Automatic Detection of Gait Asymmetry

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Abstract: Gait analysis, and gait symmetry assessment in particular, are commonly adopted in clinical settings to determine sensorimotor fitness reflecting body's ability to integrate multi-sensory stimuli, and use this information to induce ongoing motor commands. Inter-limb deviation can serve as a non-invasive marker of gait function to identify health conditions and monitor the effects of rehabilitation regimen. This paper examines the performance of machine learning methods (decision trees, k-NN, SVMs, ANNs) to learn and predict gait symmetry from kinetic and kinematic data of 42 participants walking across a range of speeds on treadmill. Classification was conducted for each speed independently with several feature extraction techniques applied. Subjects elicited gait asymmetry, yet ground reaction forces were more discriminative than joint angles. Walking speed affected gait symmetry with larger discrepancies registered at slower speeds; the highest F1 scores were noted at the slowest condition (decision trees: 87.35%, k-NN: 91.46%, SVMs: 88.88%, ANNs: 87.22%). None of the existing research has yet addressed ML-assisted assessment of gait symmetry across a range of walking speeds using both, kinetic and kinematic information. The proposed methodology was sufficiently sensitive to discern subtle deviations in healthy subjects, hence could facilitate an early diagnosis when anomalies in gait patterns emerge.

1 INTRODUCTION

Gait is scientifically recognised as a highly coordinated cooperation between the central nervous and musculoskeletal systems. Its classification has the potential to provide an insight into patient's quality of life, predict cognitive decline (Verghese et al., 2007) and estimate fall risk (Beauchet et al., 2009). Healthy gait can be viewed as a recurring and rhythmic process of translating the centre of mass (COM) through space whilst keeping the energy expenditure at minimum implying optimal path of the COM motion (Zhang et al., 2010). Conversely, pathological gait can be conceptualised as an attempt to maintain body economy by introducing compensatory exaggerations of movements at unaffected levels (Inman and Eberhart, 1953) which may be manifested by deviations in gait patterns that are indicative for health problems of various origins including neurological (e.g. Parkinson, multiple sclerosis, post-stroke hemiplegic gait) and systemic (e.g. cardiopathies, osteoporosis) diseases (Muro et al., 2014).

Gait (a)symmetry, defined as a measure of the parallels of lower extremities with respect to a selected gait parameter (Viteckova et al., 2018), is one of the markers argued as capable of capturing these deviations thereby reflecting the (dis)order within/between systems controlling the human locomotion. Up to date, gait symmetry assessment relied predominantly on algebraic formulas e.g. *symmetry index* (Robinson et al., 1987), expressing bilateral difference of spatio-temporal (e.g. stride length), kinetic (e.g. ground reaction forces (GRF)) or kinematic (e.g. joint angles) variables. However, it has been proven that these traditional approaches have limitations related to the degree of reported detail due to its discrete nature and that they are insufficient to capture complex discriminative information contained in patterns over a complete gait cycle (Kutilek et al., 2014).

In this paper, we present, to our knowledge, the first machine learning-assisted gait asymmetry assessment carried out across a range of speeds. Our study includes a population of 42 healthy subjects. Four traditional classifiers were trained to discriminate between left/right gait patterns based on the lower-limb kinematics or kinetics. Results showed that gait asymmetry was discernible although its magnitude varied as a function of the walking speed with larger asymmetries occurring at slower speeds for which classification performance was superior.

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2 RELATED WORK

Scarcity of quantitative tools to diagnose motor symptoms popularised automated movement classification which already enriched medical practice and selected studies are presented in section 2.1. However, only few attempts (section 2.2) specifically targeted gait asymmetry detection by means of ML techniques.

2.1 Diagnosis of Gait Disorders using Machine Learning

Several studies have explored machine learning for gait disorder prediction. Mezghani et al. (2016) used *classification and regression tree algorithm* to improve objectivity of joint replacement surgery recommendation for osteoarthritis (OA) patients. 3D knee angles time-series of each patient with a moderate-to-severe knee OA were used to predict surgical recommendation. Results showed high ability of the model to differentiate between surgical and non-surgical candidates as expressed by sensitivity (79.5%), specificity (90%), accuracy (84.7%) and ROC curve (0.8477) metrics. However, authors did not report whether any hyperparameter tuning was performed. In fact, by optimising model's structure, potential gains in performance might be medically meaningful.

