Engineering Applications of Artificial Intelligence 123 (2023) 106487

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

Predicting physical activity levels from kinematic gait data using machine learning techniques

Svonko Galasso [a,b,c,*], Renato Baptista [a,c], Mario Molinara [b], Serena Pizzocaro [a,d], Rocco Salvatore Calabrò [e], Alessandro Marco De Nunzio [a,c]

[a] Department of Research and Development, LUNEX International University of Health, Exercise and Sports, Avenue du Parc des Sports, 50, 4671 Differdange, Luxembourg
[b] Department of Electrical and Information Engineering, University of Cassino and Southern Lazio, via Gaetano Di Biasio, 43, 03043 Cassino, Italy
[c] Luxembourg Health & Sport Sciences Research Institute ASBL, Avenue du Parc des Sports, 50, 4671 Differdange, Luxembourg
[d] Department of Electrical, Computer and Biomedical Engineering, University of Pavia, S. da Nuova, 65, 27100 Pavia, Italy
[e] Istituto di Ricerca e Cura a Carattere Scientifico Centro Neurolesi "Bonino Pulejo", S.S. 113, Via Palermo C/da Casazza, 98123 Messina, Italy

ARTICLE INFO

Keywords:
Kinematic gait data
Gait analysis
Inertial measurement unit
Machine learning

ABSTRACT

Objective analysis of gait abilities (Gait Analysis, GAn) in clinic is an essential motor assessment to improve clinical decision-making and provide precision rehabilitation approaches to recover gait functions. GAn is usually based on wearable motion sensors or camera-based systems, which generate an extensive set of data which are challenging to manage, analyse, and interpret. This makes GAn a time-consuming unfeasible assessment approach in clinical practice. Machine Learning (ML) techniques can provide a viable solution, as they can handle massive time series and complex data.

This study aims to correctly classify subjects' physical activity levels, using as ground truth a self-reported questionnaire (International Physical Activity Questionnaire, IPAQ), via kinematic features provided by wearable wireless Inertial Measurement Unit (IMU) sensors. Kinematic gait data were collected from 37 healthy subjects (24 male and 13 female) while walking on a sensorised treadmill at natural speed. Velocity, acceleration, jerk, and smoothness were calculated using the kinematic features and used to perform statistical feature extraction. The Neighbourhood Component Analysis (NCA) algorithm was used to process the statistical features space and select the most significant ones.

Several models have been trained and tested before and after the feature selection to validate the approach's effectiveness. Feature reduction resulted in a significant increase in accuracy for K-Nearest Neighbours (KNN) (81.978 ± 0.368), Random Forest (84.044 ± 3.409) and Rough-Set-Exploration-System Library K-Nearest Neighbours (RSesLib KNN) (83.956 ± 0), with an improvement of ≈20%. The performance of the best-performing classifiers was then analysed, observing the behaviour of accuracy by varying the number of features considered.

1. Introduction

Gait analysis (GAn) is a standard diagnostic laboratory procedure to assess and analyse human body motion quantitatively. GAn has been used in various fields, including rehabilitation and health diagnostics (Tao et al., 2012). GAn has a crucial function in the healthcare system to provide timely interventions and keep track of recovery, as it allows the extraction of clinically relevant parameters to assess the overall level of walking ability (Hollman et al., 2011; M et al., 2014; Macellari et al., 1999). Physical activity level (PAL) directly affects gait parameters, influencing both balance control and propulsion of inactive versus active individuals (Katsiaras et al., 2005; O'Connor et al., 2007). Moreover, PAL also influences walking speed: Niang and McFadyen (2005) shows that active individuals have higher walking speeds during unobstructed and obstructed walking. Subjective questionnaires are the most common method of assessing PAL, as it is an inexpensive and easily applicable tool for large populations (Vanhees et al., 2005). The International Physical Activity Questionnaire (IPAQ) long form is a 27-item self-reported physical activity measure for use with adults aged 15–69 years. The IPAQ is organised into five sections covering different

* Corresponding author at: Department of Research and Development, LUNEX International University of Health, Exercise and Sports, Avenue du Parc des Sports, 50, 4671 Differdange, Luxembourg.

E-mail addresses: svonko.galasso@lunex-university.net (S. Galasso), renato.baptista@lunex-university.net (R. Baptista), m.molinara@unicas.it (M. Molinara), serenamarialui.pizzocaro01@universitadipavia.it (S. Pizzocaro), roccos.calabro@irccsme.it (R.S. Calabrò), alessandro.denunzio@lunex-university.net (A.M. De Nunzio).

https://doi.org/10.1016/j.engappai.2023.106487
Received 6 December 2022; Received in revised form 5 April 2023; Accepted 17 May 2023
Available online xxxx

Nomenclature

GAn	Gait Analysis
ML	Machine Learning
IPAQ	International Physical Activity Questionnaire
IMU	Inertial Measurement Unit
NCA	Neighbourhood Component Analysis
PAL	Physical Activity Level

types and domains of physical activity and behaviours. The IPAQ aims to provide a set of well-developed tools that can be used internationally to obtain comparable estimates of physical activity (Bauman et al., 2009; Hagströmer et al., 2006). Although the IPAQ is a clinically validated instrument, it remains a subjective evaluation of gait and may be susceptible to the biases and level of experience of the evaluator. This can lead to errors and inconsistencies of the GAn, which can affect the accuracy of the diagnosis and the effectiveness of the treatment plan. Objective measures of gait provide a more comprehensive understanding of a patient's movement patterns, which can help identify underlying biomechanical issues and guide the development of an appropriate treatment plan (Muro-de-la Herran et al., 2014).

