the identification and tracking of these disorders, gait analysis becomes increasingly critical from the clinical perspective.(20)

Among the many walking gait abnormalities, foot drop, which is defined as dorsiflexion weakness, is a frequent condition. Foot drop occurs when the front of the foot drops following the heel strike and obstructs the swing phase. In severe cases, the toe may contact the ground before the heel, which will cause tripping, falling and fear of falling.(23–27)

2.1.4 Aim

The objective of this review is to assess and compare the available gait analysis methods that have been used in clinical applications. The review will evaluate and appraise the available literature and determine gaps in the existing research regarding the analysis of foot drop gait pattern in the clinical environment.

2.2 Scoping review

2.2.1 Search method

A scoping review of the literature was conducted to provide an overview of the range and depth of the gait analysis research.(28) A scoping review aims to address the following (29):

- investigations about the proposed research question to ascertain whether it has been researched elsewhere;
- identification of the key problems, current arguments and related research trends to the topic;
- identification of research gaps;
- definition of the scope of the research.

The following sections provide details about the search methodology.

2.2.2 Study design

For this scoping review, a search was conducted in the IEEE database to identify full-length articles in the English language that were published from January 2009 until 10 June 2019.

The search was conducted using a combination of keywords and Boolean logic expressions.(30) The following is the search strategy used. The term ((("Gait analysis") AND (("clinical application*") OR ("medical application*") OR ("biomedical application*")))) was used in the search, and filters were applied on publication year and language. Moreover, the reference list of the included articles was manually searched to identify articles that met the eligibility criteria in Section 2.2.3. Additionally, some significant articles, such as review papers or highly cited articles related to this topic, were included from other databases, such as Scopus.

2.2.3 Eligibility criteria

Initially, the search included articles published from January 2009 until the search date, 10 June 2019. Among these search results, only the gait assessment studies that focused on clinical applications were included. Studies on military applications, indoor navigation applications or general applications, such as gaming or animations, were excluded.

Studies that focused on lower limb movements were included, whereas those on other body movements, such as wrist or arm movements, were excluded. Studies (except review articles) that employed one, or a combination of, gait measurement and recognition methods for capturing the human participant's movements were considered eligible for inclusion. Studies that provide an overview of the included studies were also included.

In addition, studies that had at least one human participant were included. Studies on animals were excluded. No limits were placed on age, gait symptom or severity level of the gait symptom. Studies that conducted a primary investigation on gait modelling and simulation, gait speed, muscle behaviour analysis or sensor design and production were excluded.

2.2.4 Data extraction and synthesis

The initial search extraction revealed clear heterogeneity among articles, which differed in their methods, outcomes and the way they reported results. This appears as an evident fact about the studies examining human gait. Because of the considerable variation observed between articles, a narrative review method was applied to find the most appropriate articles to summarise. Figure 2-3 presents a flow chart about the method and number of articles selected in line with the eligibility criteria.

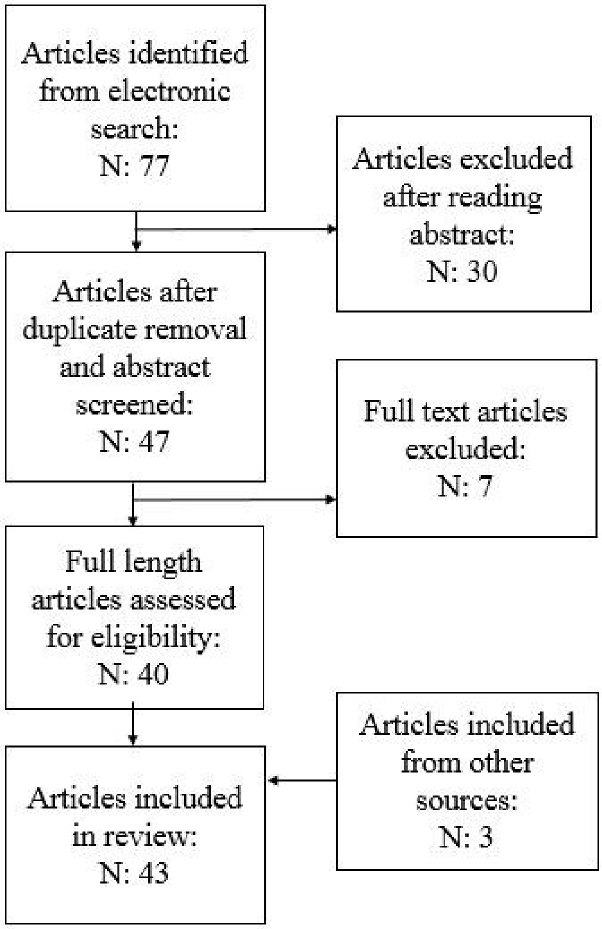

Figure 2-3 Article selection method in accordance with the eligibility criteria

2.2.5 Study evaluation

For each article, general information, such as the title, citation, publication year and the study model, was collected. Participant demographic data and information about their normal or abnormal gait were extracted. These data include the number of healthy participants, and the number of participants with a gait abnormality and their related gait symptoms.

Information pertaining to the experimental design or data extraction method were also extracted. Moreover, the article's hypothesis, key findings and the statistical methods it utilised were also recorded for further comparisons. The information collected is provided in Table 2-3 and discussed in section 2.4.

For the purposes of quality evaluation in this review, the levels of evidence of the National Health and Medical Research Council (NHMRC) were utilised to assign the relevance level for each study. The reviewer assessed the quality of included studies based on the NHMRC levels of evidence hierarchy (Table 2-2), which provides a quality evaluation of the methods.(31)

Table 2-2 NHMRC Evidence Hierarchy.(32)

Level	Intervention	Diagnostic Accuracy	Prognosis	Aetiology	Screening Intervention
I	A systematic review of level II studies	A systematic review of level II studies	A systematic review of level II studies	A systematic review of level II studies	A systematic review of level II studies
II	A randomised controlled trial	A study of test accuracy with an independent, blinded comparison with a valid reference standard, among consecutive persons with a defined clinical presentation	A prospective cohort study	A prospective cohort study	A randomised controlled trial
III-1	A pseudorandomised controlled trial (i.e. alternate allocation or some other method)	A study of test accuracy with an independent, blinded comparison with a valid reference standard, among non-consecutive persons with a defined clinical presentation	All or none	All or none	A pseudorandomised controlled trial
III-2	A comparative study with concurrent controls: • Non-randomised, experimental trial • Cohort study • Case-control study • Interrupted time series with a control group	A comparison with reference standard that does not meet the criteria required for Level II and III-1 evidence	Analysis of prognostic factors amongst persons in a single arm of a randomised controlled trial	A retrospective cohort study	A comparative study with concurrent controls: • Non-randomised, experimental trial • Cohort study • Case-control study
III-3	A comparative study without concurrent controls: • Historical control study • Two or more single arm study • Interrupted time series without a parallel control group	Diagnostic case-control study	A retrospective cohort study	A case-control study	A comparative study without concurrent controls: • Historical control study • Two or more single arm study
IV	Case series with either post-test or pre-test/post-test outcomes	Study of diagnostic yield (no reference standard)	Case series, or cohort study of persons at different stages of disease	A cross-sectional study or case series	Case series

2.3 Search Results

The initial search of the IEEE database resulted in 77 articles. First, by reviewing the titles and abstracts of these articles, 47 studies were selected for the next review level. Next, the secondary level of review that considered the full texts excluded seven studies and included an additional three articles from the reference lists of the included articles. Finally, 43 articles in total were included in the review (Table 2-3).

Table 2-3 The search results including the selected studies. The author does not have any claim over the text in columns Hypothesis and Key Findings of this table—this information is obtained directly from the studies and the author only gathered the information together in the table form. Please note the abbreviations used in the table explained in the text except for Not applicable (NA) and Nothing (NUN).

Title	**Citation**	**Year**	**Study Model**	**Data Extraction Method**	**Number of participants**		**Gait symptom**	**NHMRC evidence level**	**Hypothesis**	**Statistical Analysis**	**Key Findings**
					Normal	**Abnormal**					
Human motion tracking for rehabilitation-A survey	H. Zhou et. al	2008	Survey article	NA	NA	NA	NA	NA	This paper provides a survey of technologies embedded within human movement tracking systems, which consistently update spatiotemporal information with regard to human movement. Existing	NA	Review of the developments in human motion tracking systems and their application in stroke rehabilitation. State-of-the-art tracking techniques have been classified
Design and Testing of a Generic Algorithm for Assessment of Human Walking	J. Wu	2009	Research article	Marker based optical motion capture system 3D-Optotrak®	30	30	old subjects	II	Seek more advanced feature extraction technique for capturing the high-order statistical information among gait variables, which discover the change of human walking pattern.	Independent component analysis	Addressed a novel scheme of training Support Vector Machines (SVMs) for automatic discrimination of the change of human walking patterns. Provides statistical information about the change of young-old walking pattern applying ML algorithms.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
A mobile force plate system and its application to quantitative evaluation of normal and pathological gait	T. Liu et. al	2010	Research article	force plate and wearable sensors	1	0	NA	IV	A mobile force plate and 3D motion analysis system (M3D) is introduced.	Nun	an application experiment is introduced to quantify and evaluate human gait. The M3D system can be used to obtain multidimensional motion and force data on successive gait in nonlaboratory environments. Developed a new method based on measurements from the mobile system for quantifying gait variability. Moreover, a statistical analysis of the multi-dimensional GRF and orientation data extracted from successive gait measurements used to evaluate normal and pathological gait.
A new intelligent model for automated assessment of elder gait change	J. Wu	2010	Research article	3D-Optotrak (optical motion system)	24	24	old subjects	II	Intelligent model for automatic evaluation of the change of elder gait function based on kinematic gait data. In order to recognize the change of elderly gait patterns with higher accuracy, the wavelet analysis technique was proposed as a new approach to extract gait features,	Accuracy, Feature extraction	The proposed model can be used as an effective tool for diagnosing the change of gait function for old people in clinical application. Pressure plate can more deeply detect the abnormal plantar. The experimental results demonstrated that our proposed intelligent model is able to extract the more useful information from gait data effectively

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
A Hybrid Multi-classifier to Characterize and Interpret Hemiparetic Patients Gait Coordination	L. Hartert et. al	2010	Research article	Optical motion capture system and force platform	27	66 hemiparetic patients_14 patients pre and post treatment.	hemiparetic patients	II	Aim to classify intersegmental coordination patterns using in parallel a structural and a statistical PR method applied to the thigh-shank and shank-foot CRPs measured	Nun	Proposed multi-classifier has permitted to classify and to interpret gait coordination patterns. Pattern recognition techniques allow an automation of the subjects' classification and can help clinicians in the coordination analysis. In this study, the hybrid proposed approach has combined results obtained by a structural and a statistical method to improve the classification results.
Methods for gait event detection and analysis in ambulatory systems	J. S. Rueterbories et. al	2010	Review article	NA	NA	NA	NA	NA	In this review, we analyse existing methods for monitoring gait and detecting gait events that could be used in an ambulatory rehabilitation system.	NA	This review outlines the latest research carried out on methods of gait analysis and event detection in relation to an ambulatory use.
Automatic Detection of Temporal Gait Parameters in Post stroke Individuals	P. Lopez-Meyer et. al	2011	Research article	Wearable Sensors	16	7	Post-stroke	II	The purpose of this study is to describe a methodology to automatically identify temporal gait parameters of post stroke individuals to be used in the assessment of functional utilization of the affected lower extremity as a part of behaviour enhancing feedback.	confidence interval, T-test, P-value	Automatic Detection of Temporal Gait Parameters post stroke. The methodology is based on inexpensive and user-friendly technology that will enable research and clinical applications for rehabilitation of people who have experienced a stroke.
Regression models for estimating gait parameters using inertial sensors	B. K. Santhiranayagam et. al	2011	Research article	wearable Sensors	5	0	NA	III-3	looks at the application of advanced regression models for estimating key foot parameters in falls prevention research	RMSE	Investigate the notion of falls prediction through the use of portable, lightweight, easy to use and inexpensive sensors along with advanced computational intelligence estimation models. Used IMU to measure the foot kinematics and an optoelectronic motion capture system to validate the results.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Prediction of lower extremities movement using characteristics of angle-angle diagrams and artificial intelligence	P. Kutilek et. al	2011	Research article	Motion capture system	10	0	NA	III-3	New methods based on an analysis of gait angles using cyclograms (also called angle-angle diagrams or cyclokinograms) and AI to predict human motion of legs.	T-test	Neural networks learned by cyclogram characteristics predicted cyclogram curve and offer wide applications in prosthesis control systems
Interpersonal synchrony-based dynamic stabilization in walking rhythm of Parkinson's disease	H. Uchitomi et. al	2011	Research article	Walk mate pressure sensor	0	2	Parkinson's disease	III-3	In this study, gait cycle fluctuation was focused on as the index of dynamic stability of a gait.	Nun	Applied an interpersonal synchrony emulation system to Parkinson's disease patients with festinating gait.
Validated extraction of gait events from 3D accelerometer recordings	M. Boutaayamou et. al	2012	Research article	wearable Sensors	7	0	NA	III-3	This paper presented a new low-cost, wireless, 3-axis accelerometer-based system and a signal-processing algorithm that were successfully used to automatically extract relevant gait events to accurately determine the stance and the swing phases of walking.	Mean STD	This system automatically extracts relevant gait events such as the heel strikes (HS) and the toe-offs (TO), which characterize the stance and the swing phases of walking. The performances of the low-cost accelerometer hardware and related algorithm have been compared to those obtained by a kinematic 3D analysis system and a force plate, used as gold standard methods.
High precision ultrasonic positioning using phase correlation	W. Tao et. al	2012	Research article	Ultrasonic sensors	0	0	NA	NA	The proposed system uses improved signal processing techniques to provide a 3D ultrasonic positioning system with the sub-millimeter precision required for many medical applications. The system is designed to overcome multipath distortion and uses a narrowband ultrasonic chirp	Nun	Proposed a high-precision 3D ultrasonic positioning system which is comparable with the alternative optical systems

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Automated recognition of human gait pattern using manifold learning algorithm	J. Wu	2012	Research article	strain gauge force platform	30	30	old subjects	II	In this study, the aim of the application manifold learning algorithm in gait data analysis is to obtain more significant information about human gait change for improving the gait classification performance.	Nun	Used ML for gait recognition. Demonstrates that the manifold learning algorithm can be applied in gait data analysis for obtaining the useful information about the intrinsic nonlinear dynamics of human movement.
Prediction of muscle length during walking by neural networks	P. Kutilek et. al	2012	Research article	Optical motion capture system and Pressure sensor	8	0	NA	III-3	The aim of this article is to introduce a possible method of predictions of muscle behaviour which can be used for rehabilitation, and also for controlling the artificial muscles, actuators of prosthesis or rehabilitation facilities of the future. Our work focuses on predicting muscle-tendon lengths during human gait with the use of angle-time diagram.	Nun	Introduce a possible method of predictions of muscle behaviour which can be used for rehabilitation, and also for controlling the artificial muscles, actuators of prosthesis or rehabilitation facilities of the future time diagrams. In conjunction with artificial intelligence, time diagrams offer a wide area of medical applications. the study tested and verified new way of prediction of muscle-tendon length based on neural networks. In general, artificial neural networks for predicting the muscle behaviour learned by time diagrams predicted the muscle-tendon behaviour of healthy children.
An Overview of Gait Analysis and Step Detection in Mobile Computing Devices	M. L. McGuire	2012	overview	mobile devices	NA	NA	NA	NA	The most important problems to be solved to improve gait analysis and these applications are also identified.	NA	Provides an overview of the methods used for accelerometer-based gait analysis in mobile devices. It also shows how this analysis has been used in state-of-the-art applications. The most important problems to be solved to improve gait analysis and these applications are also identified.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Gait analysis using wearable sensors	W. Tao et. al	2012	Review article	NA	NA	NA	NA	NA	Purpose of the current paper is to review the current status of gait analysis technology based on wearable sensors.	NA	Indicates gait analysis using wearable sensors provided quantitative and repeatable results over extended time periods with low cost and good portability, showing better prospects and making great progress in recent years.
Toward a Passive Low-Cost In-Home Gait Assessment System for Older Adults	F. Wang et. al	2013	Research article	webcam-based system against GAITRite mat and Vicon motion capture	13	8	old subjects	II	Proposed and validated a low-cost webcam system for passive and continuous in-home gait assessment. Using 3-D voxel data without explicitly tracking human body parts is computationally efficient, eliminates the constraint of walking path direction,	Intraclass coefficients, repeatability coefficient	The system results demonstrate the capability of being used as a daily gait assessment tool for fall risk assessment and other medical applications. The system has achieved a high accuracy based on in-lab and in-home validation. The system provides a clear overview of the person's daily gait parameters and has a good potential to be used to identify people at high risk of falling. large differences in gait patterns have been observed between the in-home tests versus clinical tests.
Evaluation of muscular moment asymmetry using bilateral cyclograms	P. Kutilek et. al	2014	Research article	Optical motion capture system	7	6	cerebral palsy	II	proposed technique based on the shape of the synchronized bilateral cyclogram of the muscle moment contributions to joint moments can be used for the study of complex muscle behaviour	Nun	The bilateral cyclograms used to study asymmetry of the moments of muscle forces. Find the moments of muscles of the subjects with cerebral palsy are significantly asymmetric. Also, Calculations of parameters of gait were performed using the OpenSim.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Ambulatory measurement of foot kinematics using wearable ultrasonic sensors	Y. Qi et. al	2014	Research article	Ultrasonic sensors	1	0	NA	IV	This study proposes a novel measurement system using wearable ultrasonic sensor to measure the foot kinematics continuously during walking. To evaluate the performance of the proposed system, the foot kinematics was measured and validated against the reference camera based motion capture system.	Mean, STD PCC	Results from the proposed ultrasonic measurement system have high correspondence with the results from camera based motion capture system over long walking period. Additionally, the proposed system is easy to wear and to use. It does not restrict the movement of patients or subjects with bulky cables.
Application of gait analysis for hemiplegic patients using six-axis wearable inertia sensors	Q. Fang et. al	2014	Research article	wearable Sensors	7	8	old stroke patients	II	This paper proposed a gait analysis system for hemiplegic gait based 6-axis wearable wireless inertial sensor data. The raw inertia data sampled are processed to obtain features including step length, hip and knee joint range of motion	Nun	Demonstrated that the abnormalities in gait pattern such as irregularity and asymmetry can be found and quantified. The hemiplegic gait patterns produce significantly shorter step length and more restricted joint motion. The autocorrelation function of the inertia data was also studied for healthy and hemiplegic gait symmetry and regularity comparison. The result has proven that it is possible to identify hemiplegic gait based on inertia measurements only and the quantified outcome can be produced to evaluate lower extremity functioning impairment and rehabilitation progress.
A Knowledge-Based Modelling For Plantar Pressure Image Reconstruction	S. Ostadabbas et. al	2014	Research article	Pressure sensor	10	0	NA	III-3	Presented a knowledge-based regression model (SCPM) that used PCA to reduce model order and improve performance over our previous work. SCPM performs significantly better than blind interpolation techniques for fewer than 60 pressure sensors.	Nun	Pressure on the plantar area is one of the main factors in developing foot ulcers. With current technology, electronic pressure monitoring systems can be placed as an insole into regular shoes to continuously monitor the plantar area and provide evidence on ulcer formation. SCPM has the