Salazar et al. (2004) addressed the limitations of a manual classification of the Spastic Hemiplegia (SH) varieties. Joint angles of the hemiparetic limb were used to train 7 binary SVM models and *one-against-all scheme* was adopted to account for 7 different classes (6 SH types + 1 healthy). The *specificity* metric ranged between 84.61% and 98.69% yet the study lacked a systematic testing to prevent the overfitting.

Alam et al. (2017) extracted 13 statistical features from vertical ground reaction force (VGRF) and centre of pressure time-series of 29 Parkinson's disease (PD) sufferers and 18 age-matched healthy subjects and trained several ML models to diagnose Parkinsonian gait. Gait of patients afflicted by a Parkinson's disease was identified with an accuracy of 85.1%, and 91.6% obtained by *k-nn* and SVMs with a linear kernel, respectively. However, considering complexity of human gait, other dimensions of the force vector or alternative movement descriptions e.g. joint angles, may contain diagnostically meaningful information.

2.2 Machine Learning-based Detection of Gait Asymmetry

Most gait symmetry research aims to (1) determine the magnitude and locations of asymmetries in gait-impaired subjects as well as (2) investigate if healthy population exhibits inter-leg differences. In diagnosed locomotor dysfunctions, gait asymmetry reduction is used as a tool attesting to the appropriateness of rehabilitation regimen (Lewek et al., 2014). The literature regarding gait asymmetry in able bodied individuals is equivocal as no significant differences in ground reaction forces (Hamill et al., 1984) or joint angles (Hannah et al., 1984), are confronted by contrary findings (Vaughan et al., 1992). The inherent asymmetry of healthy gait is becoming increasingly evidenced (Sadeghi et al., 2000); although, its cause is unknown, methods detecting minor deviations in normal gait should emerge.

2.2.1 Naturally Occurring Gait Asymmetry

Wu and Wu (2015) used SVMs to assess gait symmetry. Researchers gathered 10 trials from left and right legs of 60 elderly individuals. First, the relative variability of collected parameters (3 peak forces and corresponding times) was obtained for each leg by calculating the Coefficient of Variation (CV $\leq$ 12.5%), followed by Absolute Symmetry Index (ASI $\leq$ 10%), and t-test with a null hypothesis indicating gait symmetry. The t-test demonstrated significant differences ($p \leq 0.05\%$.) for 3 out of 6 parameters. Despite managing to report explicit inter-limb asymmetries, SI proved inadequate in revealing more complex relationships. To confront the standard method a SVM model was developed. The collective input (120 samples) containing gait variables for both legs undergone a 6-fold cross-validation resulting in the creation of corresponding subsets. Feature inputs sets comprised of 101 data points vector of a normalised gait waveform, PCA extracted components and 6 aforementioned gait variables with 3 kernel functions (i.e. polynomial, radial basis (RBF) and linear applied to each). SVM was superior to SI in determining subtle asymmetries in gait. Moreover, polynomial and RBF outperformed the linear kernel most significantly when carried out on PCA-based input features. For this configuration (kernel: Polynomial/RBF, input: PCA-derived), external metrics reported were highest with accuracy, sensitivity and specificity of 90%, 88-90%, 80%, respectively. PCA minimised potential redundancies of the original 101 dimensions vector, thus boosting classification performance; and provided more gait symmetry information compared to the discretised set of 6 gait attributes. The findings can be criticised as the random division of the gait pattern pool spread subject-specific data across training and testing subsets, hence the results were affected by the information leakage (Halilaj et al., 2018).