To date, several technologies have been adopted to objectively assess GAn motion data. Optical motion capture systems, force plates and instrumented walkways are the most used ones, as they represent the "gold standard" in laboratory settings. However, these instruments are expensive to acquire and operate, and requires specialised locomotion laboratories, reducing their feasibility for clinical use (Akhtaruzzaman et al., 2016). Inertial measurement units (IMUs) represent a wearable, portable, light, low-cost alternative to the classic GAn laboratory equipment. IMUs consist of 3D accelerometers, gyroscopes, and magnetometers arranged to provide comprehensive information about the sensor's linear acceleration, angular velocity, and magnetic orientation (Li et al., 2009; Luinge et al., 2007). By analysing the motion signal recorded by IMUs, it is possible to measure the various characteristics of human gait and then perform GAn (Bonato, 2003; Engin et al., 2005). Due to their portability, IMUs are preferred over traditional camera-based (SR, 2004) GAn systems in clinical practice (Aminian et al., 2002; Auvinet et al., 2002; Pappas et al., 2004; Tao et al., 2012; Tong and Granat, 1999), but they are still unpractical in clinical use given the massive amount of data generated, especially if the full-body analysis is needed.

Machine Learning (ML) and Deep Learning (DL) approaches have recently emerged as viable options in multiple fields, including healthcare research (Dua et al., 2014). Recent advances in these fields have paved the way for their widespread applications in various fields, especially for different data analysis and processing techniques. These algorithms are being used to make predictions, classify data, recognise patterns, and automate tasks. As a result, they have become indispensable in various fields such as data science (Namar et al., 2022), engineering (Roy, 2022; Tao et al., 2022; Zhuang et al., 2022), and computer science (Matkovic et al., 2022; Stojanovic and Nedic, 2016), particularly in the subfield of computer vision (Lawal, 2021). Such techniques can automatically learn data features by identifying complicated patterns within a large amount of data, such as the gait biometrics, which are usually large and contain complex characteristics. ML approaches have already been used to analyse IMUs data (Mannini et al., 2016). Hutabarat et al. (2021) present a comprehensive review of GAn using wearable sensors, covering different types of sensors, ML algorithms, and applications in healthcare and rehabilitation. They may even be used to identify different gait phases (Williamson and Andrews, 2000) and humans from gait patterns (Nowlan, 2009).

Previous studies on GAn through ML already exist, in which various methods and techniques have been implemented, and different datasets have been used for analysis. These studies have demonstrated both the possibilities and the limitations of current approaches. Whittle's seminal work on GAn provided a comprehensive introduction to the topic and has served as a foundation for much of the research in this field (Whittle, 1996). Early applications of ML in GAn focused on biometric authentication. Ailisto et al. (2005) and Begg et al. (2005) demonstrated the potential of using ML algorithms, such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN), to identify individuals based on their unique walking patterns. The use of ML to analyse pathological gait patterns has also gained attention, with (Pogorelc and Gams, 2013) using a multidimensional dynamic time-warping approach to detect gait-related health problems in the elderly. Mannini et al. (2014) employing hidden Markov mode algorithm to differentiate between different gait events. These studies suggest that ML can be a powerful tool for the early detection of gait-related disorders and for assessing treatment outcomes. As of today, no one as highlighted the prediction of a clinically validated questionnaire via ML algorithm based on human motion data. Aminian and Najafi (2004), Ayachi et al. (2016) and Tudor-Locke and Myers (2001) explore various aspects of PAL assessment using GAn, with applications ranging from general physical activity monitoring, and daily living activities recognition to specific clinical conditions. While some of these papers may not explicitly use ML techniques, they provide valuable insights into evaluating PAL through GAn.

Considering the abilities of ML algorithms and the need to provide clinical meaning to the massive amount of data generated via GAn, we have aimed to correctly classify the PAL of healthy subjects via ML models fed by the IMUs-acquired kinematic features (3D Joints Range of Motion). In order to explore the extracted statistical features space and to improve the performance of the considered ML models, the Neighbourhood Component Analysis (NCA) was used. Identify kinematic features with the highest reliability to detect PAL, allowed us to reduce the complexity of the problem and focus only on the discriminative features. To provide clinically valuable indications on the least time-consuming IMU sensors' set-up, the secondary aim of this study is to evaluate the best-performing ML model with the minimum number of kinematic features. The remainder of this paper is organised as follows: Section 2 presents the materials and data acquisition protocol, as well as the preprocessing techniques adopted to analyse the raw data and extract statistical features. The achieved results are presented Section 3. In Section 4 the obtained results are discussed, followed by conclusions and future study in Section 5.