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
											potential to become an important tool bridging medical need and technological capability and can ultimately improve the quality of life for many people suffering from foot problems.
Understanding human gait: A survey of trails for biometrics and biomedical applications	N. M. Bora et. al	2015	Survey	NA	NA	NA	NA	NA	The prime objective of this paper is to understand the human gait in biometric and biomedical applications.	NA	Study of human gait biometrics approaches involved, various impacting factors for gait recognition and applications of gait analysis in biomedical engineering. Various recent advancements in gait recognition are highlighted. Biomedical applications of gait are described.
A body-worn visual cue device for ambulation training	H. Huang; C. Yu	2015	Research article	Motion capture system & force plate	1	0	NA	IV	The purpose of this paper is to develop the experiment protocols to evaluate the functionality of the latest version device for future clinical applications	Nun	The body-worn ambulation training device with visual cues developed to assist the therapist to train the patient with limited verbal cues and contact guidance.
Investigation of tibialis anterior muscle activation patterns during walking on different terrains	H. Zhou et. al	2015	Research article	pressure sensor and EMG	5	0	NA	III-3	In this study, the EMG activation pattern of TA muscle when walking on different terrains was investigated on five normal subjects, which would provide some guiding information on how to design a suitable stimulation envelope for walking over different terrains.	Average, Min, Max	Helpful suggestions on how to design a suitable stimulation envelope for walking over different terrains. Observed that the different TA muscle activation patterns would be induced when subjects were walking on level ground, upstairs and downstairs respectively.
Toward Pervasive Gait Analysis With Wearable Sensors: A Systematic Review	S. Chen et. al	2016	Review	NA	NA	NA	NA	NA	The aim is to provide a systematic review of current techniques for quantitative gait analysis and to propose key metrics for evaluating both existing and emerging methods for qualifying the gait features extracted from wearable sensors.	NA	Demonstrates that wearable sensors can replace laboratory gait analysis systems, offering portable, objective, quantitative, continuous, and rich information for gait analysis.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
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Accelerometer-based gait assessment: Pragmatic deployment on an international scale	S. Del Din et. al	2016	Research article	wearable Sensors	50	47	Parkinson's disease	II	This study examines the use of a single tri-axial accelerometer within modern gait analysis and it's utility to shape pragmatic patient assessment in clinical free-living environments.	STD, Variance, Average	Free-living conditions tested between groups showing greater sensitivity in Parkinson. Provide encouraging results to support the use of the suggested framework for large clinical application.
Quantitative evaluation of parameters affecting the accuracy of Microsoft Kinect in GAIT analysis	Z. Jamali et. al	2016	Research article	Microsoft Kinect	1	0	NA	IV	The purpose of this research is determining the Kinect sensor error model during walking, according to affecting parameters on the sensor accuracy such as the type of joint and the sensor position.	RMSE	Presents a method for accuracy assessment of Kinect in GAIT analysis for normal walking. The main purpose was to determine the best position for Kinect relative to the walkway. GAIT parameters such as stride length, stride time, ankle, knee, and hip joint angles were considered in the assessment. The results indicated that the best position for Kinect is in front of the subject.
A view invariant gait cycle segmentation for ambient monitoring	H. Wu et. al	2016	Research article	videos from a single non-calibrated camera	14	0	NA	III-3	this paper describes a method that uses the temporal duration of spatial features.	Nun	Use the temporal duration of spatial features to achieve fast, robust and accurate gait cycle segmentation. method does not rely on the spatial dimensions or relationships between body parts, but on the temporal properties of some detected image features.
Inverse optimal control based identification of optimality criteria in whole-body human walking on level ground	D. Clever et. al	2016	Research article	Optical motion capture system	6	0	NA	III-3	identification of optimality in whole-body walking motions on level ground	Mean, Deviation, Correlation matrix	inverse optimal control (IOC) based approach to identify the optimality criteria in human walking also identify suitable optimality weights for all trials. The weights differ subject-wise to explain the different walking styles.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Validation of temporal gait metrics from three IMU locations to the gold standard force plate	M. R. Patterson et. al	2016	Research article	force plate and wearable sensors	33	0	NA	III-3	The purpose of this work is to compare temporal gait parameters from three different IMU locations to the gold standard force platform	mean, max, STD, Confidence interval	Suggest that the foot location would be most appropriate for clinical applications where very precise temporal parameter detection is required.
Validation of a Footwear-Based Gait Analysis System With Action-Related Feedback	S. Minto et. al	2016	Research article	wearable Sensors	14	0	NA	III-3	The goal of this work is to experimentally assess accuracy and precision of gait analysis performed with SoleSound. After describing the latest design of the device. a novel, wearable, shoe-based gait analysis system, which can further deliver auditory and vibrotactile feedback in response to measured gait parameters to help the user regulate her gait	Nun	A fully portable instrumented footwear that can measure spatiotemporal gait parameters and deliver action-related audio-tactile feedback
Use of accelerometer for walk-run or shot analysis for sport and rehabilitation purposes	M. Stork et. al	2016	Research article	wearable sensors (accelerometer)	1	0	NA	IV	In this paper, the electronic system based on Bluetooth with two types of accelerometer sensors for run-walk or shot analysis for medical or sports purposes was described.	Nun	Bluetooth system with two types of accelerometer sensors for run-walk or shot analysis for medical or sports purposes was described. Sampling frequency for such an application must be much higher then sampling frequency usually used. The results can be used for medical and sport purposes and also for biometric identification.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Novel Foot Progression Angle Algorithm Estimation via Foot-Worn, Magneto-Inertial Sensing	Y. Huang et. al	2016	Research article	Wearable Sensors	13	0	NA	III-3	The purpose of this paper is to present a novel algorithm for estimating the FPA by using a single magneto-IMU worn on the foot and combining computed heading vectors and foot vectors.	RMS	Enables future wearable systems gait research to assess or train walking patterns outside a laboratory setting in natural walking environments.
Assessment of Foot Trajectory for Human Gait Phase Detection Using Wireless Ultrasonic Sensor Network	Y. Qi et. al	2016	Research article	Ultrasonic Sensor against optical motion capture system	10	2	foot injured subjects.	II	This paper presents a new highly accurate gait phase detection system using wearable wireless ultrasonic sensors, which can be used in gait analysis or rehabilitation applications. The gait phase detection system uses the foot displacement information during walking to extract the following gait phases: heel-strike, heel-off, toe-off, and mid-swing	Mean, STD	The gait phase detection system uses the foot displacement information during walking to extract the following gait phases: heel-strike, heel-off, toe-off, and mid-swing. The displacement of foot-mounted ultrasonic sensor is obtained from several passive anchors placed at known locations by employing local spherical positioning technique, which is further enhanced by the combination of recursive Newton-Gauss method and Kalman Filter.
Evaluation of the patient-specific electromyography (EMG)-driven neuromuscular model for cerebral palsy patients	Y. Ma et. al	2016	Research article	EMG and Optical motion capture system	0	4 specified group	cerebral palsy	III-3	This study investigates the joint moment estimation performance and clinical application in studying muscle functions of the patient-specific EMG-driven neuromuscular model (PENm) for cerebral palsy patients. T	Mean, Min, Max, STD, RMSE	The PENm is a modified hill-type model designed for robotic application. The PENm evaluation employs the gait analysis technique using three-dimensional motion capture system combined with EMG recording devices and the musculoskeletal modelling technique. The results show that the PENm could predicted joint moment based only on two EMG channels with an acceptable accuracy.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Magneto-Gyro Wearable Sensor Algorithm for Trunk Sway Estimation During Walking and Running Gait	P. B. Shull et. al	2017	Research article	wearable device & Motion capture system	10	0	NA	III-3	The purpose of this paper is to introduce a novel algorithm to estimate trunk sway for walking and running gait. The algorithm is based on magnetometer and gyroscope data fusion and performance is directly compared to other common algorithms during walking and running experiments.	RMSE	Determine the optimal placement of the wearable sensor device on the back and a second experiment was performed to characterize the accuracy of the algorithm
The overview of automatically supported gait analysis methods for medical diagnoses and rehabilitation	A. Michalczuk et. al	2017	Overview article	NA	NA	NA	NA	NA	present a review of gait analysis methods used for medical applications. First of all, we introduce a system of real-time gait acquisition. Next, three ways of gait data representation: trajectories, Euler angles and medical angles are described along with the most promising methods of gait analysis based on those representations like gait indices, Dynamic Time Warping, manifold methods and a ranking of most significant joints for different disease units.	NA	Introduce a system of real-time gait acquisition. Three ways of gait data representation including trajectories, Euler angles and medical angles are described along with the most promising methods of gait analysis.
Design, Analysis, and Multicriteria Optimization of an Overground Pediatric Robotic Gait Trainer	A. J. McDaid	2017	Research article	Pro-GaiT (exoskeleton)	4	3	cerebral palsy	II	This paper proposes a novel pediatric robotic overground gait trainer (Pro-GaiT) based on a nonanthropomorphic linkage design and walking frame. The robot configuration is a 2 degree-of-freedom 5 bar linkage “end effector” and considers the human as part of the kinematic chain.	Mean, Max RMS	Proposes a novel pediatric robotic overground gait trainer (Pro-GaiT) based on a nonanthropomorphic linkage design and walking frame. Design analysis is conducted and a genetic algorithm is used to optimize the robot configuration

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
A Review on Accelerometry-Based Gait Analysis and Emerging Clinical Applications	N. Kumar et. al	2018	Review	NA	NA	NA	NA	NA	In this paper, we review research regarding accelerometer sensors used for gait analysis with particular focus on clinical applications	NA	provide a brief introduction to accelerometer theory followed by other popular sensing technologies. Commonly used gait phases and parameters are enumerated. Also, review several gait analysis software. Then provide an extensive report of accelerometry-based gait analysis systems and applications, with additional emphasis on trunk accelerometry.
Automated Kinematic Analysis Using Holistic Based Human Gait Motion for Biomedical Applications	C. Prakash et. al	2018	Research article	Camera based system	1	0	NA	IV	This study relies on silhouette image of the subject to obtain human walking posture, frame by frame. Thus the first step is an extraction of a noise free silhouette. In this paper, a method is proposed to extract the thigh and shin angle for left and right leg to calculate the knee angle which is then compared with the angle obtained through marker based approach	Max, Min, RMSE, MAE	new approach has been proposed for an automated marker less gait system to describe, quantify and analyse human gait motion. A mixture of Gaussian based image segmentation is performed for feature extraction to identify the knee joint angle. Marker-free vision based gait analysis has a wide scope for the clinical purpose
An ICA-EBM-Based sEMG Classifier for Recognizing Lower Limb Movements in Individuals With and Without Knee Pathology	G. R. Naik et. al	2018	Research article	Surface electromyography	11	11	knee pathology	II	An ICA-based classification scheme for lower limbs EMG data has been designed and tested with signals recorded from healthy individuals as well as subjects suffering from knee pathology.	Sensitivity, Specificity, Accuracy, Confusion matrix	Improvements in the clinical application of sEMG-based pattern recognition system for walk, sitting, standing using ML analysis.

Title	Citation	Year	Study Model	Data Extraction Method	Number of participants		Gait symptom	NHMRC evidence level	Hypothesis	Statistical Analysis	Key Findings
					Normal	Abnormal					
Foot Plantar Pressure Measurement System Based on Flexible Force-Sensitive Sensor and its Clinical Application	B. Li et. al	2018	Research article	Pressure sensor	45	Knee OA 48 Sports injury 31	Knee OA _Sports injury	II	Pressure plate developed and used for remote detection and track monitoring of patients, and the testing process is completely harmless to the subjects.	Average, STD	A foot plantar pressure measurement system was developed to analyse dynamic plantar pressure of subjects with the knee joint injury and normal control subjects. Various plantar pressure related parameters collected by the pressure plate can help us to understand the gait characteristics.
Floor Based Sensors Walk Identification System Using Dynamic Time Warping with Cloudlet Support	R. Hughes et. al	2019	Research article	floor-based monitoring system smart carpet	7	0	NA	III-3	We studied the characteristics and behavior of the sensor's waveform. Seven subjects performed multiple walks on the sensor, and their data recorded and studied.	Linear Prediction Coefficient.	Results showed that our system identifies walks using a dynamic time warping algorithm and KNN classifier with 86% precision, 76% recall, 81% accuracy.

2.3.1 Methodological quality

According to the NHMRC levels of evidence, the first and highest level (i.e. level I) refers to the studies that are a systematic review of the randomised control trials; however, this search did not reveal any article of this nature. Nevertheless, the research revealed a total of 13 studies that have been assigned to level II because these involved two randomised study groups of individuals with healthy and unhealthy gait patterns. The level III-assignment presented 15 studies in which just one group of participants was assessed. Levels III-1 and III-2 could not be assigned to any study. However, six case studies assessed the gait for only one human participant and were hence assigned to level IV. Table 2-4 summarises the assigned quality level for each study.

Notably, seven review, overview or survey studies could not meet the level I criteria, and therefore, no level was assigned to this type of review. These reviews assessed the current gait analysis methods for medical diagnoses and rehabilitation,(33) such as wearable gait analysis methods,(34-35) ambulatory measurement technologies (36) and accelerometer-based gait assessment methods.(37) Of the two specific surveys included, one studied movement tracking technologies (38) and the other conducted research on trials for biometrics and biomedical applications.(39)

2.3.2 Participant characteristics

In most studies, normal healthy individuals were included as the comparison group, but a subset of studies had no comparison group or considered only healthy participants as the sample set. In addition, seven review articles did not involve any participants. Only in one of the studies four different cerebral palsy groups compared.(40)

As shown in Table 2-4, elderly participants, patients with cerebral palsy and Parkinson’s disease and patients recovering from a stroke were the most common groups that had clinical gait symptoms. A few studies considered participants who had general knee, foot or sports injuries.(41-43) Further, one study examined gait in patients with hemiparesis.(44)

2.3.3 Data extraction method

In 12 studies, wearable devices, such as IMU, accelerometer or gyroscope sensors, were utilised, whereas 10 studies conducted gait monitoring via optical motion capture systems.(45-46) Further, 10 studies used pressure sensors in the form of walking mats (47-48) or specified systems such as GAITRite (49) to assess the gait. Many studies employed more than one of the aforementioned systems simultaneously.(44) Some other methods, such as ultrasonic sensors,(42,50-51) electromyography (EMG),(40-41,52) Microsoft Kinect,(53) mobile devices,(54) and a robotic exoskeleton device (55) were also used to assess gait events.