2.2.2 Artificially Induced Gait Asymmetry

Schlafly et al. (2019) aimed to determine the importance of feature selection for classifications of potentially overlapping gait pathologies. Artificially induced locomotion asymmetries interspersed normal walking trials of 20 healthy subjects. The 10 perturbations resulted from a combinations of shoe heights (2.7/5.2 cm) and ankle weights (2.3/4.6 kg), and were grouped into 3 leg length categories (none, small, large) and 5 distal mass classes: large/small ankle weights attached to either leg (4 conditions) or a no-added weight condition (1). The recordings (max. 20 steps for both limbs) provided 21 discrete variables/step which encapsulated three feature modalities (2 spatio-temporal, 12 kinematic, 7 kinetic). SVMs, k-NN, and ANNs were trained on all trials belonging to 16/20 subjects whereas the data of the 4 remaining participants was used to evaluate the performance of each classifier. For each experimental condition, classification with a PCA-transformed features was repeated 100 times equating to 4000 tested instances. Subsequently, the results derived from all 21 features were contrasted with those generated by possible combinations of 3-element feature subsets. Overall, SVMs (Gaussian and polynomial kernels) outperformed other models across all conditions. Lower leg lengths were best classified by all 21 features (72.9%); the combination of the 3 feature modalities (64.8%) was more accurate than kinetic (61.1%), kinematic (55.9%) and spatio-temporal (32.9%) results separately. The distal mass was examined most accurately by kinetic (68%) parameters alone. This outperformed the collective 21 attributes (66.3%), the best performing subset (66.9%) and other feature modalities (kinematic (43%) and and spatio-temporal (43.7%)).

Authors emphasised that the most discriminative variables may be directly dictated by the underlying cause of the gait impairment. Nonetheless, the study did not include speed variations which is an important factor that may influence gait dynamics and amplify or nullify inter-limb deviations (Fukuchi et al., 2019).

3 DATASET

The dataset used in this paper containing gait kinetics and kinematics of 42 healthy subjects walking at a range of speeds was developed by Fukuchi et al. (2018). For each signal, authors specified the body side recorded, thereby providing a class label (left/right) for a gait pattern classification.

- **Kinetics.** Force precedes and causes motion and the branch of Newtonian mechanics that explores these vector quantities is known as *kinetics*. Contact forces must be measured and the measurement relies on *Newton's Third Law of Motion*. Specifically, by applying the force to the ground (force platform) at each step, the ground (load cells) reacts by exerting the *ground reaction force* that acts on the body with the same magnitude but opposite in direction. The raw kinetics comprised of numerous GRFs traces generated at each step over the final 30 s treadmill-based conditions and while walking across five force platforms during the overground trials.
- **Kinematics.** On the other hand, *kinematics* is the study of motion without regard to causes. The unprocessed kinematics contained 3-D trajectories of each marker that was affixed to a distinct body landmark and these were are used to obtain positions of anatomical segments allowing relevant variables e.g. joint angles to be computed. As a result, 3-D joint angles for the hip, knee and ankle segments were obtained.

Each of the 11 experimental conditions were expressed as a percentage of the pre-determined comfortable speed and reflected treadmill (T01 to T08) or overground (OS, OC, OF) trials. However, to elucidate the main trends of speed's effect on gait asymmetry, only the results for the three boundary speeds i.e. slow: T01 (40%), self-selected: T05 (100%) and fast: T08 (145%) on treadmill are reported.

3.1 Data Processing

To present an overall trend of a signal across multiple trials (or cycles as in gait) for a given individual thereby discarding within-subject variance, an ensemble average was obtained. All ipsilateral gait patterns recorded during a given speed condition were extracted and linearly interpolated to a 101-point series. Then, values at each time-point across all derived gait cycles were averaged yielding three representative signals (XYZ GRF or joint angle) for each limb per speed condition/subject.

3.2 Analysis

Initial data exploratory attempts led to a hypothesis that, in the context of the present dataset, gait symmetry might vary as a function of the walking speed. Also, it can be argued that kinetics might be more discriminative with respect to limb classification than kinematics, and that walking speed is a potentially important factor that should be controlled.