2. Material and methods

2.1. Design and participants

A single-session study was conducted within the IRCCS "Bonino Pulejo" Neurolesi Center in Messina, Italy. Thirty-seven young, healthy subjects were recruited for the study. Subjects were contacted via email, provided information about the study, and asked to sign a written consent form before proceeding with the testing session. The testing session lasted one hour and a half.

The inclusion criteria were: (a) age between 18–40, (b) entirely out of any pain in the last month, (c) not under active health management or receiving therapies (e.g., physiotherapy) in the last three months. The exclusion criteria were: (a) gait impairments given by neurological, cardiovascular, orthopaedic, or rheumatologic conditions, (b) being pregnant for the female participants. The enrolled participants' characteristics are reported in Table 1.

At the end of the testing session, subjects filled out the long version of the IPAQ, which was used as ground-truth for the classification task. A Python script was realised to translate the answers provided on the questionnaire into a categorical score. Three possible values of PAL are proposed: "Low", "Moderate", or "High". Table 2 shows

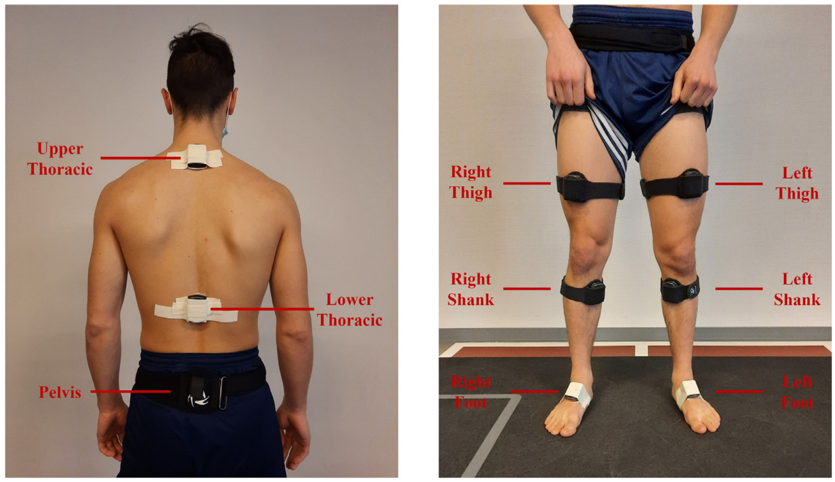

Fig. 1. IMUs sensors placement.

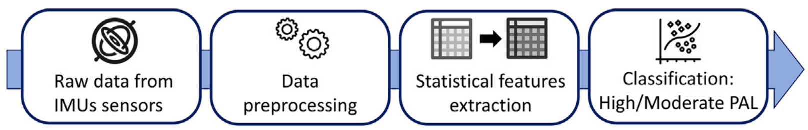

Fig. 2. Overall methodology followed.

Table 1
Subjects' characteristics.

	Male	Female	Overall
Number (%)	24(65%)	13(35%)	37
Age (*mean* ± *std_dev*)	24 ± 3	22 ± 2	23 ± 3
Height (*mean* ± *std_dev,* cm)	177 ± 9	167 ± 7	173 ± 10
Body Mass (*mean* ± *std_dev,* kg)	73 ± 9	63 ± 8	69 ± 10

Table 2
IPAQ level distribution.

IPAQ level	Number of subjects
Low	0
Moderate	11
High	26

the distribution of subjects' IPAQ levels. None of the participants were labelled with a "Low" level of PAL.

All the participants gave their written informed consent to participate in the study. The acquired data were fully anonymised following ethics recommendations. The study was conducted in accordance with the guidelines of the Declaration of Helsinki, and all the procedures were fully approved by the ethics committee of the Istituto di Ricerca e Cura a Carattere Scientifico Centro Neurolesi "Bonino Pulejo".

2.2. Measurement system

The participants were asked to perform two walking tasks at natural speed, without shoes, for five minutes on a treadmill (Gait Trainer 3; Biodex medical system, Shirley, New York). The order of execution was randomised to avoid bias. Full body motion data were captured with 9 IMUs sampling at 100 Hz (MyoMotion, NORAXON, USA). Upper and lower body motions were acquired while performing the walking task. Upper body sensors were securely fixed directly to the skin via a skin-safe tape (Hypafix, BSN medical GmbH) on the upper thoracic and lower thoracic (respectively below C7 and on T12/L1). Lower body sensors were placed on the pelvis and both legs. Elastic belts were used on the sacrum, thighs and shanks. The remaining sensors were taped to the feet. Fig. 1 shows the sensors' placement. The participant acquisition file reported all the information provided by each IMU's tri-axial accelerometer and tri-axial gyroscope, resulting in 102 features.

2.3. Project overview

Fig. 2 shows the procedure implemented from the raw IMUs data to the training of several ML classifiers to validate the proposed approach, going through data pre-processing, and the statistical feature extraction.

MSI Vector GP66 laptop with 12th Gen Intel(R) Core (TM) i7-12700H (2.70 GHz), 16.0 GB DDR4 RAM was used for the data analysis, training, and testing of ML models.