In general, five different data collection methods were recognised in this review: wearable sensors, optical measurements methods with various characteristics, force or pressure sensors, EMG and ultrasonic sensors. A review of these methods will be presented in section 2.4.

2.3.4 Statistical methods

Most of the studies presented their results based on statistical methods and different measures. The search results indicate that several statistical measures were examined by the articles. Hence, a summary is presented of the most frequently examined statistical measures provided in articles.

Most of the studies used statistical tools to evaluate the similarity levels of the gait measurements between different groups of participants. In this case, minimum (Min), maximum (Max), mean and standard deviations (STD) are the most commonly used measures. To demonstrate the categorisation of the gait samples into distinct groups, the inter-class coefficient (ICC),(49) *t*-test and *p*-value were utilised in a few studies.(56) In addition, root mean square (RMS),(57) root mean square error (RMSE),(40) mean absolute error (MAE),(45) Pearson correlation coefficient (PCC),(51) and confidence interval (CI) were used occasionally.(58)

2.4 Discussion

2.4.1 Wearable devices

The accelerometer and gyroscope are the most commonly used sensors in clinical motion studies.(59) These sensors can be attached to the body to measure the acceleration or angular velocity of different body parts to detect movements such as gait events. These sensors can be used simultaneously, for example, in an IMU sensor or in mobile devices, to provide accurate measurements using sensor fusion methods.(60)

The use of such wearable devices for analysing the gait has significantly increased owing to their advantages such as ease of use, low cost, light weight, portability and the ability to be integrated into wireless embedded platforms with low power. Although the devices have a few disadvantages, such as noise and data drift, these can be addressed using sensor fusion and filtering.

It has been noted that these sensors have been used more than any other gait analysis method in the past 10 years. Typically, a single device is used for gait assessment: (60-61) however, using multiple devices on different body sections can provide more comprehensive information about the gait. Wearable sensors have the ability to provide biomechanical information about gait (62) to obtain features such as range of motion for hip, knee and step length.(63) They also help to identify temporal gait parameters in individuals post stroke during the rehabilitation procedure.(56) IMUs have been used in a shoe-based system to provide vibro-tactile feedback for users about their gait.(64) These devices have been utilised and validated in combination with other gait assessment methods, such as pressure sensors (58,65) or optical motion capture systems,(66) and ML and regression techniques have been applied to assess the IMU data.(67)

2.4.2 Optical motion capture systems

Camera and video-based systems (45-46) are used to provide a visual clue about the gait.(68) Marker-based optical motion capture systems are the choice for gait analysis when accuracy is important. Marker-based optical motion tracking is a well-known technique in which a set of markers on the body and cameras are used to track human movements. Systems such as Vicon or Optotrack (69) are usually used as a gold standard of human motion capture because of their high measurement accuracy.(38) Despite this great advantage for medical applications, a major drawback of using this system is its high cost and complexity.

These systems are used to study complex muscle behaviours, for example, muscle movement contributions to joint movements,(70) and to identify the optimality criteria in human walking gait.(71) Based on this system, a model has been provided for automatic evaluation of changes in gait functions of the elderly (72) and AI techniques have been applied for analysing system data.(73) Because of their accuracy, optical motion capture systems are often used to validate other gait assessment devices.(40,42,49,66,74)

2.4.3 Pressure sensors

Pressure measurement sensors are a category of devices that are used frequently to provide information about the gait. Piezoelectric, piezoresistive or capacitive sensors can be used as the pressure sensor in gait analysis.(37) These sensors are sometimes utilised to fit completely inside a shoe with wireless communication or occasionally designed as pressure plates including multiple pressure sensors for monitoring and detecting gait pattern.(43)

Among the most important factors in pressure-based systems are the design and mechanical wear, which have a direct impact on system reliability and measurement accuracy. These systems have some disadvantages in gait analysis applications in which they are exposed to the repetitive force changes of gait. In addition, identification of load changes in the walk that has abnormal gait patterns, such as shuffling gait, is challenging with these sensors.(36)

The Walk Mate is a system based on pressure sensors that is used to assess the gait stability of patients with Parkinson's disease.(47) By combining the pressure sensor information and EMG signals, activation patterns of the tibialis anterior muscle are studied during the walking activity.(52) The pressure sensor data are used to introduce a prediction method for muscle behaviours, which can be used in rehabilitation. Neural networks (74) and regression methods are used for pressure image recognition.(75)

2.4.4 Force plates

Force platforms consist of a flat rectangular surface that has multiple transducers underneath, to measure displacements of the surface in each axis.(76) In this method, force platforms are used to measure the vertical force reaction applied to the ground during walking activities. Force platforms suffer from a number of drawbacks, such as having a stationary short measurement area and being expensive.(37)

Three force platforms have been used simultaneously with the Vicon optical motion capture system to assist the therapist in training patients.(68) This method was utilised in the form of a GAITRite mat (49) and a smart carpet to identify gait characteristics using a dynamic time warping algorithm and the K-Nearest Neighbour (KNN) classifier.(48) Further, the recognition of human gait pattern was performed utilising the manifold learning algorithm (77) and intersegmental coordination patterns of the gait were classified.(44)

2.4.5 Ultrasonic sensors

Ultrasonic sensors are acoustic-based systems that collect, sense and transmit sound waves. Although these systems are popular in clinical application, they have been rarely used for motion and gait analysis. This is because of their drawbacks, such as dependence on the active surface area and therefore the necessity to have large devices for higher accuracy; in addition, the frequency of ultrasonic waves must be low and a short distance is desirable between the sender and receiver devices. To resolve some of these issues, ultrasonic systems can be used in combination with other gait assessment methods.(38) Some studies based on this system have considered a 3D ultrasonic positioning system that offers sub-millimetre precision (50) and a wearable ultrasonic sensor to measure foot kinematics continuously during walking activities.(51) Moreover, foot trajectory has been assessed for human gait phase detection using these sensors.(42)

2.4.6 EMG

EMG signals provide information about the activity and timing of muscle movements, which can be recorded from surface, fine wire and needle electrodes.(37) Information about muscle activity is useful in gait analysis and assessments of walking performance for people with gait impairments. Use of EMG in gait analysis has some limitations. First, it provides limited information about muscle strength. Second, obtaining accurate recordings from a participant during walking activities is challenging. However, the information that EMG provides about muscle activation timings is valuable in gait assessment.(76)

A combination of pressure sensors and EMG signals is used in the investigation of tibialis anterior muscle activation patterns during walking activities,(52) and in a similar study, an EMG-driven neuromuscular model was provided for cerebral palsy patients by investigating the joint movement estimation performance.(40) By taking advantage of classification algorithms and ML techniques, individuals with and without knee pathology were categorised based on lower limb movements.(41)

2.4.7 Other methods

Devices such as Microsoft Kinect (78) and robotic exoskeletons (55) are occasionally used to assess the human gait; however, these sensors are not practical in clinical applications.

According to this search, a very common, recent method of data analysis among the above gait assessment devices is the use of ML methods. ML methods introduce techniques and tools to assist with managing diagnostic and prognostic problems in the medical field,(79) which is highly suitable for interconnected gait data and measurements. Classification and regression methods are the most commonly used methods for gait assessment. In general, AI and ML methods can be applied for any gait-related data gathered from any of the aforementioned gait analysis systems. The ML-based data analysis methods are one of the most common methods among the studies in this review.(41,44,74-75)

2.5 Conclusion and Recommendation

The aim of this scoping review is to present an overview of the current literature and state-of-the-art of gait analysis in clinical settings. Studies were categorised based on the gait measurement and assessment methods they utilised. It was observed that the pathologic gait was always assessed via comparisons with the normal gait pattern regardless of the gait analysis method applied.

The results summarised in this review indicate that using wearable sensors for the diagnosis and assessment of the gait is the most efficient method among the available tools. Moreover, considering the advantages, such as being lightweight and portable, and the low cost, IMU devices show great promise for the future of gait analysis in clinical applications. However, off-the-shelf IMU systems do not provide the advantages of portability, low cost and access to raw data simultaneously; therefore, most of the studies used a customised IMU system that can be easily attached to different body sections, depending on the number of sensors and the purpose of the data collection.

Although several studies have used wearable sensors for gait analysis, optical motion capture systems remain the 'gold standard' for gait data collection owing to their high accuracy. Therefore, they have been used mainly as a reference to validate the measurements of other gait measurement devices. In addition, AI and ML are emerging techniques that have been used recently to successfully process and assess a vast range and quantity of gait data.(80) Applying these techniques can provide high-quality results and information about interconnected gait parameters.(81)

However, these studies usually applied one or two AI/ML algorithm and did not make any attempts at comparing different algorithms. A comparison between various algorithms would provide a better understanding of the suitability of these algorithms to the specific dataset. Additionally, it was found that none of the studies in this review applied gait analysis before and after applying a treatment to assess the effectiveness of treatment. Finally, based on the results of this review, no current study has assessed the foot drop gait pattern using an objective method.

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Chapter 3:

The application of Inertial Measurements Unit for the clinical evaluation and assessment of gait events

This chapter is covered by the following publication:

Sharif Bidabadi, S., Murray, I. and Lee, G.Y.F., 2017. The application of inertial measurements unit for the clinical evaluation and assessment of gait events. Journal of medical engineering & technology, 41(8), pp.612-622.

Publication has been removed due to copyright restrictions

Please find the publication at the following DOI:

https://doi.org/10.1080/03091902.2017.1382588

Chapter 4:

Validation of foot pitch angle estimation using inertial measurement unit against marker-based optical 3D motion capture system

This chapter is covered by the following publication:

Sharif Bidabadi, S, Murray, I. and Lee, G.Y.F., 2018. Validation of foot pitch angle estimation using inertial measurement unit against marker-based optical 3D motion capture system. Biomedical engineering letters, 8(3), pp.283-290.

Publication has been removed due to copyright restrictions

Please find the publication at the following DOI:

https://doi.org/10.1007/s13534-018-0072-5

Chapter 5:

Classification of foot drop gait characteristic due to lumbar radiculopathy using machine learning algorithms

This chapter is covered by the following publication:

Sharif Bidabadi, S.S., Murray, I., Lee, G.Y.F., Morris, S. and Tan, T., 2019. Classification of foot drop gait characteristic due to lumbar radiculopathy using machine learning algorithms. Gait & posture, 71, pp.234-240.

Gait & Posture 71 (2019) 234–240

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Classification of foot drop gait characteristic due to lumbar radiculopathy using machine learning algorithms

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ARTICLE INFO

Keywords:
Foot drop
Inertial measurement unit
Machine learning
Gait classification

ABSTRACT

Background: Recently, the study of walking gait has received significant attention due to the importance of identifying disorders relating to gait patterns. Characterisation and classification of different common gait disorders such as foot drop in an effective and accurate manner can lead to improved diagnosis, prognosis assessment, and treatment. However, currently visual inspection is the main clinical method to evaluate gait disorders, which is reliant on the subjectivity of the observer, leading to inaccuracies.

Research question: This study examines if it is feasible to use commercial off-the-shelf Inertial measurement unit sensors and supervised learning methods to distinguish foot drop gait disorder from the normal walking gait pattern.

Method: The gait data collected from 56 adults diagnosed with foot drop due to L5 lumbar radiculopathy (with MRI verified compressive pathology), and 30 adults with normal gait during multiple walking trials on a flat surface. Machine learning algorithms were applied to the inertial sensor data to investigate the feasibility of classifying foot drop disorder.

Results: The best three performing results were 88.45%, 86.87% and 86.08% accuracy derived from the Random Forest, SVM, and Naive Bayes classifiers respectively. After applying the wrapper feature selection technique, the top performance was from the Random Forest classifier with an overall accuracy of 93.18%.

Significance: It is demonstrated that the combination of inertial sensors and machine learning algorithms, provides a promising and feasible solution to differentiating L5 radiculopathy related foot drop from normal walking gait patterns. The implication of this finding is to provide an objective method to help clinical decision making.

1. Introduction and background

There is a wide range of walking gait related disorders that can have significantly negative impacts on the patient's life. From a clinical point of view, characterisation of gait could assist in the identification and tracking of gait related disability. To this end, gait analysis has received significant attention in recent times.

Foot drop is a term that describes dorsiflexion weakness. It occurs in a range of conditions including injury of the peroneal nerve, muscular pathology, peripheral neuropathy, post stroke and L5 radiculopathy. Foot drop occurs when the front of the foot drops following the heel strike and hinders the swing phase of gait resulting in compensatory hip hitching and excessive hip flexion during stepping. In severe cases toe strike may occur prior to heel strike and during the swing phase and the toe may catch the ground resulting in tripping, falling, and fear of falling [1,2].

Laboratory based gait analysis is time consuming and expensive as it requires specialised equipment, travel to an appropriate facility and expert skill. In the absence of a practical gait analysis system and the limitations of the current gait analysis methods [3], the evaluation of foot drop in a clinical environment is performed by visual inspection of the patient's walking pattern. This is subjective and may be inaccurate as it relies on the medical practitioners' experience and judgment [4]. It would be valuable to provide clinicians with an objective, efficient, and

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https://doi.org/10.1016/j.gaitpost.2019.05.010
Received 6 March 2019; Received in revised form 13 April 2019; Accepted 3 May 2019

accurate tool to identify foot drop symptoms in early stages and monitor the trajectory of gait related problems during the disease process and during treatment.

Inertial measurement units (IMUs) are sensors that combine accelerometers, gyroscopes, and magnetometers as a single sensor unit, which provides comprehensive information about the acceleration, angular velocity, and sensor movement [5,6]. IMUs are preferred to traditional gait analysis due to the long-term reliability and portable recordings for ambulatory measurements [7–11].

This research paves the way for clinicians to identify foot drop gait related symptoms in early stages in an objective, efficient, and accurate manner. To be more specific, the aim and significance of this study is to determine if foot drop gait patterns due to L5 radiculopathy can be distinguished accurately from normal gait patterns utilizing IMU sensors. The study will classify gait patterns using machine learning (ML) algorithms which have been used previously in medical applications including gait related research [12,13]. A ML approach is a promising choice in gait analysis, as the gait biometrics are usually large and contain complex characteristics. For instance, the ability of different ML algorithms has been compared in distinguishing walking gait patterns of patients with Parkinsons disease [14]. In a related study, the freezing of the gait in Parkinsons patients has been identifiable using ML techniques [15]. ML has also been used to detect gait problems in elderly patients who are then referred to a physician in real time [16]. In a similar study, automatic recognition of gait changes has been achieved using motion capture system data [17].

Machine learning algorithms have been implemented previously to analyse the gait data gathered from IMU sensors [18]. For example, by using these sensors and harvesting ML algorithm capabilities, researchers were successful in identifying different gait phases [19], as well as identifying humans using their gait patterns [20]. This method proved to be the feasible solution to detect gait related medical symptoms, such as recognising lower extremity muscular fatigue [21] and fall detection [22]. In general, the integration of inertial sensors and ML algorithms leads to the diagnosis of neurological disorders involving gait [23].

2. Methodology and experimental design

Three custom made IMU sensors were used to collect the gait data taken from a series of walking trials [24]. The data was transmitted via a wireless transmitter to the base station and stored for each walking trial and the details regarding the sensor fusion and filtering algorithm for the IMU data provided in a previous study by authors [24]. The sensors were attached to the foot, shank, and thigh segments of the affected limb for patients (limb with foot drop) and the right limb for non-patients. Data recorded from the three sensors over time in pitch (x-sagittal plane), roll (y-coronal plane), and yaw (z-transverse plane) during walking trial.

The feasibility of using the IMU sensors to measure the gait pattern of the leg was performed in another study by authors. In that study, the accuracy of the IMU was compared and validated against the Vicon motion capture system (with 18 camera setup) [25], which is the gold standard used for three dimensional motion analysis [26]. It has been reported that there was a strong correlation (over 96.9%) between the IMU system and Vicon motion capture system [27].

2.1. Protocol

he IMU sensors were securely attached to the affected leg's thigh, shank, and foot using double-sided tape to ensure that the orientation of the sensors with respect to the body parts do not change during the data collection. Participants undertook three to seven walking trials, depending on their situation and capabilities at St John of God Subiaco hospital. Each trial required the participant to walk 10–20 steps. A walking trial consisted of a two-second standstill phase and then participants were asked to walk as they normally would at a self- selected comfortable walking speed in a straight line.

During the post process stage, the sensor readings were subtracted from the offset reading during the first 500 ms of data. The data was obtained from the sensors using a wireless radio transmitter, and captured at a base station while running the test [24].