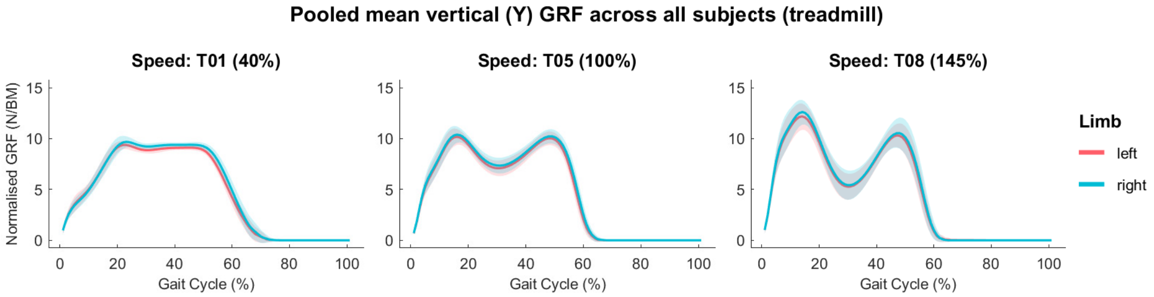

Figure 1: The shaded area represents the standard deviations across all subjects.

3.2.1 Pooled Analysis of Between-limb Differences

All overground and most distinct treadmill conditions (slow, comfortable, fast) of the entire population were ensemble-averaged into 3-D signals (i.e. ground reaction forces, joint angles) for both limbs, and colour-coded according to body side. Overall, an inter-limb similarity was present across the subject pool. In treadmill trials (see Figure 1), vertical GRF was least symmetrical at the slowest (T01, 40%) speed (the red curve protrusion spanned approx. 20-60% of the gait cycle) yet much more similar at faster conditions (T05, 100% and T08, 145%). For the overground walking, curves largely overlapped across all speeds and the same merely discernible trends characterised kinematics regardless of speed and walking environment, hence their visualisations were omitted.

3.2.2 Principal Component Analysis

PCA was applied to standardised kinetic and kinematic time-series. Biplots of the first two PCs showed discernible clusters of left/right kinetic gait patterns for the treadmill walking at slow (T01) and comfortable (T05) speeds. No clear groupings emerged for the fastest treadmill (T08) and overground (b) conditions. PCA-reduced kinematic waveforms provided lesser insight into gait asymmetry, regardless of the walking environment.

3.3 Feature Extraction

Classification results obtained by using the high-dimensional gait waveforms were contrasted with its discretised and reduced (PCA) representations. Each feature vector was standardised and this was carried out on each training and test folds during CV cycle. Mean and variance computed for the training partition were used to obtain z-scores for the test split.

3.3.1 Baseline Discrete Gait Parameters

Nine parameters corresponding to forces at three discrete instants (see Figure 2) as well as their respective chronological times of occurrence expressed as a percentage of the gait cycle were extracted from the vertical GRF. First and second peaks denote weight acceptance at heel-strike impact push-off preceding toe-off, respectively whilst the minimum in-between refers to the maximum knee flexion prior to forward propulsion; these points are considered as representative characteristics reflecting an overall quality of gait (Chao et al., 1983), thus were used as a feature vector for classification.

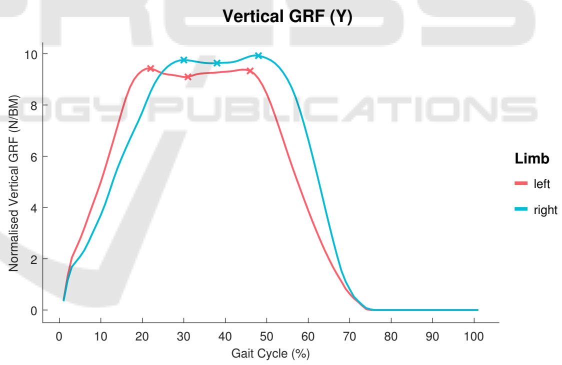

Figure 2: Discrete features extracted from the vertical GRF.