2.4. Data analysis

MATLAB R2019b (The MathWorks Inc., Natick, MA, USA) and the Python 3 (Van Rossum and Drake, 2009) *Pandas* library were used for data processing. Data augmentation was performed by identifying the participants' gait cycles to increase the number of pares considered in the ML approach. Gait cycles and heel strike detection were realised via acceleration peak detection of the right-foot IMU sensor. Triaxial accelerometer and gyroscope data were zero-lag filtered using a 4th-order low-pass Butterworth filter with a cut-off frequency of $\omega_c = 4$ Hz to remove undesirable sensor noise (Cho et al., 2016; Jayalath et al., 2013). The acceleration magnitude was calculated from the filtered accelerometers signals ($\sqrt{Right\_Foot\_a_x^2 + Right\_Foot\_a_y^2 + Right\_Foot\_a_z^2}$), as shown in Fig. 3.

For each participant, consecutive windows of 6 gait cycles were considered. In this way, each gait cycle window was equated with an instance of the resulting dataset. Six gait cycles are sufficient to perform averaging procedures and thus minimise artefacts caused by natural gait variability (Macellari and Giacomozzi, 1996). The MATLAB "findpeaks" function, with *MinPeakProminence* = 200 and *MinPeakDistance* = 80, automatically identified the heel strike. Single gait cycle detection was based on two consecutive peaks (Mahoney and Rhudy, 2019; Rhudy and Mahoney, 2018) (Fig. 4).

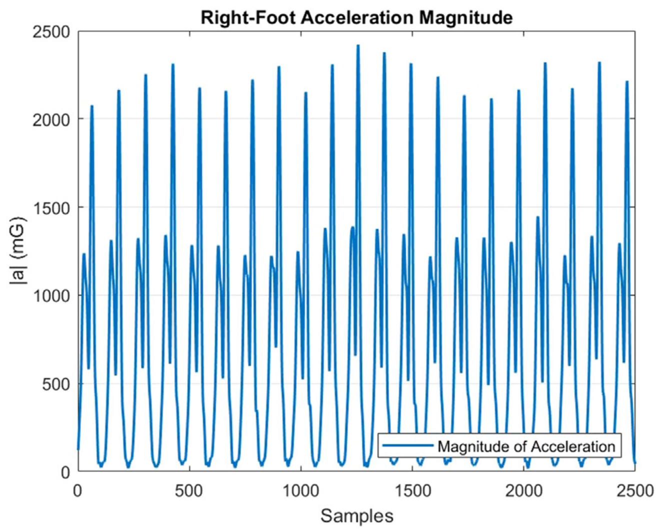

Fig. 3. Magnitude of right foot IMU acceleration signal.

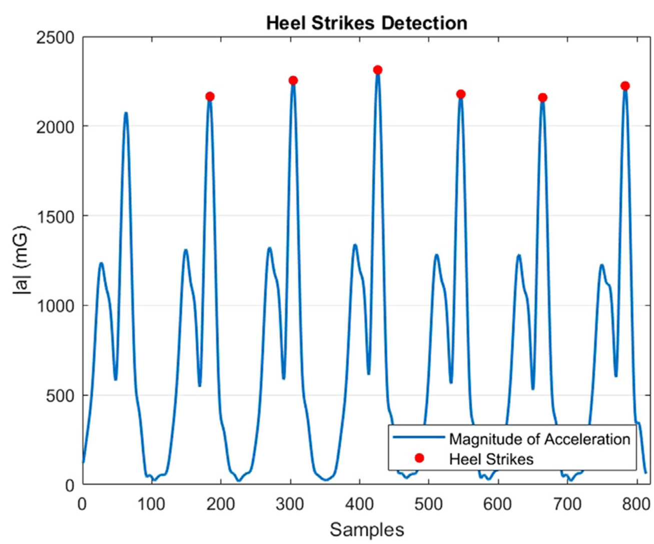

Fig. 4. Example of six gait cycles identification from heel strike detection (marked in red).

After data augmentation, a dataset of 1520 instances was created from the 37 participants' acquisition dataset. Each of the instances contained 102 kinematic features provided by the sensors. Considering the absence of participants' laterality, only the right-sided 3D Joints' Range of Motion was considered, resulting in 30 kinematic features (Table 3).

Velocity, acceleration, and jerk were computed for each of the 30 considered features, resulting in 120 new signals (30 initial features × 4). The smoothness (Shahbazi et al., 2018) was computed by calculating the jerk magnitude, resulting in a total of 130 signals ([(30 initial features × 4) + 10 smoothness]). Statistical features, such as mean, root mean square, maximum, and standard deviation, were extracted from the 130 new features. Statistical extraction resulted in 520 derived features (130 new features × 4 statistic measures) (Fig. 5). The described procedure allows to move from a time series dataset, in which each subject was characterised by 130 signals (considered as features), to a tabular dataset, in which each subject is represented by a row in the table and characterised by 520 columns (considered as features).

After data augmentation and statistical feature extraction, the resulting dataset consisted of 1520 instances described by 520 statistical

Table 3
3D joints range of motion features.