2.2. Participants

Data were collected from two groups of participants. The first group consisted of 30 healthy subjects with no reported gait abnormality, whereas the second group consists of 56 patients recruited from a single neurosurgery practice, having presented with L5 radiculopathy and related ankle dorsiflexion weakness with observable foot drop. All these patients had MR imaging studies of their lumbar spine which confirmed compressive pathology of the L5 nerve root and referred to undergo lumbar spine surgery. Where feasible, electrophysiological studies were also performed to confirm the L5 radiculopathy.

As the study involves human subjects, the relevant ethical approvals obtained from Curtin University (Human Research Ethics Office): HR 12/2016 and St John of God Hospital (HREC): 823. The patient consent was not required for this study.

2.3. Data preprocessing and feature extraction

Each IMU sensor captured angular rotations in three planes over time in the form of time series data. To extract features of the different styles of walking, the Fast Fourier Transform (FFT) was implemented on the time series data. FFT has been proven to be useful when analysing gait and IMU data in other studies, as provides the gait details in frequency domain [21,28]. Using FFT, the angle variation over time can be modeled as follows:

$$F(t) = \sum_{i=0} P_i \sin(i.\ 2\pi f_0 + \boldsymbol{\phi}_i)$$

Where f_0 is the fundamental frequency, P_i is the amplitude, and $\boldsymbol{\phi}_i$ is the phase shift of the i^{th} harmonic. By applying FFT to each of the angular rotation of the IMU data, and considering the first five harmonics for the frequencies (F), amplitudes (A) and phases (P), a 15 measurement (i.e. feature) set can be obtained. Therefore, a total of 135 (15 × 3x3) frequency measurements can be produced for the three movements (i.e. roll, pitch and yaw) and for the three sensor placements (i.e. thigh, shank and foot) [29]. In addition to these frequency domain features, the raw angle measurement of the IMU is also included to produce a final set of features consisting of 144 features (see below).

$$144\,Features = \Big(\overbrace{\underbrace{5}_{F_{1-5}} + \underbrace{5}_{A_{1-5}} + \underbrace{5}_{P_{1-5}}}^{Frequency\ domain} + \overbrace{\underbrace{1}_{Angle}}^{Time\ domain}\Big) \times \overbrace{\underbrace{3}_{Pitch,\ Roll,\ Yaw}}^{Movements} \times \overbrace{\underbrace{3}_{Thigh,\ Shank,\ Foot}}^{Sensors}$$

2.4. Classifiers specifications

In this study 11 Machine Learning (ML) algorithms were evaluated for their ability to classify the measurement data into two distinct categories, the healthy group and the foot drop group. The Waikato Environment for Knowledge Analysis (WEKA) software (The University of Waikato, New Zealand) version 3.8 was used as the workbench for this purpose [30]. The algorithms and their specifications are included: Deep Learning, Multilayer Perceptron, K-Nearest Neighbour (IBK), Logistic Regression, Bayes Net, Naive Bayes, C4.5 decision tree (J48), Random forest (unlimited depth with 100 iterations), Random tree (unlimited depth with 100 iterations), support vector machine (with Radial Basis function kernel), and OneR (1R). For the deep learning algorithm, the Deeplearning4J library was used with five layers which comprises of one input, three hidden and one output layer. The Mean Squared Error was chosen as the loss function.

Two measures were used in this study to evaluate the performance of the ML algorithms: accuracy and the Receiver Operating Characteristic (ROC) curve. The accuracy of an ML algorithm over a dataset was defined as the number of correct predictions over the total number of instances in that dataset. The ROC curve illustrates sensitivity or the true positive rates (i.e. positive predictions that are labeled as positive) on the y-axis and false positive rates (i.e. negative predictions that are labeled as positive) on the x-axis while changing the threshold of the classifier from 0 to ± 1. The area under the ROC (AUC) curve provides an overall performance measure of the ML algorithm. The ROC plot and the AUC used as metrics to demonstrate ML algorithm performance [31].

To ensure the maximum coverage of the data in terms of training and testing, the cross-validation technique was used. In this approach, the dataset was divided into 10 non-overlapping groups. During each run, one set was reserved for testing and the other nine sets used for training the ML algorithm. This process was repeated 10 times with different testing sets, so that every dataset was used once for testing and nine times for training. The final result was the average of the ten runs for each algorithm.

2.5. Feature selection

Out of the 144 features identified, some features may have higher contributions in distinguishing between the foot drop and the healthy gait patterns. To identify the features with the most significant impact, a wrapper feature selection technique was applied. In this technique, a classification algorithm examined each feature and determined its impact on the accuracy of the final classification. The outcome was a vector of scores for each feature, where the score indicated its significance. In this study, all the 11 mentioned classifiers underwent wrapper feature selection process [32].

3. Results

This section illustrates the results obtained from analysing the performance of the ML algorithms in classifying the data and the determination of features that contributed most to the classification.

Table 1 (second column) illustrates the accuracy and the AUC of each ML algorithm while utilising all the 144 features for each walking trial. The Random Forest performed best among the classifiers with the accuracy of 88.5% and AUC of 0.97. The next two best performing classifiers were SVM and Naïve Bayes with accuracies of 86.9%, and 86.1%, respectively. The ROC curve for all 11 ML algorithm is presented in Fig. 1 using 144 features. The Random forest ROC plot in red consistently outperformed the other algorithms.

Table 1
The comparison of 11 ML algorithms using all 144 features and selected features.

Algorithm	All features		Selected features		
	Accuracy (%)	AUC	Accuracy (%)	AUC	Number of selected features
Bayes Net	80.31	0.91	90.02	0.95	17
Deep Learning	86.06	0.94	90.35	0.95	25
IBk	76.90	0.76	89.76	0.90	25
J48	83.72	0.86	87.13	0.88	20
Logistic Regression	83.46	0.90	**92.91**	**0.96**	21
Multilayer Perceptron	85.54	0.93	89.50	0.95	18
Naïve Bayes	86.08	0.91	88.18	0.92	27
OneR	76.90	0.77	76.90	0.77	3
Random Forest	**88.45**	**0.97**	91.60	0.97	29
Random Tree	81.10	0.81	86.35	0.86	14
SVM	86.87	0.87	88.71	0.88	24
Average	**82.98**	**0.87**	**87.95**	0.91	NA

As explained in the methodology section, different features have different levels of contribution to the classification process. To select a smaller subset of more effective features, the wrapper feature selection technique applied using 11 mentioned ML algorithms to obtain the best performing set of features. As the next step, a new round of classifications was done using the selected feature sets provided by the wrapper technique.

The third column of Table 1 shows the accuracy and the AUC for the same 11 ML algorithms using selected feature sets. All the ML algorithms had their performances boosted by the use of the selected features. The number of features selected for each of these classifiers are shown in the last sub-column of Table 1. Overall, the Logistic Regression (accuracy of 92.91% and AUC of 0.96) was the best performing classifier and the Random Forest (accuracy of 91.60% and AUC of 0.97) demonstrated a similar high performance. It can also be observed that performance improvement was accomplished with a significantly reduced number of features (i.e. between 3 and 29 selected features) compared to the original 144 features.

Fig. 2 illustrates the ROC curve of the 11 ML algorithms utilising the selected features.

As is illustrated in Table 1, the minimum, maximum and average of the accuracy were 76.9%, 93.18%, 85.84% respectively, while the majority of classifiers reported the accuracy of 80% or greater. The minimum, maximum and average of the AUC were 0.76, 0.97 and 0.89, respectively.

The accuracy baseline in this study considered as 53.2%, which calculated as the ratio between the populations of the largest class (i.e. normal trials) to the total number of instances.

It is noticeable that the maximum AUC was gained from Random Forest applied on all features (Fig. 1), the next highest AUC obtained from Logistic Regression applied on the selected features with a negligible difference (Fig. 2).

As the next step, the collective set of features investigated to check if the more frequently selected features can provide a more generalised feature set which will be suitable for all types of classifiers. Fig. 3 indicates the number of times a particular feature was selected using the wrapper technique reported in the previous experiments.

Fig. 3 summarises the number of times each feature has been selected by ML algorithms in the wrapper feature selection technique. For example, S1_Pitch_F3_Hz has been selected by all 11 ML algorithms. Moreover, features which are selected less than four times have been removed from the histogram in Fig. 3.

Table 2 illustrates the accuracy and AUC results of ML algorithms applied on four groups of approximately top 10% of the selected features. In fact, each group represents a number of features (e.g. 14, 16, 18 and 20) that selected mostly during the feature selection procedure. In all cases, Random Forest outperformed other algorithms.

Also, the random forest as the best classifier used 16 selected features. Table 3 indicates the origin of the 16 most selected features.

4. Discussion

The result of this study proved IMU sensors along with ML analysing techniques as a potential clinical identification and monitoring tool for foot drop due to L5 lumbar radiculopathy in adults.

The major finding of this study is demonstrated in Table 2 which the Random Forest algorithm classified foot drop subjects with 93.18% accuracy. This result is aligned with other studies using ML algorithms to detect anomalies in human gait [14,21]. Additionally, performance improvements have been reported in classification results by using different feature selection methods [33–35]. In this research, the use of wrapper feature selection method improved the performance of the

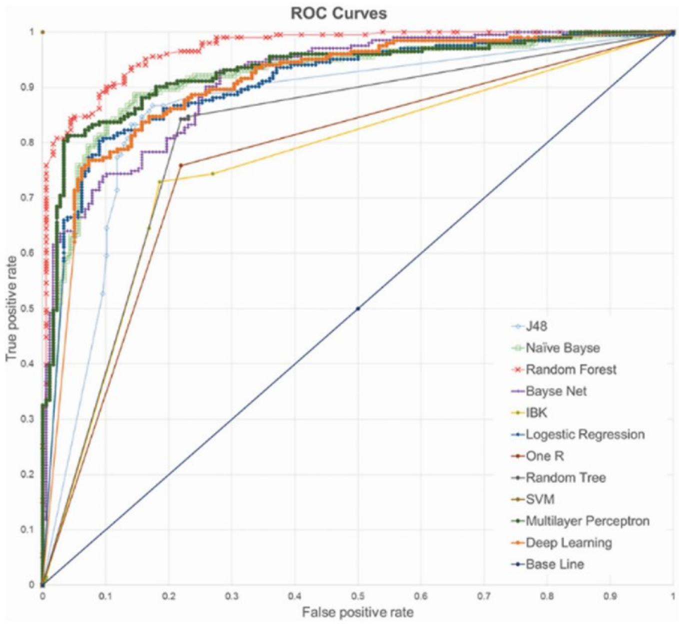

Fig. 1. ROC curves for 11 ML algorithms applied to all features.

11 ML algorithms with the average accuracy and AUC improved by 4.97% and 0.04 units, respectively when using selected features instead of all features.

Table 2 also indicates the optimal classification using the top 10% of most selected features by all 11 ML algorithms as a collective feature set [36]. These frequently selected features were originated from foot and

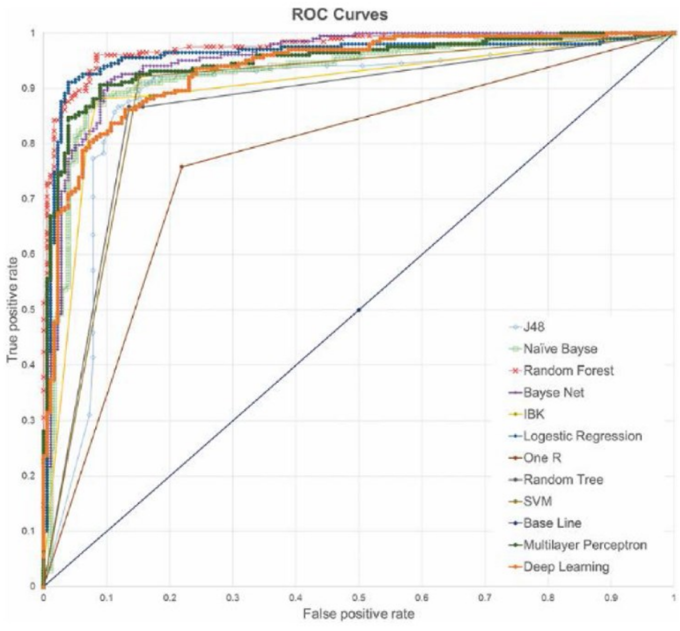

Fig. 2. ROC curves of 11 ML algorithms applied on selected features.

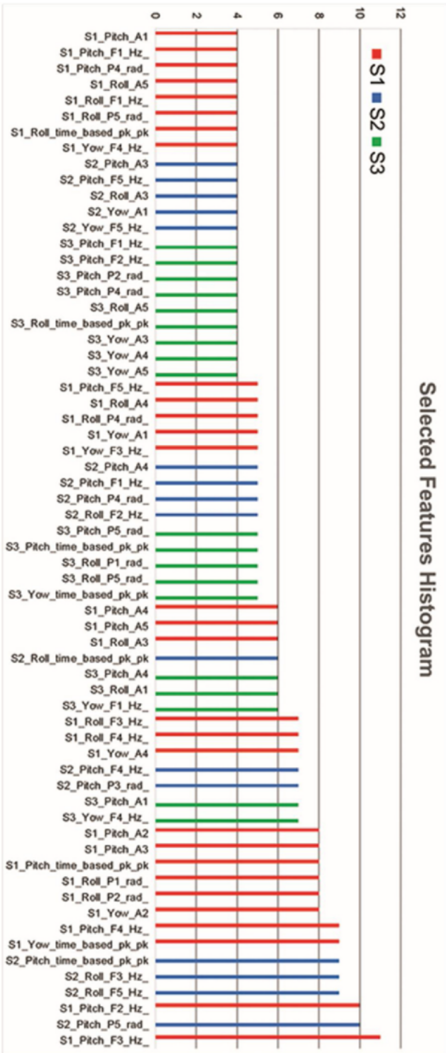

Fig. 3. Cumulative histogram for the number of times each features selected. Due to limited space, only those features with counts equal to or exceeding 4 selection are shown. The naming convention of the features in Fig. 3 matches the description of the features in section 2.3. In this format, the first two letters indicates the sensor where data been captured from (i.e. S1 for foot, S2 for shank and S3 for thigh), the second part of the name shows rotation type of the movement (e.g. pitch, roll or yaw) and the last part shows the parameter of the model (i.e. A for amplitude, P for phase shift, F for the frequency and time-based for the peak-peak value of the angle in time domain).

shank movements, particularly the foot pitch angle which defined as dorsiflexion and is in direct relation with foot drop symptoms [1,37].

Table 2 illustrates that by adding more features to the top 10% feature set, the accuracy and AUC average values remained relatively constant, which indicates the stability of the classifiers' performance. This is due to the "course of dimensionality" phenomena which states that for some ML algorithms the classification becomes exponentially harder as the number of features grows [38].

Whilst investigating the results of the Random Forest as the most accurate classifier, it was noticed that most of the incorrect classifications were from particular subjects. In fact, it can be concluded that the incorrect predictions were because either the subject's walking style was significantly different from their associated group or the sample set was not covering the walking variations comprehensively.

Preliminary observation of the classification results produced by the Multilayer Perceptron and Deep Learning algorithm suggests that by increasing the number of hidden layers of the classifiers, the classification performance improves. Future work will investigate how deep and wide the Deep Learning algorithm have to be to achieve optimal classification performances [39].

In addition to the work in this study, the proposed system has the potential to track the recovery procedure and the changes following the surgery by offering an objective index. In order to provide this index, the walking style of the subjects must be analysed in various stages during the recovery process. As a secondary outcome, the index may offer an earlier and more objective detection of any gait disturbance that can prompt early physical therapy or consideration of surgery.

The presented approach in this study investigated only two groups of subjects and the classification was done for these two groups.

5. Limitations

In regards to the limitations, firstly, the number of participants was a constraint for this study since the number of foot drop patients with L5 origins was limited to 56 people. Increasing the number of participants would have a direct impact on the accuracy of the results. Secondly, the IMU sensors have particular restrictions including data loss and the sampling rate. Although adding more sensors to the system helps to capture more details from the gait movement, the probability of data loss grows by increasing the number of IMU sensors [24].

6. Conclusion

In this study, the feasibility of ML algorithms in the detection of foot drop gait symptoms has been investigated. For this purpose, 11 ML algorithms were evaluated over a dataset consisting of walking gait data from a sample of healthy subjects with normal gait patterns and a group of foot drop subjects. The evaluation was based on the accuracy and the AUC in classifying the foot drop gait patterns from normal style walking gait data. The majority of classifiers resulted in AUCs of 0.80 or greater, while the highest AUC (0.97) was obtained by the Random Forest algorithm. Initial results using the Random Forest algorithm indicated the accuracy of 88.45%. However, by applying the wrapper feature selection technique for Random Forest algorithm, the accuracy improved to 93.18%.