3.3.2 Complete Waveforms

For the kinetics data, all three components (Y - vertical, X - anterior-posterior, Z - medial-lateral) of the GRF were horizontally concatenated yielding the 2x303 matrix for each subject (2 - left and right limb, 303 - combined GRFs). Given three planes of motion (XYZ) and three joints (hip, knee, ankle), kinematic feature matrix was much larger (2x909).

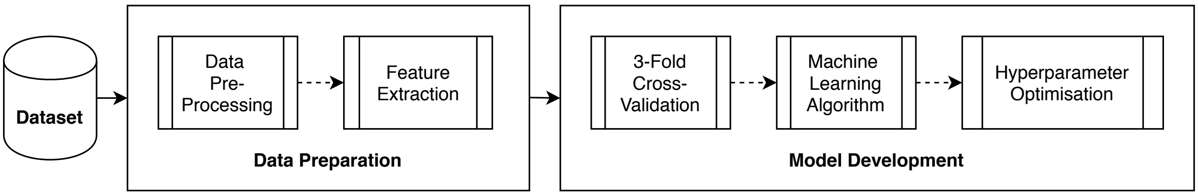

Figure 3: Classification Pipeline.

3.3.3 PCA-processed Gait Patterns

PCA was applied to the complete kinetic/kinematic time-series. Number of principal components used as an input varied at each CV cycle, and these were programmatically added until at least 90% of the variance was explained.

4 AUTOMATIC GAIT ASYMMETRY DETECTION

The methodology workflow is shown in Figure 3.

4.1 Decision Trees

Decision trees were trained by recursive binary stratification of the predictor space X (root) into a set of hyper-rectangular regions (inferior nodes) with the goal to find clearer class separation according to the Information Gain as per equation 1:

$$\Delta I(N, A_t) = I(N) - \sum_{i=1}^{k} \frac{S_i}{N} \cdot I(S_i) \quad (1)$$

where:

- $N \subseteq T \leftarrow$ training set (if a root node) or a subset thereof (if an inferior node)
- $A_t \leftarrow$ logical test that divides N, yielding k candidate child nodes $S_i, S, ..., S_k$
- $I \leftarrow$ an arbitrary measure of impurity (e.g. Gini Index, Entropy)

Recursive grow continued until either a subset contained only homogenous samples or there was no further benefit of segmentation in terms of purity. To optimise the tree, two hyperparameters: 1) minimum leaf size (1-25) and 2) splitting criterion (Gini Diversity Index, Entropy) were varied.

4.2 k-Nearest Neighbours (k-NN)

k-nearest neighbours uses a proximity measure to gather the most frequent label of k closest instances in a local neighbourhood of the unseen record and classifies it accordingly (Hastie et al., 2013).

Two hyperparameters: 1) k-neighbours (1-20) and 2) distance metric (Euclidean, Manhattan) were varied to optimise the model.

4.3 Support Vector Machines (SVM)

SVM is a hyperplane-based discriminator which addressed limitations of previous approaches such as a linear separability constraint imposed by the *maximal margin classifier* and consolidated the concept of *soft margin* introduced in the *support vector classifier*.

Classification was tested with a linear kernel, an RBF kernel, and a polynomial kernel.

4.4 Artificial Neural Netoworks (ANN)

Artificial Neural Networks are non-linear black-box models and proven to be capable of approximating any function given that the optimised architecture has been established (Velten, 2009).

Single-hidden layer feedforward network with a sigmoid activation function was fitted and trained for 1000 epochs. The number of hidden neurons was varied (1-30) to optimise the network.

5 EXPERIMENTAL SETUP

All the data for a given subject (i.e. two gait patterns) were placed within either training or a test subset. Thus, 3-fold cross-validation was carried out dividing 42 subjects into three groups so that at each iteration the model was fitted on a training data comprising 56 gait patterns of 28 subjects (66.6%) and evaluated on the 28 gait patterns belonging to 14 left out cases (33.3%).

