



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

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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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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:

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

Where f_0 is the fundamental frequency, P_i is the amplitude, and ϕ_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 ($15 \times 3 \times 3$) 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).

$$144 \text{ Features} = \left(\underbrace{\underbrace{\underbrace{5}_{F_{1-5}} + \underbrace{5}_{A_{1-5}} + \underbrace{5}_{P_{1-5}}}_{Sensors}}_{\underbrace{3}_{Thigh, Shank, Foot}} + \underbrace{1}_{Angle} \right) \times \underbrace{\underbrace{3}_{Pitch, Roll, Yaw}}_{Movements}$$

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

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	83.46	0.90	92.91	0.96	21
Regression					
Multilayer	85.54	0.93	89.50	0.95	18
Perceptron					
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

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.

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

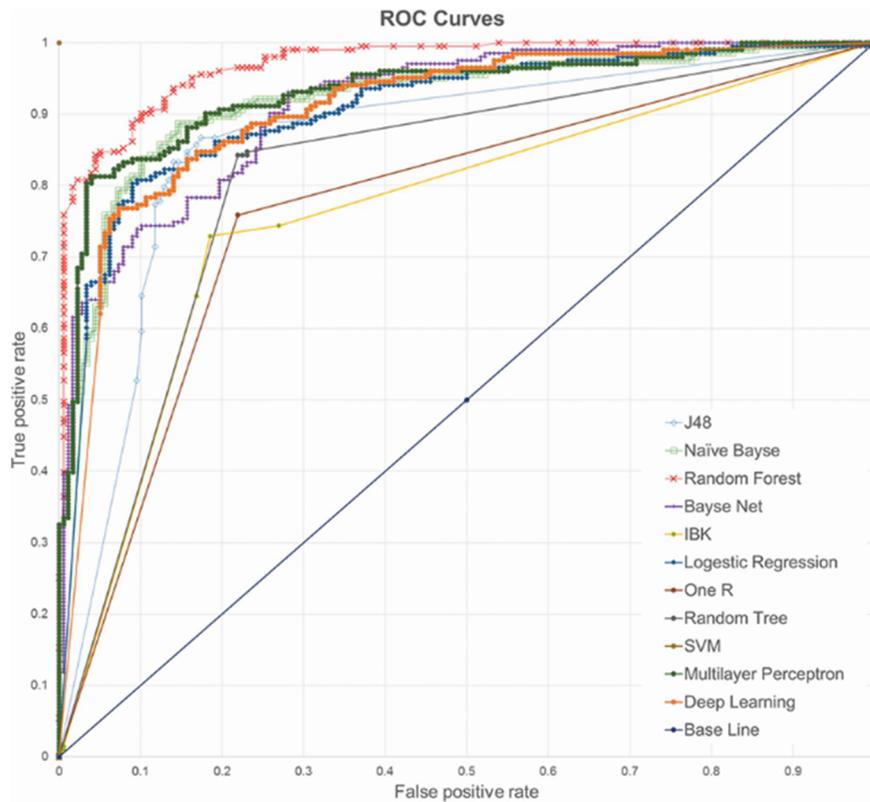


Fig. 1. ROC curves for 11 ML algorithms applied to all features.