Ethical Approval

This study involves human subjects and the relevant ethical approvals have been obtained from Curtin University of Technology (Human Research Ethics Office): HR 12/2016 and St John of God healthcare group (HREC): 823.

CRediT authorship contribution statement

Shiva Sharif Bidabadi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - original draft. **Iain Murray:** Supervision, Writing - review & editing. **Gabriel Yin Foo Lee:** Supervision, Writing - review & editing. **Susan Morris:** Writing - review & editing. **Tele Tan:** Supervision, Writing - review & editing.

Table 2
The comparison of 11 ML classification algorithms using top 14, 16, 18, and 20 most selected features.

Algorithm	Most selected features (Top 14)		Most selected features (Top 16)		Most selected features (Top 18)		Most selected features (Top 20)	
	Accuracy (%)	AUC	Accuracy (%)	AUC	Accuracy (%)	AUC	Accuracy (%)	AUC
Bayes Net	87.93	0.95	85.56	0.94	87.40	0.95	85.04	0.95
Deep Learning	90.01	0.95	89.88	0.95	90.02	0.95	88.87	0.94
IBk	85.83	0.86	85.04	0.85	86.09	0.86	85.83	0.86
J48	84.51	0.84	84.78	0.84	84.78	0.83	83.99	0.82
Logistic Regression	90.03	0.96	88.98	0.95	89.76	0.95	90.55	0.96
Multilayer Perceptron	89.24	0.95	88.98	0.95	89.50	0.95	87.66	0.94
Naïve Bayes	88.98	0.93	87.66	0.93	89.24	0.94	88.71	0.94
OneR	78.22	0.78	78.22	0.78	78.22	0.78	78.22	0.78
Random Forest	91.60	0.97	93.18	0.97	91.60	0.97	92.13	0.97
Random Tree	85.04	0.85	86.35	0.86	84.25	0.84	86.09	0.86
SVM	81.89	0.81	81.10	0.80	76.64	0.75	77.43	0.76
Average	86.38	0.89	86.07	0.89	85.97	0.89	85.68	0.89

Table 3
The origin of 16 most selected features.

Feature type	Foot	Shank	Thigh	Total
Pitch	4	3	0	7
Roll	1	0	1	2
Yaw	4	1	2	7
Total	9	4	3	16

Acknowledgements

The authors are grateful to the Kailis Foundation and the St John of God Subiaco Hospital for supporting this study. The first author is the recipient of the Kailis–Curtin University of Technology scholarship.

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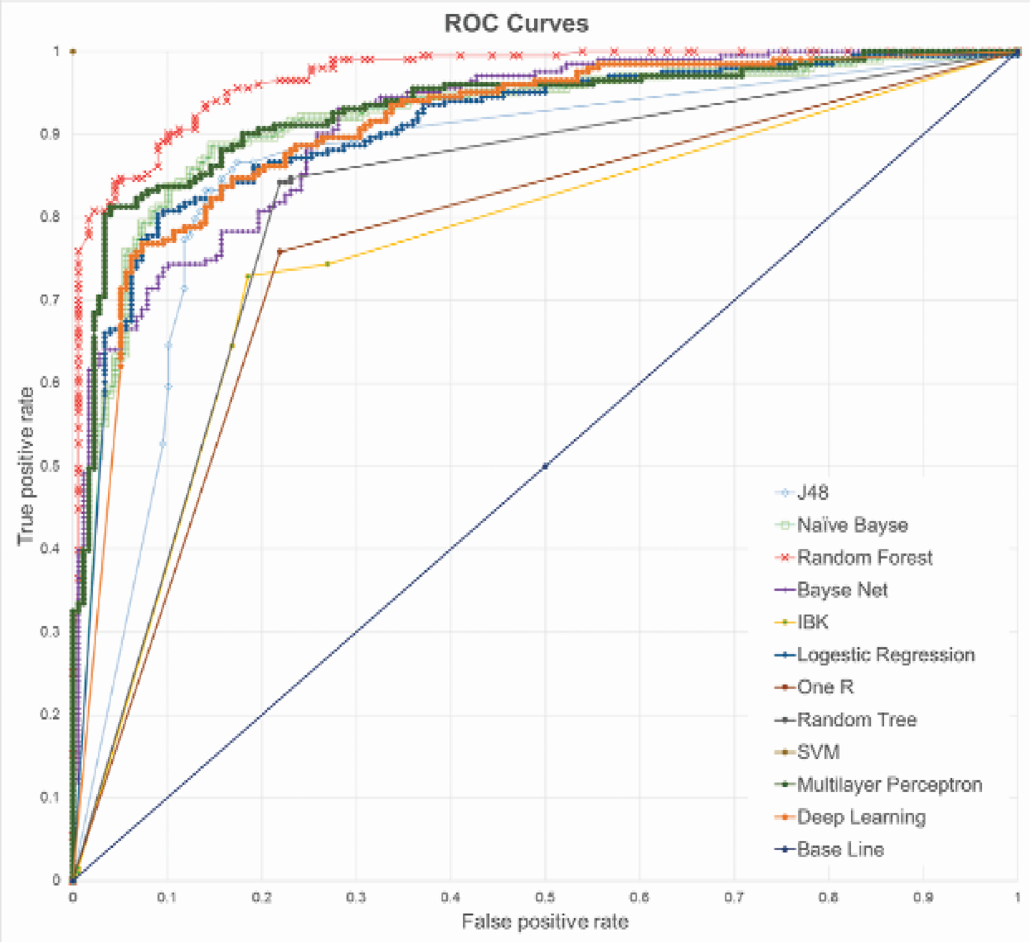
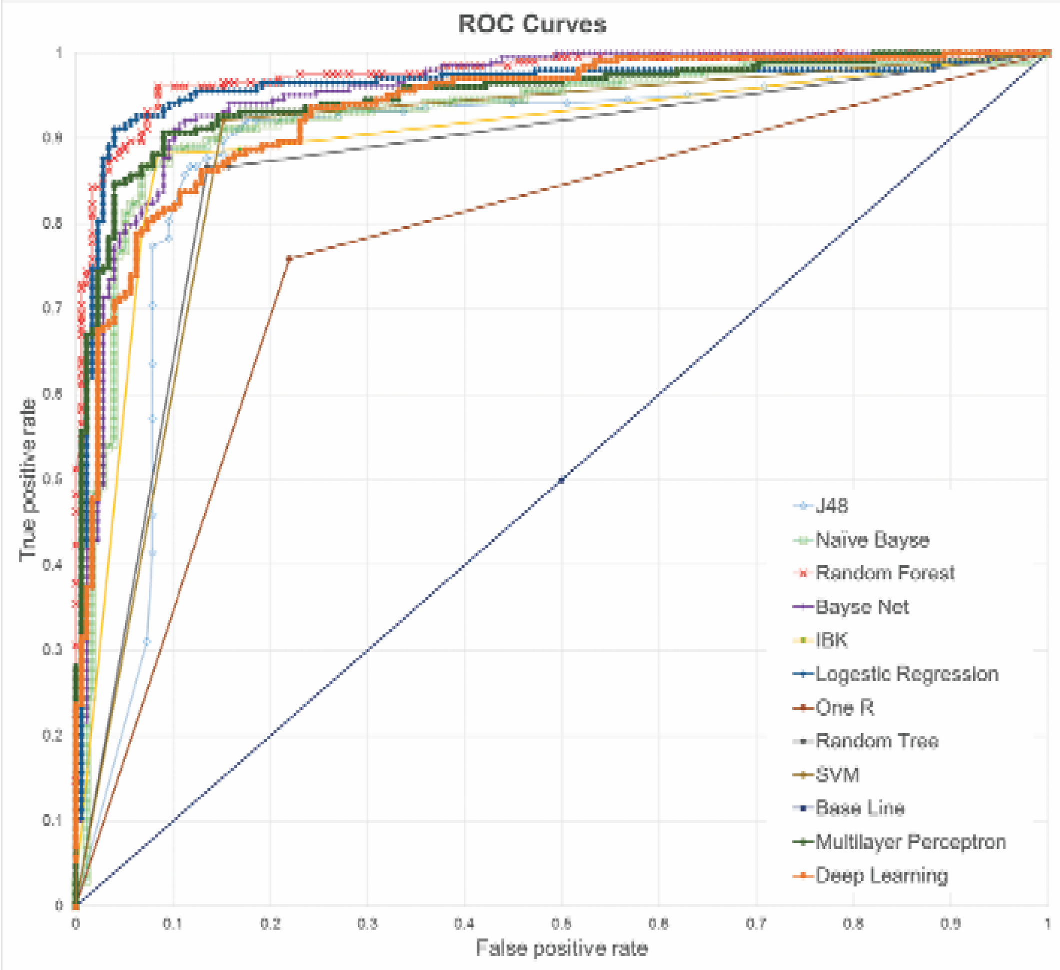
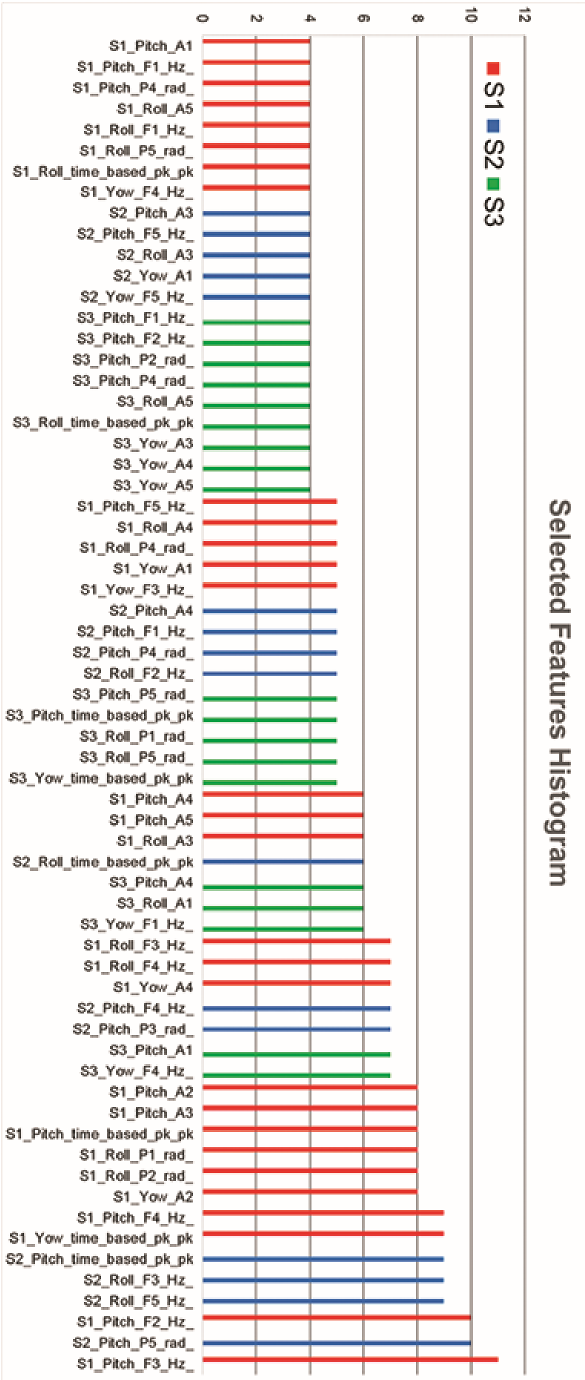


Supplementary Figure 5-1. ROC curves for 11 ML algorithms applied to all features.



Supplementary Figure 5-2. ROC curves of 11 ML algorithms applied on selected features.



Supplementary Figure 5-3. Cumulative histogram for the number of times each features selected. Due to limited space, only those features with counts equal to or exceeding 4 selection are shown. The naming convention of the features in Fig. 3 matches the description of the features in section 2.3. In this format, the first two letters indicates the sensor where data been captured from (i.e. S1 for foot, S2 for shank and S3 for thigh), the second part of the name shows rotation type of the movement (e.g. pitch, roll or yaw) and the last part shows the parameter of the model(i.e. A for amplitude, P for phase shift, F for the frequency and timebased for the peak-peak value of the angle in time domain)

Supplementary Table 5-1. The comparison of 11 ML algorithms using all 144 features and selected features

Algorithm	All features		Selected features		
	Accuracy (%)	AUC	Accuracy (%)	AUC	Number of selected features
Bayes Net	80.31	0.91	90.02	0.95	17
Deep Learning	86.06	0.94	90.35	0.95	25
IBk	76.90	0.76	89.76	0.90	25
J48	83.72	0.86	87.13	0.88	20
Logistic Regression	83.46	0.90	**92.91**	**0.96**	21
Multilayer Perceptron	85.54	0.93	89.50	0.95	18
Naïve Bayes	86.08	0.91	88.18	0.92	27
OneR	76.90	0.77	76.90	0.77	3
Random Forest	**88.45**	**0.97**	91.60	0.97	29
Random Tree	81.10	0.81	86.35	0.86	14
SVM	86.87	0.87	88.71	0.88	24
Average	**82.98**	**0.87**	**87.95**	**0.91**	NA

Supplementary Table 5-2. The comparison of 11 ML classification algorithms using top 14, 16, 18, and 20 most selected features.

Algorithm	Most selected features (Top 14)		Most selected features (Top 16)		Most selected features (Top 18)		Most selected features (Top 20)	
	Accuracy (%)	AUC	Accuracy (%)	AUC	Accuracy (%)	AUC	Accuracy (%)	AUC
Bayes Net	87.93	0.95	85.56	0.94	87.40	0.95	85.04	0.95
Deep Learning	90.01	0.95	89.88	0.95	90.02	0.95	88.87	0.94
IBk	85.83	0.86	85.04	0.85	86.09	0.86	85.83	0.86
J48	84.51	0.84	84.78	0.84	84.78	0.83	83.99	0.82
Logistic Regression	90.03	0.96	88.98	0.95	89.76	0.95	90.55	0.96
Multilayer Perceptron	89.24	0.95	88.98	0.95	89.50	0.95	87.66	0.94
Naïve Bayes	88.98	0.93	87.66	0.93	89.24	0.94	88.71	0.94
OneR	78.22	0.78	78.22	0.78	78.22	0.78	78.22	0.78
Random Forest	**91.60**	**0.97**	**93.18**	**0.97**	**91.60**	**0.97**	**92.13**	**0.97**
Random Tree	85.04	0.85	86.35	0.86	84.25	0.84	86.09	0.86
SVM	81.89	0.81	81.10	0.80	76.64	0.75	77.43	0.76
Average	**86.38**	**0.89**	**86.07**	**0.89**	**85.97**	**0.89**	**85.68**	**0.89**

Supplementary Table 5-3. The origin of 16 most selected features.

Feature type	Foot	Shank	Thigh	**Total**
Pitch	4	3	0	7
Roll	1	0	1	2
Yaw	4	1	2	7
Total	9	4	3	**16**

Chapter 6:

Tracking Foot Drop Recovery Following Lumbar-Spine Surgery, Applying Multiclass Gait Classification Using Machine Learning Techniques

This chapter is covered by the following publication:

S. Sharif Bidabadi, T. Tan, I. Murray, and G. Lee, "Tracking Foot Drop Recovery Following Lumbar-Spine Surgery, Applying Multiclass Gait Classification Using Machine Learning Techniques," Sensors, vol. 19, no. 11, p. 2542, Jun. 2019.

sensors

Article

Tracking Foot Drop Recovery Following Lumbar-Spine Surgery, Applying Multiclass Gait Classification Using Machine Learning Techniques

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Received: 14 February 2019; Accepted: 29 May 2019; Published: 4 June 2019

Abstract: The ability to accurately perform human gait evaluation is critical for orthopedic foot and ankle surgeons in tracking the recovery process of their patients. The assessment of gait in an objective and accurate manner can lead to improvement in diagnoses, treatments, and recovery. Currently, visual inspection is the most common clinical method for evaluating the gait, but this method can be subjective and inaccurate. The aim of this study is to evaluate the foot drop condition in an accurate and clinically applicable manner. The gait data were collected from 56 patients suffering from foot drop with L5 origin gathered via a system based on inertial measurement unit sensors at different stages of surgical treatment. Various machine learning (ML) algorithms were applied to categorize the data into specific groups associated with the recovery stages. The results revealed that the random forest algorithm performed best out of the selected ML algorithms, with an overall 84.89% classification accuracy and 0.3785 mean absolute error for regression.

Keywords: foot drop; gait classification; machine learning; inertial measurement unit

1. Introduction

Walking ability is a key physical behavior that can strongly influence the individual's personal independence, and therefore, the successful execution of their daily activities. Thus, assessment of the gait is frequently required in the clinical setting. It becomes increasingly necessary and important to assess the gait during the treatment of a wide range of gait disorders [1].