	Upper body sensors	Lower body sensors
Anatomical angles (deg)	Lumbar flexion	Hip flexion
	Lumbar lateral	Hip abduction
	Lumbar axial	Hip rotation
	Thoracic flexion	Ankle dorsiflexion
	Thoracic lateral	Ankle inversion
	Thoracic axial	Ankle abduction
Orientations (deg)	Upper spine course	Pelvis course
	Upper spine pitch	Pelvis pitch
	Upper spine roll	Pelvis roll
	Lower spine course	Thigh course
	Lower spine pitch	Thigh pitch
	Lower spine roll	Thigh roll
		Shank course
		Shank pitch
		Shank roll
		Foot course
		Foot pitch
		Foot roll

features with the PAL (IPAQ outcomes) as ground truth for the supervised learning application. The provided dataset was used to train several ML models to classify the PAL of input instances, identifying which features are most significant for discrimination. To explore the discrimination power of the selected features and to reduce the number of features considered, the NCA was used. NCA is a supervised learning non-parametric technique that uses the gradient ascent technique to maximise the average leave-one-out (LOO) classification performance in the transformed space. The goal is to "learn" a distance metric by finding a linear transformation of the input data. NCA proves to be an effective method for both metric learning and linear dimensionality reduction (Goldberger et al., 2004). As reported in Yang et al. (2012), NCA provides a feature ranking by learning a feature weighting vector based on features' statistical distribution and discriminatory power. The algorithm is almost insensitive to the increase in the number of irrelevant features and performs better than the neighbour-based feature weighting state-of-the-art methods in most cases, such as Simba (Iterative Search Margin Based Algorithm) (Gilad-Bachrach et al., 2004), LMFW (Large Margin Feature Weighting method) (Chen et al., 2009) and FSSun (Sun et al., 2010).

Waikato Environment for Knowledge Analysis – WEKA 3.8.6 (Waikato University, New Zealand) was used to test the efficiency of the approach (Witten et al., 2016). Several ML models were trained before and after NCA, and performance was compared using Accuracy, the Area Under the Curve (AUC), Precision, and Recall (Sensitivity) (Fig. 6).

The training and test sets were manually assigned with 70% and 30% of the statistical instances dataset, respectively. Careful data splitting was realised to keep all instances related to a single subject in one set to avoid biasing the classification results.

2.5. Classification algorithms

For the validation phase of the proposed approach, a wide range of classification algorithms were analysed to screen different possible ML approaches (Table 4). The hyperparameters has been selected in a preliminary session of experiments on the validation test.

Multilayer Perceptron (MLP) is a feed-forward artificial neural network widely used for solving supervised learning problems, characterised by several layers of input nodes connected as a directed graph between the input and output layers. The number of hidden layers between the input and output layer depends on the problem and remains one of the main challenges while tuning MLP (Ramchoun et al., 2016).

Logistic Regression is an ML classification technique that uses a logistic function to predict a binary outcome. It is an extension of the

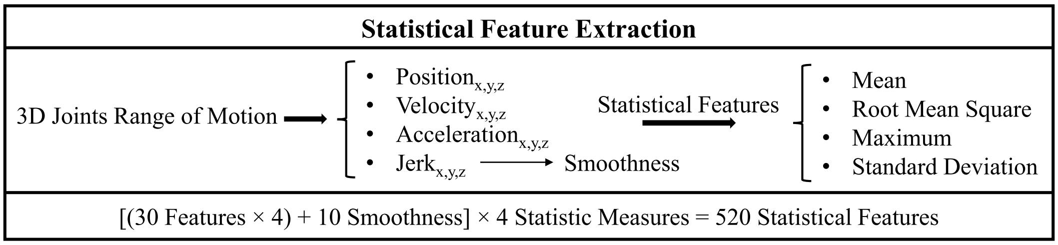

Fig. 5. Summary of the statistical features extraction procedure.

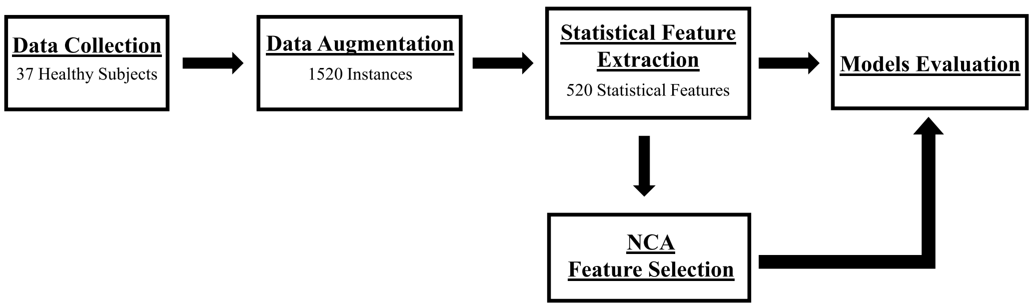

Fig. 6. Summary diagram of the data analysis process.

Table 4
WEKA classifier algorithms considered.