5.1 Evaluation Metrics

To enable comparison between speed conditions and experimental scenarios, F1 score denoting a weighted average of precision and recall was chosen to assess the performance of each of the classifiers:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

where:

- TP: cases correctly classified as a *left limb*
- TN: cases correctly identified as a *right limb*
- FP: cases falsely classified as *left*
- FN: cases falsely classified as *right*

6 RESULTS

6.1 Kinetics

The results outlined in Tables 1-3 show that on aggregate level (column-wise mean), classification performance dropped as the walking speed increased with the highest average F1 score (86.71%) achieved using discrete kinetic parameters as the feature vector and this inverse correlation between speed condition and F1 score was also noted across majority of models and feature extraction methods.

At the individual model level (row-wise mean), on average across all speeds ANNs trained on complete kinetic waveforms outperformed other algorithms (83.59%) yet k-NN was superior in identifying correctly left/right gait patterns at the slowest (T01) speed condition (91.46%).

Table 1: F1 scores - discrete kinetic parameters.

	T01	T05	T08	Mean	SD
DT	84.28%	55.72%	62.63%	67.54%	14.90%
k-NN	91.46%	72.08%	66.83%	**76.79%**	12.97%
SVM	83.88%	79.07%	63.13%	75.36%	10.86%
ANN	87.22%	74.83%	65.65%	75.90%	10.82%
Mean	**86.71%**	70.42%	64.56%	73.90%	5.24%
SD	3.50%	10.22%	2.01%	5.24%	4.37%

Table 2: F1 scores - complete kinetic waveforms.

	T01	T05	T08	Mean	SD
DT	87.35%	64.21%	69.46%	73.67%	12.13%
k-NN	84.77%	77.14%	68.89%	76.93%	7.94%
SVM	81.76%	75.08%	71.39%	76.08%	5.26%
ANN	82.46%	90.03%	78.29%	**83.59%**	5.95%
Mean	**84.08%**	76.61%	72.01%	77.57%	6.09%
SD	2.53%	10.59%	4.32%	5.81%	4.23%

Table 3: F1 scores - PCA-reduced kinetic waveforms.

	T01	T05	T08	Mean	SD
DT	76.37%	76.80%	69.22%	74.13%	4.26%
k-NN	82.46%	76.70%	69.94%	76.37%	6.27%
SVM	88.88%	80.08%	68.39%	79.12%	10.28%
ANN	86.32%	77.08%	78.26%	**80.55%**	5.03%
Mean	**83.51%**	77.66%	71.45%	77.54%	6.03%
SD	5.44%	1.62%	4.58%	3.88%	2.00%

6.2 Kinematics

As shown in Tables 4-5, in contrary to kinetics-driven classification models' performance for this modality was not inversely correlated with the walking speed.

Surprisingly, the highest F1 score (70.77%) was yielded by k-NN at the fastest condition (T08) yet on average across all speeds it ranged between 65.33-68.23%. Hence, joint angles were significantly less discriminative than VGRFs.

Table 4: F1 scores - complete kinematic waveforms.

	T01	T05	T08	Mean	SD
DT	64.93%	64.89%	68.73%	66.18%	2.21%
k-NN	66.46%	66.07%	66.91%	66.48%	0.42%
SVM	66.67%	66.67%	67.36%	**66.90%**	0.40%
ANN	64.59%	63.70%	63.82%	64.04%	0.48%
Mean	65.66%	65.33%	**66.70%**	65.90%	0.72%
SD	1.05%	1.32%	2.07%	1.48%	% 0.53

Table 5: F1 scores - PCA-reduced kinematic waveforms.

	T01	T05	T08	Mean	SD
DT	65.87%	66.70%	65.50%	66.02%	0.61%
k-NN	68.69%	68.34%	70.77%	**69.27%**	1.31%
SVM	65.76%	66.51%	67.91%	66.73%	1.09%
ANN	66.83%	67.66%	68.75%	67.75%	0.96%
Mean	66.79%	67.30%	**68.23%**	67.44%	0.73%
SD	1.36%	0.86%	2.18%	1.47%	0.67%

7 DISCUSSION

Human locomotion is elicited through a collaboration of various systems and it is assumed that gait symmetry can be viewed as the degree of order/disorder or control of this interplay (Viteckova et al., 2018). To assess inter-limb differences, gait pattern classification was carried out based on kinetic and kinematic data derived from treadmill and overground walking at a range of speeds using different ML algorithms and feature extraction approaches.