Regardless of the significance of gait disorders, there is no widely accepted method for assessing the quality of walking. The most common methods of gait evaluation are the Berg Balance Scale (BBS) [2], dynamic gait index [3], 10-Meter Walk Test [4], 6-Min Walk Test [5], and the Functional Ambulation Categories (FACs) [6]. All these methods evaluate walking ability using different ranges and through the application of different tasks and specified ranges [7]. During these tests, the medical practitioner visually observes the walking ability of the patient and ranks this ability. Therefore, the outcome of these assessments is subjective and may be inaccurate [8].

To overcome this limitation, different methods and devices have been investigated and introduced in practice. As a general measure, walking velocity has been used as an indication of gait health [9,10]. Manual muscle testers are also used to measure muscle strength, which is indirectly related to walking gait [11]. Recently, several studies have been conducted in an attempt to utilize the technology of various sensors in gait analysis. For example, the GAITRite System is a waking platform that uses a set of pressure sensors and a software system to track gait events [12]. The prosthetic activity monitor (PAM) is also used to assess physical activities based on acceleration measurements [1]. In addition, there are various complex optical motion capture systems, such as the Vicon system, that accurately measure human movements [13]. However, optical motion capture systems are expensive and require software expertise to operate; therefore, they are not practical for conducting daily clinical assessments [14]. Among the many different movement measurement methods, inertial measurement unit (IMU) sensors have been widely implemented for gait analysis due to their particular advantages, such as long-term monitoring and portable recording of ambulatory measurements [15–17].

The gait data collected from IMU sensors are generally large, noisy, complex, and interconnected. Automated methods (e.g., machine learning (ML), which can extract high-level information from raw data) are the preferred solution for managing this data characteristic [18,19]. These methods are currently being used in various medical applications [20]. For example, the walking-gait pattern of patients with Parkinson's disease has been assessed for identification of gait freeze and for distinguishing the characteristics of Parkinson's gait [21,22]. In addition, by utilizing ML algorithms, real-time monitoring of elderly patients' fall down has become possible [23].

In other research, IMU sensors used together with ML analysis have been reported to assist in the identification of different gait phases and human identification via gait patterns [24,25]. These methods have also been implemented to detect gait-related symptoms, such as fall detection or lower extremity muscular fatigue [26,27]. The integration of ML algorithms for the analysis of IMU gait data has been found to be a feasible solution for helping in the diagnosis of neurological disorders involving gait [28].

Foot drop is a common gait disorder in adults, which may be due to varied aetiologies [29]. In simplistic terms, a weakness of the muscles which dorsiflex the foot at the ankle leads to a "dropping" effect on the front of the foot when an induvial walks. This can cause tripping and recurrent falls, with potentially disastrous consequences [30,31]. In the longer term, the abnormal gait pattern leads to compensatory mechanisms, which can also have an impact on other joints. It is important to recognise that the term, foot drop, is an all-encompassing end point phenomenon, which does not relate to a precise aetiology or pathophysiological mechanism. In this particular study, the authors have attempted to recruit patients who have developed a foot drop specifically due to compressive L5 (the fifth lumbar spine vertebrae) radiculopathy. An L5 lumbar nerve root lesion results in paresis of the tibialis anterior, extensor hallucis longus, extensor digitorum brevis, and gluteal muscles of the lower limb on clinical examination, and ankle dorsiflexion, ankle eversion, toe extension, and hip abduction weakness is typically documented [32]. Consequently, a characteristic foot drop and a pathological gait develops. This uniform criteria overcomes an obvious criticism of current studies, which purport to include patients with foot drop, but which, in reality, are attributable to heterogeneous pathologies. The present research aims to provide an objective methodology for tracking the recovery process in foot drop disorder, specifically in patients with L5 radiculopathy following lumbar-spine surgery. Also introducing a gait quality index based on regression technique to assist medical practitioners in the assessment of foot drop severity and the recovery state of patients. For this purpose, the gait characteristics were captured using IMU sensors and multiple ML algorithms were applied and results compared.

2. Materials and Methods

A series of walking trials were recorded using a custom designed system based on three IMU sensors [33]. The data were captured while walking from participants' foot (barefoot), shank, and thigh in the form of different angle measurements over time (pitch (x), roll (y), and yaw (z)). This information was then transmitted and stored via wireless communication. This IMU system has been proven to be feasible for gait assessments in a previous study by the authors. That study compared the accuracy of the IMU system with the Vicon motion capture system (with an 18 camera setup) [31]. A strong correlation was observed (more than 96.9%) between the IMU system and the Vicon motion capture system [34].

2.1. Test Protocol

IMU sensors were attached to participants' lower limbs using straps and double-sided tape. Participants were asked to perform three to seven walking trials in a straight line in their usual walking style. They were also asked to pause and wait for two seconds before walking. The first 500 ms of data were used to offset the sensor readings during the post-processing stage.

2.2. Participants

The gait data were gathered from two groups of participants having specified inclusion and exclusion criteria: (1) A group of 30 participants with healthy gait styles and without any reported gait-related problems (normal group); (2) a group of 56 patients recruited from a neurosurgery practice, who presented with ankle-dorsiflexion weakness with L5 radiculopathy origins (foot drop group). Degenerative lumbar spine disorders, such as radiculopathy at L5, can cause foot drop. The mechanism is through a compression of the nerve fibers that constitute the peroneal nerve [32]. The compressive pathology of the L5 nerve root was confirmed using magnetic resonance imaging (MRI) of the lumbar spine region.

The data from the second group were captured from the affected side of the lower limb and in three different stages: First, before the lumbar spine surgery (pre); second, during the first two days following surgery (post 1); and third, two to three weeks after the surgery while recovering (post 2).

The walking capabilities of different subjects at different stages may have varied due to wound pain, patient fatigue, or other related problems. Therefore, the speed, distance, and the number of steps in different trials were not equal. To overcome this limitation, a resampling process was applied, which will be further explained in Section 2.3.

Given that the study involves human participants, the relevant ethical approvals were obtained from both the Curtin University of Technology (Human Research Ethics Office): HR 12/2016 and St John of God Hospital (Human Research Ethics Committee): 823.

2.3. Data Preprocessing

As stated, the gait data were collected from different participant groups over different periods of time. Therefore, the number of samples captured from the pre, post 1, post 2, and normal groups was 203, 199, 136, and 178 respectively. To resolve this data size problem, some of the long walking trials were subdivided into two walking sample sets, each set including at least three walking steps. For example, to match the number of samples in the post 2 data set, 67 long walking trials were selected and each was split into two trials. This increased the original number of post 2 samples by 67. After applying the mentioned resampling method to each data set, the number of walking samples for all groups was normalized to 203 trials.

The captured dataset consisted of three angle measurement in the format of a time series signal for pitch, roll, and yaw movement. Fast Fourier transform (FFT) was implemented on these time series signals to extract the signals' features, such as the fundamental harmonic, amplitude, and phase shifts. Previous studies have confirmed the capability of FFT in analyzing gait and IMU data [27,35]. The signals were modelled using FFT as follows:

$$F(t) = \sum_{i=0} P_i \sin(2\pi f_0 i + \phi_i), \tag{1}$$

where f_0, P_i, and ϕ_i are the fundamental harmonic, amplitude, and phase shift of the i^{th} harmonic, respectively. The FFT was applied to each angle from the walking samples, meaning a 15-feature model in the frequency domain was obtained [36]. The foot sensor (S1), shank sensor (S2), and thigh sensor (S3) recorded the movements, with each sensor representing the movement in the sagittal, coronal, and transverse planes as the pitch, roll, and yaw, respectively. In addition to the 15-feature model in the frequency domain, also, each angle in the time domain constituted an extra nine features. The final model consisted of 144 features as below:

$$144\, Features \left(\overbrace{\underbrace{5}_{F_{1-5}} + \underbrace{5}_{P_{1-5}} + \underbrace{5}_{\phi_{1-5}}}^{Frequency\ domain} + \overbrace{\underbrace{1}_{Angle}}^{Time\ domain} \right) \times \overbrace{\underbrace{3}_{Pitch,\ Roll,\ Yaw}}^{Movments} \times \overbrace{\underbrace{3}_{Thigh,\ Shank,\ Foot}}^{Sensors}. \quad (2)$$

2.4. Feature Extraction, Classification, and Regression

The Waikato Environment for Knowledge Analysis (WEKA) software version 3.8 was used as the workbench for evaluation of the 11 ML algorithms used to classify gait pattern based on the model with 144 features [37]. The following are the 11 classification algorithms that were analyzed: Deep learning, multilayer perceptron, K-nearest neighbors (IBK), logistic regression, Bayes net, naive Bayes, C4.5 decision tree (J48), random forest (unlimited depth with 100 iterations), random tree (unlimited depth with 100 iterations), support vector machine (SVM) (radial basis function kernel), and OneR (1R). A 10-fold cross-validation methodology was applied for each classification.

Four measures were used to compare the performance of the 11 classification algorithms. First, classification accuracy was defined as the number of correct predictions over the total number of instances in that dataset. Second, the confusion matrix, which provides information about correct and incorrect predictions, was created for each classifier [38]. The confusion matrix is a square matrix in which $C_{i,j}$ indicates the number of instances predicted as class i, where they were from class j originally. The best classification will have only zero values outside the main diagonal. In addition, the precision and F-score were calculated:

$$Precision = \frac{TP}{(TP + FP)}, \quad (3)$$

$$F\ score = \frac{2 \times TP}{2 \times TP + FP + FN}, \quad (4)$$

where TP, FP, and FN are the true positive, false positive, and false negative, respectively. True positives are items correctly labeled as belonging to their class. False positives are items incorrectly labeled as belonging to the class. False negatives are items which were not labeled as belonging to the class, but should have been. Among all 144 features describing gait in this model, some may have a higher effect in describing the severity level of foot drop. To find features with the most significant effect, the wrapper feature selection technique was implemented. The wrapper technique-based method was implemented alongside the classification algorithm to review the subset of the input features that maximizes a predefined objective function. In this case, the objective was to maximize the classification accuracy and to minimize the false alarm rate. A vector of scores for all features indicates the significance of the features. In this study, the wrapper feature selection technique was conducted using all 11 classification algorithms and the results are presented in the next section [39]. In this procedure, the data set was shuffled randomly and split into 10 groups. Each group was taken as the hold out set (or test data set) once and the remaining groups as the training data set.

Classification was done on the training set and evaluated on the test set retaining an evaluation score. The 10 fold cross-validation procedure was applied 11 times using each classification algorithm and the whole dataset was evaluated each time.

In addition to the aim of classifying gait, a further aim of this study was to find an objective index to indicate the severity of observed foot drop symptoms. To achieve this index, eight regression ML algorithms were investigated using the WEKA framework. The following are the eight regression ML algorithms that were analyzed: Deep learning, multilayer perceptron, IBK, random forest, random tree, linear regression, simple linear regression, and SVM regression. Some of the classification algorithms provide an index indicating the likelihood of their prediction, therefore they can be used as the regression algorithem. To be able to perform the regression analysis on the dataset, the state variable, which indicates in which state the sample was captured (e.g., pre, post 1, post 2), was changed to a numerical value from zero to four, which refers to the pre, post 1, post 2, and normal states, respectively.

Different measures were used to evaluate the performance of the regression algorithms. The first measure was the error between the predictions and the actual value of the class. For example, a regression algorithm may have predicted a post 2 (i.e., 2) walking sample as 2.8, and therefore the error for this sample is 0.8. Additionally, the correlation coefficient, mean absolute error, root mean square error (RMSE), relative absolute error, and root relative squared error were used as measures for evaluating the regression performance as shown below:

$$Correlation\ coefficient = \frac{N\sum y\acute{y} - (\sum y)(\sum \acute{y})}{\sqrt{\left[N\sum y^2 - (\sum y)^2\right]\left[N\sum \acute{y}^2 - (\sum \acute{y})^2\right]}}, \tag{5}$$

$$Mean\ absolute\ error = \frac{1}{N}\sum_{i=1}^{N}\left|y - \acute{y}\right|, \tag{6}$$

$$Root\ mean\ absolute\ error = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - \acute{y})^2}, \tag{7}$$

$$Relative\ absolute\ error = \frac{\sum_{i=1}^{N}\left|y_i - \acute{y}_i\right|}{\sum_{i=1}^{N}\left|\overline{y} - \acute{y}_i\right|} \times 100, \tag{8}$$

$$Root\ relative\ squared\ error = \sqrt{\frac{\sum_{i=1}^{N}(\acute{y}_i - y_i)^2}{\sum_{i=1}^{N}(\acute{y}_i - \overline{y})^2}} \times 100, \tag{9}$$

where y and $\acute{y}$ are the actual and prediction values and N is the number of samples.

3. Results

This section compares the performance of the ML algorithms on the collected data.

3.1. Analysis of the Four Classes

First, the gait patterns were classified into four classes using the entire available dataset from the patients at different stages of treatment and the participants in the normal group. These four classes were the pre, post 1, post 2, and normal class.

Table 1 presents the accuracy of the ML classification algorithms for the four classes.

Table 1. Accuracy from 11 ML algorithms classifying data into four classes.

Algorithm	Accuracy (%)
Bayes net	55.0493
Deep learning	52.3399
IBK	50.6158
J48	57.1429
Logistic regression	54.1872
Multilayer perceptron	54.6798
Naïve Bayes	51.4778
OneR	47.9064
Random forest	67.3645
Random tree	55.665
SVM	62.3153
Average	55.3400

Table 1 demonstrates that random forest and OneR have the maximum and minimum accuracy, respectively. The average overall accuracy of the algorithms is 55.34%, which is low. To investigate the cause of the low accuracy of the algorithms, the confusion matrix was generated and investigated. Figure 1 presents the confusion matrix, precision, and F-score observed from all classification algorithms. The figure is color coded so that as the value of the cell increases, the cell is colored with a darker red.

Algorithm	Confusion matrix				Prediction	Precision	F-score
	Pre	Post 1	Post 2	Normal			
One R	81	85	5	32	Pre	0.40	0.41
	90	70	14	29	Post 1	0.34	0.35
	4	7	139	53	Post 2	0.68	0.67
	18	32	54	99	Normal	0.49	0.48
Bayes Net	65	101	8	29	Pre	0.32	0.38
	56	118	11	18	Post 1	0.58	0.53
	4	5	147	47	Post 2	0.72	0.70
	18	16	52	117	Normal	0.58	0.57
Naïve Bayes	62	125	7	9	Pre	0.31	0.34
	60	128	9	6	Post 1	0.63	0.51
	12	17	116	58	Post 2	0.57	0.63
	29	27	35	112	Normal	0.55	0.58
SVM	104	24	74	1	Pre	0.51	0.64
	16	117	69	1	Post 1	0.58	0.68
	0	1	200	2	Post 2	0.99	0.60
	1	1	116	85	Normal	0.42	0.58
IBK	82	64	22	35	Pre	0.40	0.41
	72	86	20	25	Post 1	0.42	0.45
	17	12	125	49	Post 2	0.62	0.61
	26	19	40	118	Normal	0.58	0.55
Logistic	88	72	22	21	Pre	0.43	0.44
	81	88	22	12	Post 1	0.43	0.45
	19	14	123	47	Post 2	0.61	0.60
	11	13	38	141	Normal	0.69	0.67

Algorithm	Confusion matrix				Prediction	Precision	F-score
	Pre	Post 1	Post 2	Normal			
J48	95	84	11	13	Pre	0.47	0.46
	76	102	13	12	Post 1	0.50	0.49
	17	15	132	39	Post 2	0.65	0.67
	18	15	35	135	Normal	0.67	0.67
Random Tree	84	87	17	15	Pre	0.41	0.44
	60	110	16	17	Post 1	0.54	0.51
	16	12	145	30	Post 2	0.71	0.67
	20	21	49	113	Normal	0.56	0.60
Random Forest	77	98	13	15	Pre	0.38	0.47
	38	141	13	11	Post 1	0.69	0.61
	3	11	168	21	Post 2	0.83	0.79
	4	8	30	161	Normal	0.79	0.78
Multilayer perceptron	76	91	11	25	Pre	0.37	0.39
	86	89	13	15	Post 1	0.44	0.43
	13	14	138	38	Post 2	0.68	0.70
	15	15	32	141	Normal	0.69	0.67
Deep learning	64	97	20	22	Pre	0.32	0.35
	80	90	15	18	Post 1	0.44	0.44
	13	13	132	45	Post 2	0.65	0.64
	11	10	43	139	Normal	0.68	0.65

Figure 1. Confusion matrix, precision, and F-score from classifying data into four classes.

In addition to the classification algorithms, the regression method was used to compare and evaluate each class data on a numerical basis. Here, the pre category was given a base value of 1, post 1 a value of 2, post 2 a value of 3, and normal a value of 4. Table 2 presents the error measures of the eight regression algorithms for the four classes (i.e., pre, post 1, post 2, and normal).