Classifiers	AKA	Type in WEKA	Hyperparameters
Multilayer Perceptron	MultilayerPerceptron	Functions	Number of Hidden Layers = (attributes + classes)/ 2 = 11
Logistic Regression	Logistic	Functions	Ridge value = 1.0E−8
Support vector machine	LibSVM	Functions	Kernel = Radial Basis Function (RBF)
Stochastic Gradient Descent	SGD	Functions	Loss function = SVM
K-Nearest Neighbours	IBk	Lazy	K = 3
RSesLib-K-Nearest Neighbours	RseslibKnn	Lazy	K = 3
AdaBoost	AdaBoostM1	Meta	Number of iterations = 10
Random Forest	RandomForest	Trees	Number of trees = 100
Random Tree	RandomTree	Trees	Number of iterations = 100
Reduced Error Pruning Tree	REPTree	Trees	Number of folds = 3

linear regression model that cannot be used for classification problems (Kleinbaum and Klein, 2010).

Support Vector Machine (SVM) algorithm is a supervised learning classifier that constructs a transformed space of the input feature space dividing each class by constructing a boundary based on a specific kernel function (linear, polynomial, gaussian, sigmoid, etc.) (Noble, 2006). SVM in WEKA was trained with the default parameters and with the parameters optimised via Stochastic Gradient Descent (SGD) (Bottou, 2012).

The K-Nearest Neighbours (KNN) algorithm assigns each new instance of the test set to one of the classes in the training set by evaluating its distance from the nearest point in the feature space. The metric used to evaluate the distance between points was the Euclidean distance (Guo et al., 2003). In the present work, the KNN algorithm was trained in the default version of WEKA and in an extended version provided by the RSES (Rough Set Exploration System) library.

Adaptive Boosting (AdaBoost) is an ensemble learning method that combines a set of weak learners (decision stumps) into a strong learner to minimise training errors. At each iteration, the weights of AdaBoost instances are re-assigned based on the misclassification error of the previous iteration. Misclassified instances are assigned higher weights (Rokach, 2009).

Random Forest is a tree-based machine learning algorithm that leverages the power of multiple decision trees for making decisions. The Random Forest algorithm combines the output of multiple, randomly created, decision trees (ensemble approach) to generate the final output (Shaik and Srinivasan, 2019).

Random Tree combines the principles of single-model trees with the ideas of Random Forest. It selects a K number of attributes to calculate the entropy at each node without performing pruning (Thin Swe, 2019).

Reduced Error Pruning Tree (REPTree) is fast decision tree learning which uses regression tree logic to create multiple trees and selects the best among all generated trees. The mean square error on the predictions made by the tree is used to prune the tree (Kalmegh, 2015).

2.6. Performance evaluation

Precision, Recall, Accuracy (Sokolova and Lapalme, 2009), and AUC (Fawcett, 2006) score are all commonly used metrics in ML for evaluating the performance of a classification model. Each of these metrics provides different information about the model's performance, and together they can give a more complete picture of how well the model is working. Precision measures the percentage of instances that are classified as positive that are actually positive. Recall (Sensitivity) measures the percentage of positive instances that are correctly classified as such by the model. Accuracy measures the percentage of all instances that are classified correctly. AUC score measures the overall performance of the model in terms of its ability to distinguish between the two classes. The use of these metrics is important because they provide a way to objectively evaluate the performance of a model and compare it to other models. By looking at each of these metrics, it is possible to identify areas where the model is performing well and areas where it needs improvement. For example, a model with high Precision but low Recall may be good at identifying positive instances but is missing many of them.

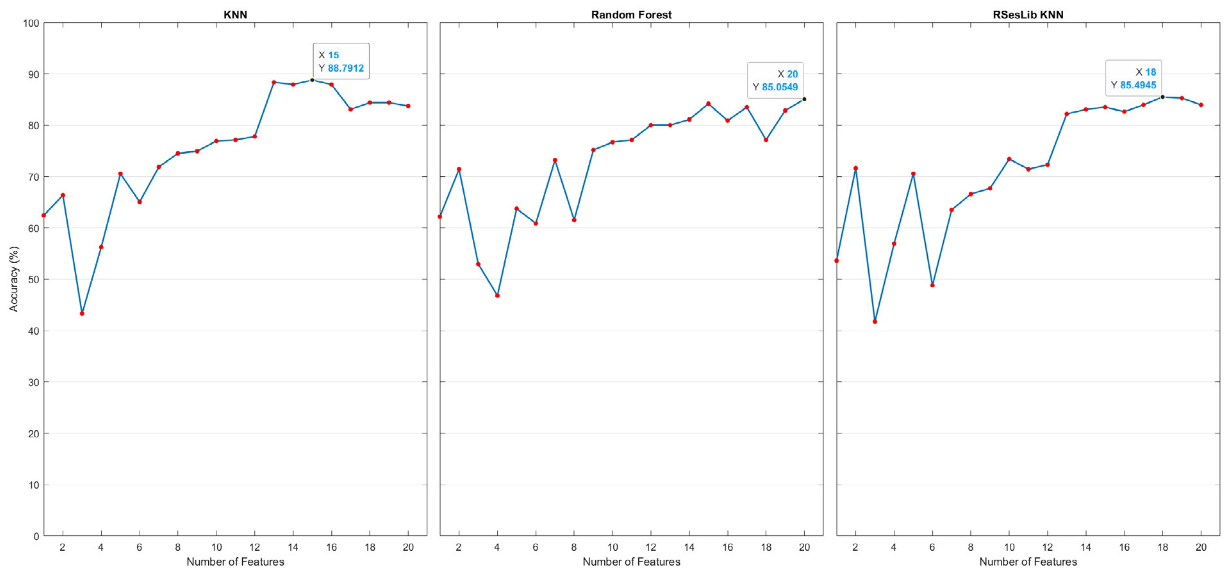

Fig. 7. Accuracy trend of best-performing classifiers by number of features selected by NCA.