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

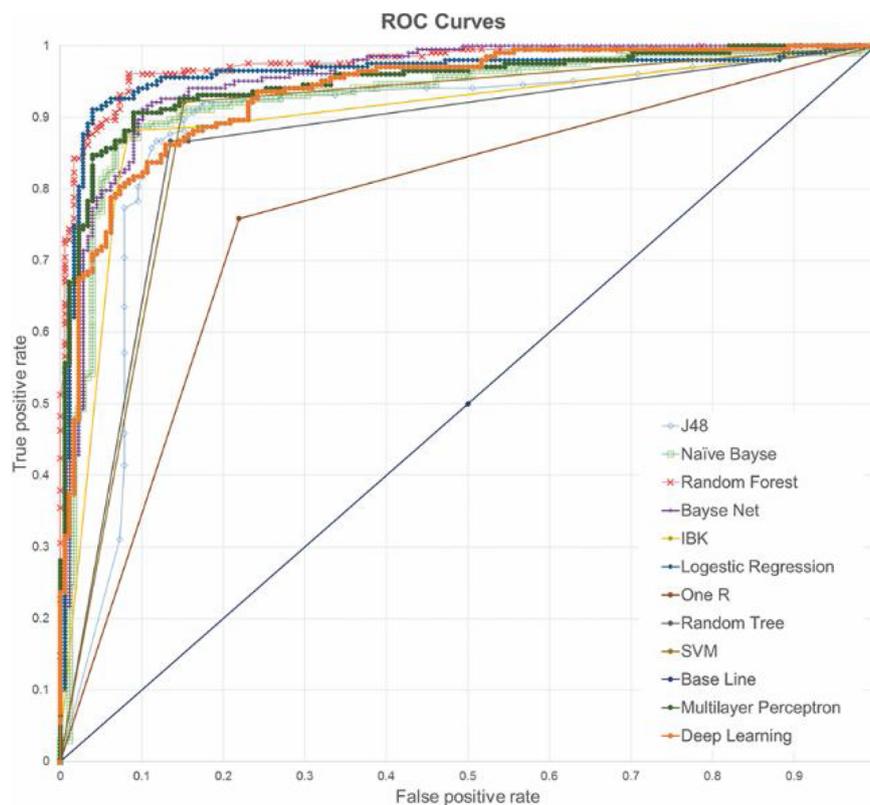


Fig. 2. ROC curves of 11 ML algorithms applied on selected features.

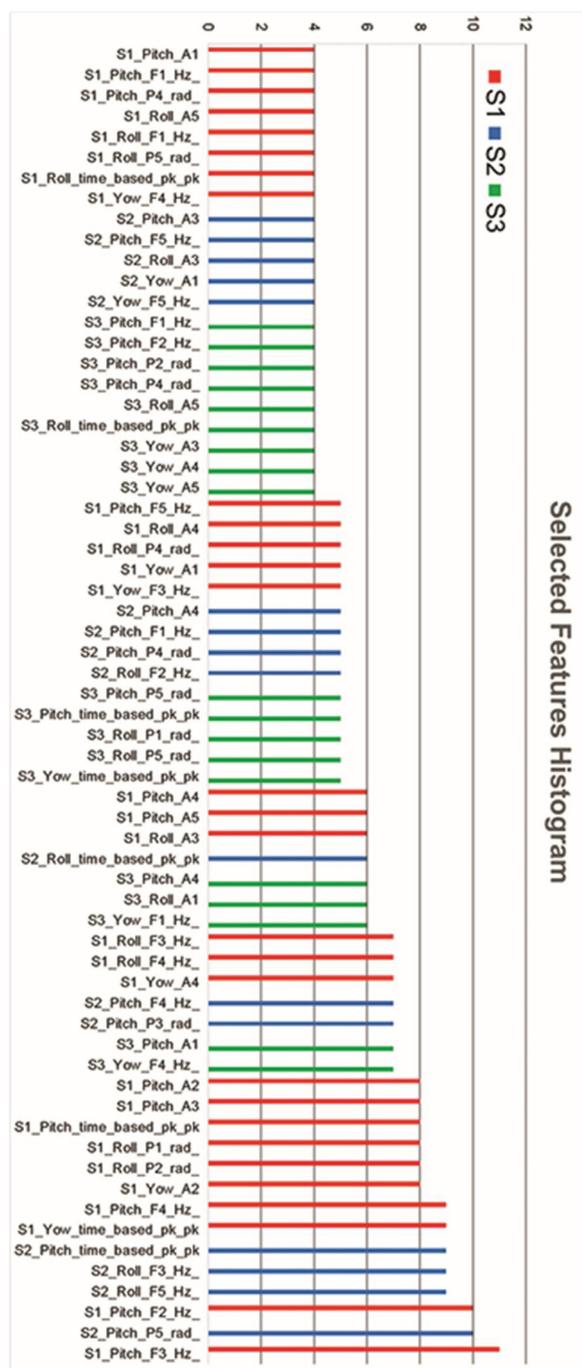


Fig. 3. Cumulative histogram for the number of times each features selected. Due to limited space, only those features with counts equal to or exceeding 4 selection are shown. The naming convention of the features in Fig. 3 matches the description of the features in section 2.3. In this format, the first 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						
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

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