Table 2. Error measures from eight regression algorithms classifying data into four classes.

Algorithm	Correlation Coefficient	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error
Deep learning	−0.0856	1.3104	1.5825	130.8814	141.4032
IBk	0.4181	0.7808	1.2217	77.9844	109.1655
Linear regression	0.6430	0.7003	0.8910	69.9453	79.6130
Multilayer perceptron	0.0026	1.2089	9.3257	120.7437	833.2870
Random forest	0.7807	0.5426	0.7119	54.1923	63.6136
Random tree	0.5748	0.6252	1.0010	62.4422	89.4466
Simple linear regression	0.4454	0.7936	1.0010	79.2604	89.4430
SVM	0.6244	0.7062	0.9067	70.5317	81.0133

Figure 2 presents the error of the predictions and the error bar plot of the regression algorithms. In Figure 2, the mean value of the prediction of each algorithm is represented by a black dot, while the standard deviation is represented by a rectangle. The minimum and maximum values are presented using thin lines in each bar. Figure 2 represents the eight regression algorithms for the four classes.

It is notable in Figure 1 that in all 11 classifications, the predictions for the pre and post 1 categories are often confused (i.e., the data from the pre class were classified as post 1 and vice versa). This error in prediction is the principal cause of the low accuracy level of the algorithms presented in Table 1.

Therefore, the following section presents the results from the classification and regression algorithms on the dataset without post 1 data.

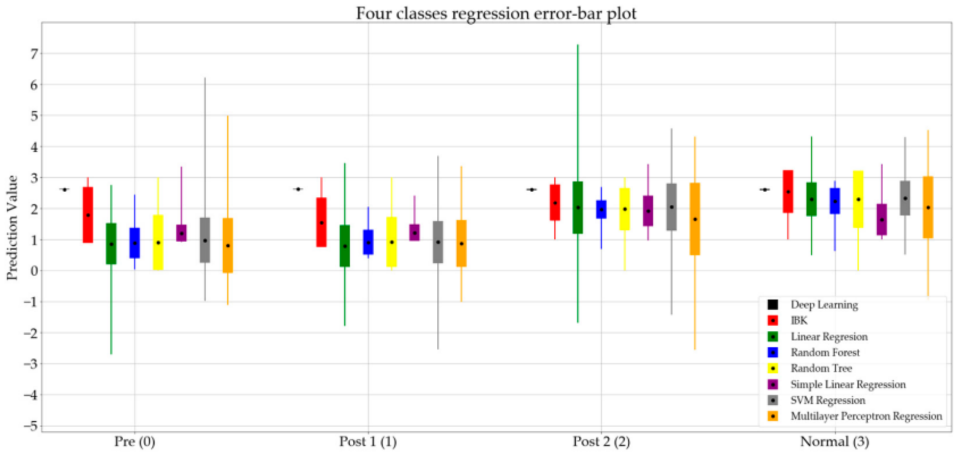

Figure 2. Error bar plot for regression algorithms classifying data into four classes.

3.2. Analysis of Three Classes

This section presents the results of the classification tests when the post 1 class was removed from the analysis. Table 3 presents the accuracy of ML algorithms when the dataset was classified into three classes of pre, post 2, and normal. The second column shows the classification results when all 144 features were used. In general, Table 3 compares the accuracy observed before and after applying the wrapper feature selection technique.

Table 3. Classification accuracy from 11 ML algorithms classifying data into three classes before and after feature selection.

Algorithm	All Features (n = 144)	Selected Features	
	Accuracy (%)	Accuracy (%)	Number of Selected Features
Bayes net	70.94	79.97	20
Deep learning	70.61	76.52	21
IBk	62.89	75.37	46
J48	73.56	76.03	22
Logistic regression	68.47	79.15	22
Multilayer perceptron	75.21	76.52	20
Naïve Bayes	68.64	76.52	44
OneR	65.85	67.98	1
Random forest	83.25	84.89	33
Random tree	69.62	75.04	21
SVM	67.82	77.83	30
Average	70.62	76.89	NA

Figures 3 and 4 present the confusion matrix, precision, and F-score of the classification algorithms before and after the feature selection, respectively.

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
One R	147	9	47	Pre	0.72	0.75
	11	135	57	Post 2	0.67	0.68
	33	51	119	Normal	0.59	0.56
Bayes Net	168	7	28	Pre	0.83	0.81
	9	148	46	Post 2	0.73	0.72
	34	53	116	Normal	0.57	0.59
Naïve Bayes	185	8	10	Pre	0.91	0.79
	29	116	58	Post 2	0.57	0.64
	53	33	117	Normal	0.58	0.60
SVM	127	75	1	Pre	0.63	0.76
	2	199	2	Post 2	0.98	0.67
	1	115	87	Normal	0.43	0.59
IBK	129	25	49	Pre	0.64	0.67
	24	123	56	Post 2	0.61	0.63
	31	41	131	Normal	0.65	0.60
Logistic	152	26	25	Pre	0.75	0.73
	34	128	41	Post 2	0.63	0.64
	25	41	137	Normal	0.67	0.67

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
J48	159	21	23	Pre	0.78	0.78
	26	145	32	Post 2	0.71	0.71
	20	39	144	Normal	0.71	0.72
Random Tree	150	25	28	Pre	0.74	0.77
	17	148	38	Post 2	0.73	0.69
	21	56	126	Normal	0.62	0.64
Random Forest	172	15	16	Pre	0.85	0.87
	12	174	17	Post 2	0.86	0.82
	10	32	161	Normal	0.79	0.81
Multilayer perceptron	163	16	24	Pre	0.80	0.81
	17	145	41	Post 2	0.71	0.73
	20	33	150	Normal	0.74	0.72
Deep learning	146	27	30	Pre	0.72	0.74
	24	137	42	Post 2	0.67	0.68
	21	35	147	Normal	0.72	0.70

Figure 3. Confusion matrix, precision, and F-score from classification algorithms classifying data into three classes before feature selection.

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
One R	147	9	47	Pre	0.72	0.75
	12	141	50	Post 2	0.69	0.70
	29	48	126	Normal	0.62	0.59
Bayes Net	175	18	10	Pre	0.86	0.86
	17	163	23	Post 2	0.80	0.77
	14	40	149	Normal	0.73	0.77
Naïve Bayes	167	9	27	Pre	0.82	0.80
	28	144	31	Post 2	0.71	0.75
	20	28	155	Normal	0.76	0.75
SVM	165	16	22	Pre	0.81	0.83
	14	161	28	Post 2	0.79	0.77
	16	39	148	Normal	0.73	0.74
IBK	167	14	22	Pre	0.82	0.84
	13	136	54	Post 2	0.67	0.71
	16	31	156	Normal	0.77	0.72
Logistic	176	9	18	Pre	0.87	0.85
	23	144	36	Post 2	0.71	0.75
	12	29	162	Normal	0.80	0.77

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
J48	165	16	22	Pre	0.81	0.80
	20	151	32	Post 2	0.74	0.75
	23	33	147	Normal	0.72	0.73
Random Tree	164	16	23	Pre	0.81	0.82
	20	149	34	Post 2	0.73	0.72
	14	45	144	Normal	0.71	0.71
Random Forest	177	17	9	Pre	0.87	0.88
	15	171	17	Post 2	0.84	0.82
	7	27	169	Normal	0.83	0.85
Multilayer perceptron	173	14	16	Pre	0.85	0.84
	18	148	37	Post 2	0.73	0.73
	17	41	145	Normal	0.71	0.72
Deep learning	175	12	16	Pre	0.86	0.84
	24	149	30	Post 2	0.73	0.73
	17	44	142	Normal	0.70	0.73

Figure 4. Confusion matrix, precision, and F-score from classification algorithms classifying data into three classes after feature selection.

As seen in Table 3, the classification performance improved after applying feature selection. The best performing classifier was random forest before and after feature selection. Also, the random forest as the best classifier had 33 selected features (Table 3) using the wrapper technique. Table 4 indicates the type and body part of the selected features.

Table 4. The features selected by wrapper techniques using the random forest algorithm.

Feature Type	Foot	Shank	Thigh	Total
Pitch	5	5	6	16
Roll	6	4	1	11
Yaw	4	1	1	6
Total	15	10	8	33

For the next step of the analysis, the regression algorithms were applied to the three classes (i.e., pre, post 2, and normal), and the regression error measures calculated are presented in Table 5.

Table 5. Error measures from eight regression algorithms classifying data into four classes.

Algorithm	Correlation Coefficient	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error (%)	Root Relative Squared Error (%)
Deep learning	−0.0598	0.9396	1.1555	140.4993	141.4422
IBk	0.4966	0.4631	0.8245	69.2432	100.9249
Linear regression	0.6109	0.5319	0.5319	79.5453	88.4125
Random forest	0.7931	0.3785	0.5099	56.6055	62.4162
Random tree	0.5861	0.3992	0.7267	59.6992	88.9477
Simple linear regression	0.2998	0.6580	0.7963	98.3908	97.4729
SVM	0.5930	0.5470	0.7221	81.8015	88.3848
Multilayer perceptron	0.5469	0.5649	0.8279	84.4696	101.3445

Figure 5 presents the error bar plot of the regression algorithms. In this figure, the pre, post 2, and normal states are represented by the numbers 0, 1, and 2, respectively.

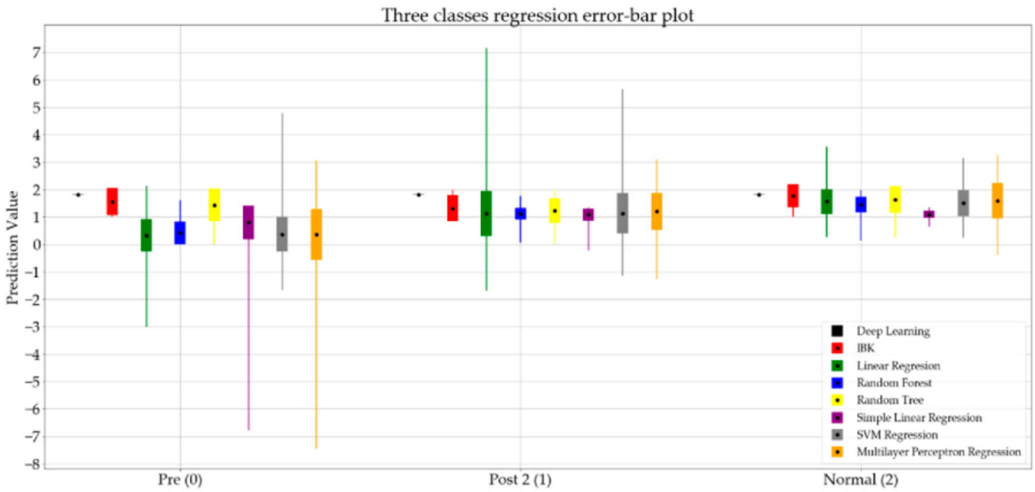

Figure 5. Error bar plot for eight regression algorithms classifying data into three classes.

4. Discussion

This research demonstrated a systematic and objective methodology for the evaluation of foot drop with L5 lumber radiculopathy origins.

As presented in Table 5, the random forest regression shows the lowest mean absolute error. After investigating the performance of the random forest regression more closely in Figure 5, and comparing the results for the pre and post 2 states, a jump in the mean value of the predictions is noticeable. This indicates that the prediction values for the random forest algorithm can be used as an index to determine the severity level of foot drop in the walking gait pattern. Therefore, the method presented in this research shows promise as a potential measurement tool for tracking the recovery process of foot drop with L5 origins in adults. However, outliers in the random forest algorithm require further investigation.

This study found that the random forest algorithm provides the best classification, with an 84.89% accuracy. The average accuracy of the classifiers improved significantly after removing the post 1 class and applying the classification to three instead of four classes. Additionally, the use of wrapper feature selection proved to be effective in improving the classification performance of the algorithms in the three class analysis (Table 3). The improvements in accuracy when decreasing the number of features indicates that the current IMU system can be simplified by reducing the number of sensors, which will lower the computation expenses. Also, Table 4 indicates that the wrapper technique, which was applied to the random forest classifier, selected features mainly from the foot and shank regions, demonstrating the correlation between the IMU sensor location and the ability to classify foot drop conditions. In addition, 48.5% of the all selected features were from pitch (flexion) movement that is known to be affected by foot drop.

As noted in Section 3 and presented in Figure 1, the confusion matrix of all the classification algorithms revealed similarity in the gait patterns of the pre and post 1 groups, which led to confusion between these two classes of movement. This raises an important question about the timeline of monitoring foot drop patients after lumbar spine surgery. According to Section 3, the improvement can be fully observed at least two to three weeks after the surgery [40]. In addition, the confusion matrixes before and after feature selection (Figures 3 and 4) showed that the highest level of confusion occurs between the post 2 and normal stages, which indicates that two to three weeks after surgery, the walking patterns of the patients are similar to the walking patterns of people who are not suffering from foot drop (i.e., the normal group). Also, referring to the F1 scores in Figures 1 and 3, it is noticeable that the false positive or false negative rates are highly reduced while remaining cases can be addressed in the clinical environment by using simultaneous assessments.

In this study, it was demonstrated that the ML algorithms are capable of classifying patients with foot drop from normal patients, without any knowledge of specific gait events (i.e., swing phase, heel contact, toe-off, etc.). This is beneficial since no extra steps are required to identify gait events before the application of ML algorithms.

Figure 2 summarizes the prediction values of the regression algorithms. Comparing the standard deviation for the normal set among the four groups, it is notable that most of the algorithms show a smaller standard deviation for the normal group, which indicates the diversity of gait patterns at different stages of spinal surgery treatment.

In addition to the work in this study, the proposed system has the potential to be used in the clinical environment for an objective evaluation and assessment of gait in the case of any gait-related disorder. While this study only investigated foot drop patients with L5 origins, the study's approach can be applied to any other group of patients with gait-related disorders, such as children with cerebral palsy [41,42].

The system presented in this study has the potential to be used for long-term patient monitoring at home, which not only helps to enable continuous tracking of patient recovery, but also provides more gait data that can help to improve the accuracy of the analysis.

In addition, the system could be used to track the walking pattern of both legs of one patient to compare the gait patterns of both the left and right leg of a patient.

5. Conclusions

This study tested the feasibility of an IMU system with ML analysis to assess the level of severity in foot drop patients by utilizing an applicable method in clinical environments. An application of this approach is to evaluate gait conditions and track the recovery of gait disorders, such as foot drop. The study applied two ML approaches to achieve its aim: Classification and regression. In each approach, multiple ML algorithms were evaluated and compared over the datasets of walking gait from a sample of healthy participants with normal gait styles and a group of patients with foot drop in different stages of lumbar spine surgery. The evaluation was based on the accuracy, confusion matrix, and mean absolute error of the algorithms after classification of the different characteristics of the gaits of participants. The random forest classifier initially resulted in the best accuracy (83.25%). The application of the wrapper feature selection technique to the random forest algorithm improved the accuracy to 84.89%.

Author Contributions: Methodology, software, validation, formal analysis, investigation, resources, data curation, visualization, writing—original draft preparation, S.S.B.; supervision, review, and editing T.T., I.M., and G.L.

Funding: This research was funded by Kailis Foundation, St John of God Subiaco Hospital and Curtin University of Technology.

Acknowledgments: The authors are grateful to the Kailis Foundation and the St John of God Subiaco Hospital for supporting this study. The first author is the recipient of the Kailis–Curtin University of Technology scholarship.

Conflicts of Interest: The authors declare no conflict of interest.