Table 5
The 20 most relevant features selected by NCA.

Rank	Features selected by NCA	Weight
1	RTFootRoll_deg_MAXIMUM	0.693
2	RTHipFlexion_deg_MAXIMUM	0.607
3	RTShankRoll_deg_MEAN	0.540
4	LumbarFlexion_deg_MEAN	0.502
5	RTThighCourse_deg_MAXIMUM	0.460
6	RTAnkleDorsiflexion_deg_MEAN	0.390
7	RTShankCourse_deg_MAXIMUM	0.382
8	RTFootCourse_deg_MEAN	0.375
9	RTFootCourse_deg_MAXIMUM	0.282
10	RTShankRoll_deg_MAXIMUM	0.188
11	RTHipRotation_Out_deg_MAXIMUM	0.117
12	RTFootCourse_deg_STD_DEV	0.091
13	LumbarFlexion_deg_RMS	0.058
14	RTShankCourse_deg_MEAN	0.043
15	RTAnkleInversion_deg_MAXIMUM	0.042
16	PelvisPitch_deg_MEAN	0.035
17	RTHipAbduction_deg_MAXIMUM	0.035
18	RTAnkleAbduction_deg_MEAN	0.032
19	LowerSpineCourse_deg_MEAN	0.027
20	LowerSpineCourse_deg_RMS	0.020

3. Results

From the initial 520 statistical features, the NCA algorithm identified 20 as the most relevant (Table 5). Features with a higher weight correspond to the most relevant features for classification. Features with lower values than the 20th represent irrelevant features discarded from the initial dataset.

Each ML model was trained and tested 10 times, normalising the data, and shuffling the training and test sets to avoid bias. The mean and standard deviation were evaluated for each performance measure. The overall performance of the models is summarised in Table 6 considering all the features and those selected by the NCA.

Table 7 shows the confusion matrix related to the Random Forest, that was found to be the best performing classifier.

Following the study's secondary aim, a further analysis was executed to find the best-accuracy-retrieving combination of the minimum set of selected features. The accuracy as a function of the number of features selected by the NCA was analysed to assess the best classifier with the fewest features (Fig. 7).

4. Discussion

In the present study, the performance of different classifiers in predicting PAL were analysed by considering statistical features extracted from kinematic gait data. The results obtained show that walking with a linear trajectory at natural speed is sufficient to predict PAL with a good level of accuracy without administering any questionnaire. Specifically, 9 IMUs were used to acquire kinematic data and considered 6 gait cycles (recording only 8 s of walking) to validate the methodology. In addition, the NCA algorithm was used to rank the derived statistical features and understand which IMUs are found to be most discriminating and to which body segment they belong. The NCA results showed that considering only four sensors is sufficient to predict PAL, as the algorithm recognised only features derived from lower body IMUs as relevant. The behaviour of the best-performing classifiers was then analysed by varying the 20 most relevant features selected by NCA.

Table 5 shows how the NCA algorithm considers features derived from position data of the lower body sensors more discriminating than those derived from velocity, acceleration, jerk, and smoothness. In Jiménez-Grande et al. (2021), the authors used NCA to identify the body segments and corresponding significant features that have the greatest discriminatory power in classifying asymptomatic individuals from those with chronic neck pain while performing linear and nonlinear gait trajectories. Although nonlinear walking trajectories provided the best classification performance, a comparison can be made between the results obtained from the linear walking trajectory and the results presented in this study. It is reported that for a linear walk path, the most representative body segments appear to be those related to the upper body sensors, such as the head and trunk, while the features related to jerk smoothness and speed turn out to be the most discriminative (higher feature weight). The differences between the studies result from having similar walking direction, while the kinematic features may be different. This can be attributed to the absence of constraints on maintaining a constant speed during overground walking. As reported in Alton et al. (1998), statistically significant differences exist between overground and treadmill walking in healthy subjects for some joint kinematic and temporal variables. Specifically, significant increases were seen during treadmill walking in hip range of motion, maximum hip flexion joint angle, and cadence. Differences between overground and treadmill walking in temporal gait parameters were also reported in Chockalingam et al. (2012). The authors reported a lower pelvic obliquity motion for treadmill walking compared to overground walking, and the pelvic rotation movement pattern showed

Table 6
Model's classification performance (*std_dev* = standard deviation).