Gait asymmetry in healthy subjects was identified and generally high classification accuracy was noted for all models, however, *k-NN* and *ANNs* on average outperformed *SVMs* and *decision trees*. By examining F1 maxima from the kinetic-based classification, it can be argued that gait asymmetry gradually dissipated as the walking speed increased. This resonates with the dynamical systems theory and motor control research proposing a plausible explanation of an enhanced movement coordination at faster velocities of execution. According to these domains, limbs can be modelled as coupled oscillators that are more easily controlled at higher movement frequencies whilst when afforded to decouple at slower speeds, limbs might employ distinct functional strategies leading to the hypothesis of a non-dominant/dominant roles of lower extremities (Gobble et al., 2003).

Another observation was a noticeable drop in classification performance when models relied on kinematic as opposed to kinetic data. This can be interpreted within the context of the study conducted by Schlafly et al. (2019) in which a spectrum of artificially induced gait asymmetries was investigated. It was concluded that the discriminatory power of features of various modalities and combinations thereof may depend on a particular type of gait asymmetry being examined. Authors demonstrated that features extracted from the force plate data (kinetic) exclusively, best classified gait asymmetries caused by distally affixed mass to either limb. Conversely, when a limb length and not the mass was manipulated, the best result was obtained by incorporating both, kinetics and kinematics. Thus, considering the fact that forces provide an insight into the musculoskeletal dynamics that generate the movement and that these were found to be more effective in differentiating between left/right gait patterns, it is then possible that inter-limb differences present in healthy individuals are manifested in kinetic inequalities.

When applied to the kinetic waveform, PCA had a varied influence on the classification performance. For example, SVM and ANN benefited from the dimensionality reduction for the slowest walking speed. On the other hand, it had a negative or no effect on the k-NN's and DT's results overall. As to the hyperparameters tested, both distance metrics examined in *k-NN* produced similar results whereas the value of *k* for the best F1 scores noted ranged predominantly between 8-14. This parameter is highly dataset-specific, however, usually profoundly small values magnify the effects of outliers whilst increasingly larger settings yield smoother decision boundaries thereby introducing bias. In terms of SVMs, its performance was superior when the *linear kernel* was adopted whilst the least favourable results were observed for the *rbf kernel*. It is possible that non-linear kernels did not improve classifications performance due to already large dimensionality of the data (Ben-Hur and Weston, 2010). To find the best decision tree, minimum number of instances per leaf (MLS) and split criterion (SC) were varied. The MLS imposes a rule on how many instances in a given node are required to justify the split, thereby providing a mean to control a tree depth. In general, the best gait pattern classification accuracy was obtained when MLS was kept either very low (1-4) or just above/below ten (7-13). With regard to the branching criterion, trends generated by varying MLS were also remarkably congruent between the Gini Diversity Index and Entropy. Finally, potentially due to a small sample size as for ANNs, the number of hidden neurons did not have a visible effect on classification performance.

8 CONCLUSION

Machine learning and gait analysis co-occur more frequently in the literature than ever before. This study used an alternative approach to quantify gait asymmetry in which its assessment was considered as a binary classification problem where a given gait pattern was assigned to one of the two available categories namely, left or right limb. Consequently, F1 score was computed and regarded as a quantitative measure of gait symmetry with low and high values denoting symmetrical and asymmetrical gaits, respectively. Future research should also examine ensemble methods and other cross-validation approaches. Additionally, the role of laterality should be addressed but this would require a dataset comprising a balanced number of right- and left- footed subjects. Also, provided that sufficiently large dataset becomes available, sophisticated techniques e.g *LSTM* coupled with advanced methods to extract discriminative information from signals such as time-frequency spectral analysis via the wavelet transform could boost classification performance.

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