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Algorithm	Confusion matrix				Prediction	Precision	F-score
	Pre	Post 1	Post 2	Normal			
One R	81	85	5	32	Pre	0.40	0.41
	90	70	14	29	Post 1	0.34	0.35
	4	7	139	53	Post 2	0.68	0.67
	18	32	54	99	Normal	0.49	0.48
Bayes Net	65	101	8	29	Pre	0.32	0.38
	56	118	11	18	Post 1	0.58	0.53
	4	5	147	47	Post 2	0.72	0.70
	18	16	52	117	Normal	0.58	0.57
Naïve Bayes	62	125	7	9	Pre	0.31	0.34
	60	128	9	6	Post 1	0.63	0.51
	12	17	116	58	Post 2	0.57	0.63
	29	27	35	112	Normal	0.55	0.58
SVM	104	24	74	1	Pre	0.51	0.64
	16	117	69	1	Post 1	0.58	0.68
	0	1	200	2	Post 2	0.99	0.60
	1	1	116	85	Normal	0.42	0.58
IBK	82	64	22	35	Pre	0.40	0.41
	72	86	20	25	Post 1	0.42	0.45
	17	12	125	49	Post 2	0.62	0.61
	26	19	40	118	Normal	0.58	0.55
Logistic	88	72	22	21	Pre	0.43	0.44
	81	88	22	12	Post 1	0.43	0.45
	19	14	123	47	Post 2	0.61	0.60
	11	13	38	141	Normal	0.69	0.67

Algorithm	Confusion matrix				Prediction	Precision	F-score
	Pre	Post 1	Post 2	Normal			
J48	95	84	11	13	Pre	0.47	0.46
	76	102	13	12	Post 1	0.50	0.49
	17	15	132	39	Post 2	0.65	0.67
	18	15	35	135	Normal	0.67	0.67
Random Tree	84	87	17	15	Pre	0.41	0.44
	60	110	16	17	Post 1	0.54	0.51
	16	12	145	30	Post 2	0.71	0.67
	20	21	49	113	Normal	0.56	0.60
Random Forest	77	98	13	15	Pre	0.38	0.47
	38	141	13	11	Post 1	0.69	0.61
	3	11	168	21	Post 2	0.83	0.79
	4	8	30	161	Normal	0.79	0.78
Multilayer perceptron	76	91	11	25	Pre	0.37	0.39
	86	89	13	15	Post 1	0.44	0.43
	13	14	138	38	Post 2	0.68	0.70
	15	15	32	141	Normal	0.69	0.67
Deep learning	64	97	20	22	Pre	0.32	0.35
	80	90	15	18	Post 1	0.44	0.44
	13	13	132	45	Post 2	0.65	0.64
	11	10	43	139	Normal	0.68	0.65

Supplementary Figure 6-1. Confusion matrix, precision and F-score from classifying data into four classes.

Supplementary Figure 6-2. Error-bar plot for regression algorithms classifying data into four classes

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
One R	147	9	47	Pre	0.72	0.75
	11	135	57	Post 2	0.67	0.68
	33	51	119	Normal	0.59	0.56
Bayes Net	168	7	28	Pre	0.83	0.81
	9	148	46	Post 2	0.73	0.72
	34	53	116	Normal	0.57	0.59
Naïve Bayes	185	8	10	Pre	0.91	0.79
	29	116	58	Post 2	0.57	0.64
	53	33	117	Normal	0.58	0.60
SVM	127	75	1	Pre	0.63	0.76
	2	199	2	Post 2	0.98	0.67
	1	115	87	Normal	0.43	0.59
IBK	129	25	49	Pre	0.64	0.67
	24	123	56	Post 2	0.61	0.63
	31	41	131	Normal	0.65	0.60
Logistic	152	26	25	Pre	0.75	0.73
	34	128	41	Post 2	0.63	0.64
	25	41	137	Normal	0.67	0.67

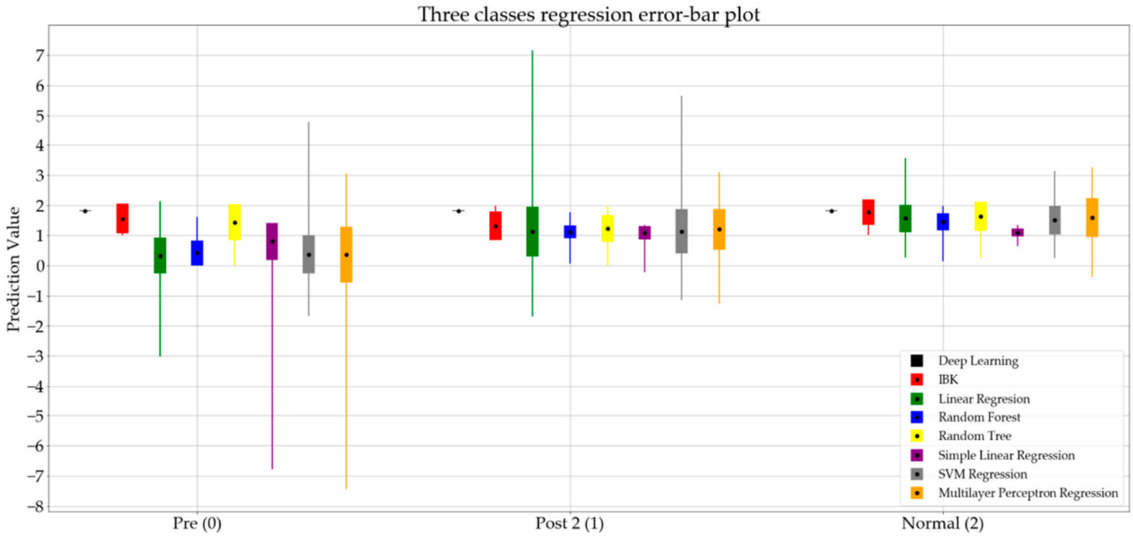
Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
J48	159	21	23	Pre	0.78	0.78
	26	145	32	Post 2	0.71	0.71
	20	39	144	Normal	0.71	0.72
Random Tree	150	25	28	Pre	0.74	0.77
	17	148	38	Post 2	0.73	0.69
	21	56	126	Normal	0.62	0.64
Random Forest	172	15	16	Pre	0.85	0.87
	12	174	17	Post 2	0.86	0.82
	10	32	161	Normal	0.79	0.81
Multilayer perceptron	163	16	24	Pre	0.80	0.81
	17	145	41	Post 2	0.71	0.73
	20	33	150	Normal	0.74	0.72
Deep learning	146	27	30	Pre	0.72	0.74
	24	137	42	Post 2	0.67	0.68
	21	35	147	Normal	0.72	0.70

Supplementary Figure 6-3. Confusion matrix, precision and F-score from classification algorithms classifying data into three classes before feature selection.

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
One R	147	9	47	Pre	0.72	0.75
	12	141	50	Post 2	0.69	0.70
	29	48	126	Normal	0.62	0.59
Bayes Net	175	18	10	Pre	0.86	0.86
	17	163	23	Post 2	0.80	0.77
	14	40	149	Normal	0.73	0.77
Naïve Bayes	167	9	27	Pre	0.82	0.80
	28	144	31	Post 2	0.71	0.75
	20	28	155	Normal	0.76	0.75
SVM	165	16	22	Pre	0.81	0.83
	14	161	28	Post 2	0.79	0.77
	16	39	148	Normal	0.73	0.74
IBK	167	14	22	Pre	0.82	0.84
	13	136	54	Post 2	0.67	0.71
	16	31	156	Normal	0.77	0.72
Logistic	176	9	18	Pre	0.87	0.85
	23	144	36	Post 2	0.71	0.75
	12	29	162	Normal	0.80	0.77

Algorithm	Confusion matrix			Prediction	Precision	F-score
	Pre	Post 2	Normal			
J48	165	16	22	Pre	0.81	0.80
	20	151	32	Post 2	0.74	0.75
	23	33	147	Normal	0.72	0.73
Random Tree	164	16	23	Pre	0.81	0.82
	20	149	34	Post 2	0.73	0.72
	14	45	144	Normal	0.71	0.71
Random Forest	177	17	9	Pre	0.87	0.88
	15	171	17	Post 2	0.84	0.82
	7	27	169	Normal	0.83	0.85
Multilayer perceptron	173	14	16	Pre	0.85	0.84
	18	148	37	Post 2	0.73	0.73
	17	41	145	Normal	0.71	0.72
Deep learning	175	12	16	Pre	0.86	0.84
	24	149	30	Post 2	0.73	0.73
	17	44	142	Normal	0.70	0.73

Supplementary Figure 6-4. Confusion matrix, precision and F-score from classification algorithms classifying data into three classes after feature selection.



Supplementary Figure 6-5. Error-bar plot for eight regression algorithms classifying data into three classes.

Supplementary Table 6-1. Classification accuracy from 11 ML algorithms classifying data into four classes.

Algorithm	Accuracy (%)
Bayes Net	55.0493
Deep Learning	52.3399
IBk	50.6158
J48	57.1429
Logistic Regression	54.1872
Multilayer Perceptron	54.6798
Naïve Bayes	51.4778
OneR	47.9064
Random Forest	**67.3645**
Random Tree	55.665
SVM	62.3153
Average	**55.3400**

Supplementary Table 6-2. Error measures from eight regression algorithms classifying data into four classes.

Algorithm	Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error	Root relative squared error
Deep Learning	-0.0856	1.3104	1.5825	130.8814	141.4032
IBk	0.4181	0.7808	1.2217	77.9844	109.1655
Linear Regression	0.6430	0.7003	0.8910	69.9453	79.6130
Multilayer Perceptron	0.0026	1.2089	9.3257	120.7437	833.2870
Random Forest	**0.7807**	**0.5426**	**0.7119**	**54.1923**	**63.6136**
Random Tree	0.5748	0.6252	1.0010	62.4422	89.4466
Simple linear regression	0.4454	0.7936	1.0010	79.2604	89.4430
SVM	0.6244	0.7062	0.9067	70.5317	81.0133

Supplementary Table 6-3. Classification accuracy from 11 ML algorithms classifying data into three classes before and after feature selection.

Algorithm	All features (n = 144)	Selected features	
	Accuracy (%)	Accuracy (%)	Number of selected features

Algorithm	All features (n = 144)	Selected features	
	Accuracy (%)	Accuracy (%)	Number of selected features
Bayes Net	70.94	79.97	20
Deep Learning	70.61	76.52	21
IBk	62.89	75.37	46
J48	73.56	76.03	22
Logistic Regression	68.47	79.15	22
Multilayer Perceptron	75.21	76.52	20
Naïve Bayes	68.64	76.52	44
OneR	65.85	67.98	1
Random Forest	**83.25**	**84.89**	33
Random Tree	69.62	75.04	21
SVM	67.82	77.83	30
Average	**70.62**	**76.89**	NA

Supplementary Table 6-4. The features selected by wrapper techniques using Random Forest algorithm.

Feature type	Foot	Shank	Thigh	**Total**
Pitch	5	5	6	16
Roll	6	4	1	11
Yaw	4	1	1	6
Total	15	10	8	**33**

Supplementary Table 6-5. Error measures from eight regression algorithms classifying data into four classes.

Algorithm	Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error (%)	Root relative squared error (%)
Deep Learning	-0.0598	0.9396	1.1555	140.4993	141.4422
IBk	0.4966	0.4631	0.8245	69.2432	100.9249
Linear Regression	0.6109	0.5319	0.5319	79.5453	88.4125
Random Forest	**0.7931**	**0.3785**	**0.5099**	**56.6055**	**62.4162**
Random Tree	0.5861	0.3992	0.7267	59.6992	88.9477
Simple linear regression	0.2998	0.6580	0.7963	98.3908	97.4729
SVM	0.5930	0.5470	0.7221	81.8015	88.3848
Multilayer Perceptron	0.5469	0.5649	0.8279	84.4696	101.3445

Chapter 7:

Conclusion

7.1 Summary of research contributions

The main purpose of this thesis was to develop automated tools to assist clinicians to perform gait assessments more efficiently and reliably. It is a shift away from current methods that rely predominantly on the visual observations of trained clinical practitioners which are subjective and highly dependent on the practitioners' experience and judgement.(1) The limitations and drawbacks associated with the current gait analysis methods limit their application in the clinical environment.(2)

In general, this research takes advantage of new technologies and state-of-the-art tools, such as ML, to assist clinical practitioners in their assessments and diagnosis of gait-related symptoms in an objective manner.

The first outcome of this research is the development of an IMU-based gait analysis system to assess the foot drop gait pattern in the clinical environment. The proposed system was used to capture gait data from two groups of participants, namely, patients with foot drop (n=56) and participants without any gait-related problems (n=30). The second outcome is the implementation of the IMU based gait capture device and using ML to model and classify normal and foot drop gait patterns. These models are useful for identification of foot drop symptoms in early stages. In addition, the normal gait model is beneficial in evaluating other gait-related disorders that are difficult to identify through visual inspections.

Another outcome of this study is the introduction of an objective measure to evaluate the severity of foot drop symptoms. This measure is an objective evaluation tool for checking the effectiveness of treatments during patients' recovery.

Considering these results, we believe that the major goals of the study have been achieved. The study's key contributions are as follows:

1. Chapter 2 provided the background and a scoping review of gait analysis in clinical applications. We identified the current trends in the market and the key problems and gaps around gait analysis that helped in setting the scope and aim of the thesis.
2. Chapter 3 presented design details of a simple gait analysis system to capture gait data specifically in the clinical environment. The requirements for this system are that it has to be low cost, portable and lightweight while maintaining measurement accuracy. Therefore, the system was designed based on IMU sensors to measure the movements of the thigh, shank and foot in three dimensions during the walk. The system consists of three separate IMU devices and a receiver dongle. In addition, a data communication protocol, a filtering algorithm and a drift cancellation technique were utilised for this purpose.
3. In Chapter 4, an experiment was designed to evaluate the accuracy of the system measurements. IMU system data were compared and validated against the Vicon optical motion capture system,(3) as the gold standard for motion analysis.(4) The comparison showed a strong correlation between the results of the two systems.(5) Since the accuracy of the system was confirmed, the data collection phase was started from a group of participants with foot drop and a group of participants without any gait-related issues.
4. Chapter 5 presented the classification of gait patterns based on the foot drop gait model and normal style walking gait model. To compare the performance of these methods for the classification task, 11 different ML algorithms were investigated. The random forest classifier achieved the highest accuracy and AUC among the tested algorithms. Cross-validation and feature selection

techniques were applied to validate and increase the performance of the proposed model.

5. Chapter 6 tested the ML methodologies for tracking the recovery procedure of patients with foot drop following the surgical treatment. This became possible by utilising the regression technique. The regression method provided an objective scale for evaluation of the gait pattern. The result indicated that a two-week recovery period is necessary prior to commencement of further gait monitoring.

7.2 Future work

This section proposes the following possible directions for further research and highlights some open questions:

1. *Identifying different gait abnormalities:* Using a similar gait analysis system and methodologies based on ML algorithms, the identification and diagnosis of other gait abnormalities (e.g. out-swing) would be possible.
2. *Investigating sensor placements:* Expand the foot drop gait analysis by having a validation trial for possible changes to the number of sensors and their placement on the body.
3. *Expanding gait data*: Expand the current method to observe and monitor a wide range of lower limb movement symptoms by investigating larger sample of walking gait abnormalities from various root causes (e.g. paralysis, strokes and knee replacement).
4. *Predicting sports injuries*: Use the current system to predict possible sports injuries.
5. *Integrating OMCS*: Integrate a mini-optical motion capture system (mini-OMCS) with the current IMU system, which adds gait visualisation ability to the significance of the system to help medical practitioners in decision making.

7.3 References

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Appendix A

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I warrant that I have obtained the below agreement from all the supervision team as the people contributed to the published material in this thesis. The agreement signed by all the contributors.

Shiva Sharif Bidabadi

	Chapter 3: The application of inertial measurements unit for the clinical evaluation and assessment of gait events, Journal of Medical Engineering & Technology, 2017			Chapter 4: Validation of foot pitch angle estimation using inertial measurement unit against marker-based optical 3D motion capture system , Biomedical Engineering Letters, 2018			Chapter 5: Classification of foot drop gait characteristic due to lumbar radiculopathy using machine learning algorithms, Gait & Posture, 2019					Chapter 6: Tracking Foot Drop Recovery Following Lumbar-Spine Surgery, Applying Multiclass Gait Classification Using Machine Learning Techniques, Sensors, 2019			
	Shiva Sharif Bidabadi	Prof. Iain Murray	Prof. Gabriel Lee	Shiva Sharif Bidabadi	Prof. Iain Murray	Prof. Gabriel Lee	Shiva Sharif Bidabadi	Prof. Tele Tan	Prof. Iain Murray	Prof. Gabriel Lee	Dr. Susan Morris	Shiva Sharif Bidabadi	Prof. Tele Tan	Prof. Iain Murray	Prof. Gabriel Lee
Design	x			x			x					x			
Acquisition of data & method	x			x			x					x			
Data conditioning & manipulation	x			x			x					x			
Analysis and statistical method	x			x			x					x			
Interpretation & discussion	x			x			x					x			
Final approval	x	x	x	x	x	x	x	x	x	x		x	x	x	x
Conceptualization	x	x	x	x	x	x	x	x	x	x		x	x	x	x
Data curation	x			x			x					x			
Formal analysis	x			x			x					x			
Investigation	x			x			x					x			
Methodology	x			x			x					x			
Resources	x			x			x					x			
Software analysis	x			x			x					x			
Validation	x			x			x					x			
Visualization	x			x			x					x			
Writing - original draft	x			x			x					x			
Supervision		x	x		x	x		x	x	x			x	x	x
Writing - review & editing	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

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To publish in the Journal:	Journal of Medical Engineering & Technology
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Author: Shiva Sharif Bidabadi,Iain Murray,Gabriel Yin Foo Lee,Susan Morris,Tele Tan

Publication: Gait & Posture

Publisher: Elsevier

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