All features								
Classifier	Precision		Recall		Accuracy		AUC	
	mean	*std_dev*	*mean*	*std_dev*	*mean*	*std_dev*	*mean*	*std_dev*
AdaBoost	**0.811**	**0.000**	**0.820**	**0.000**	**81.978**	**0.000**	**0.905**	**0.000**
REPTree	0.660	0.046	0.643	0.050	64.286	5.051	0.607	0.048
KNN (K-nearest neighbours)	0.632	0.009	0.631	0.006	63.055	0.577	0.528	0.011
Logistic Regression	**0.778**	**0.000**	**0.758**	**0.000**	**75.824**	**0.000**	**0.868**	**0.000**
MLP (Multilayer Perceptron)	0.586	0.014	0.604	0.012	60.440	1.167	0.635	0.007
Random Forest	0.709	0.071	0.745	0.028	74.505	2.823	0.801	0.024
Random Tree	0.680	0.109	0.687	0.097	68.681	9.679	0.588	0.128
RSesLib KNN (K-nearest neighbours)	0.661	0.000	0.648	0.000	64.835	0.000	0.568	0.000
SGD (Stochastic Gradient Descent)	0.624	0.011	0.654	0.008	65.407	0.788	0.516	0.013
SVM (Support vector machine)	**0.821**	**0.000**	**0.763**	**0.000**	**76.264**	**0.000**	**0.554**	**0.000**
NCA selected features								
Classifier	Precision		Recall		Accuracy		AUC	
	mean	*std_dev*	*mean*	*std_dev*	*mean*	*std_dev*	*mean*	*std_dev*
AdaBoost	0.751	0.000	0.752	0.000	75.165	0.000	0.733	0.000
REPTree	0.726	0.034	0.679	0.050	67.846	5.566	0.670	0.058
KNN (K-nearest neighbours)	**0.834**	**0.008**	**0.820**	**0.003**	**81.978**	**0.368**	**0.675**	**0.003**
Logistic Regression	0.626	0.000	0.618	0.000	61.758	0.000	0.590	0.000
MLP (Multilayer Perceptron)	0.787	0.052	0.799	0.049	79.846	4.508	0.766	0.051
Random Forest	**0.843**	**0.043**	**0.841**	**0.035**	**84.044**	**3.409**	**0.901**	**0.041**
Random Tree	0.726	0.092	0.697	0.090	69.736	9.768	0.639	0.118
RSesLib KNN (K-nearest neighbours)	**0.868**	**0.000**	**0.840**	**0.000**	**83.956**	**0.000**	**0.698**	**0.000**
SGD (Stochastic Gradient Descent)	0.710	0.004	0.734	0.004	73.429	0.302	0.609	0.006
SVM (Support vector machine)	0.506	0.000	0.589	0.000	58.901	0.000	0.401	0.000

Table 7
Confusion matrix of the Random Forest classifier.

		Predicted	
		High	Moderate
Ground truth	High	**326**	8
	Moderate	59	**62**

the most significant difference between walking modes. Moreover, the systematic review (Semaan et al., 2022) reported significant differences in kinematic parameters such as reduced pelvic range of motion, maximum hip flexion angle for females, maximum knee flexion angle for males, and cautious gait pattern.

Considering the accuracy reported in Table 6, the classifiers that benefited most from feature reduction were the KNN (81.978 ± 0.368), Random Forest (84.044 ± 3.409), and RSesLib KNN (83.956 ± 0). Previous studies have addressed ML classification problems using kinematic data from IMUs. Although it was shown in McGrath et al. (2021) that no ML model is the best for activity classification, as differences in sensor placement, IMU specifications and pre-processing decisions can affect model performance. In Hua et al. (2020) and Khaksar et al. (2021), the authors achieved 87.75% accuracy in classifying cerebral palsy and 98.60% in classifying upper limb exercises with the Random Forest classifier, respectively. Similar to what was found in this study, the results suggest that the Random Forest classifier demonstrates the highest classification accuracy using kinematic data from IMUs. The confusion matrix of the Random Forest is presented in Table 7, revealing that a significant number of misclassifications occur when instances are labelled as "High" instead of "Moderate" (59 misclassified instances). This result is not surprising given the prevalence of the "High" category. However, a less noticeable effect was expected since the imbalance between classes is not as obvious.

In Wang et al. (2021), the authors developed a Deep Neural Network model to detect stroke from kinematic gait data. They achieved 99.36% of accuracy in identifying stroke gaits. Further analysis of the identified stroke gaits shows that the drop foot gait, the circumduction gait, the hip hiking gait, and the back knee gait, are the four common gait abnormalities of stroke patients. As described in the articles reviewed above, several applications of ML on kinematic data have been developed, but none have aimed to predict the result of a clinically validated questionnaire such as the IPAQ. This study represents the first step towards the development of ML algorithms based on kinematic gait data able to predict clinically validated outcomes in different clinical populations e.g., predicting the Motor Section 3 of the UPDRS in Parkinson's disease patients (Goetz et al., 2008).

Of all the models analysed, only those that performed best were selected for further analysis. It can be seen from Fig. 7 that, except for the Random Forest classifier, the highest value of accuracy is obtained with fewer features than those selected by the NCA. This suggests that some of the features selected by the algorithm are redundant in that they do not provide additional discriminatory information. The KNN classifier achieves the highest accuracy with only 15 features. The KNN and RSesLib KNN overall performance deteriorates after reaching the maximum accuracy value considering the first 15 and 18 features reported in Table 5, respectively.

One of the main limitations of this study was the small number of samples considered (37 participants). Although the data augmentation technique provided us with 1520 instances, it still limits the use of typical statistical techniques for ML model evaluation. Data augmentation required manual data splitting to ensure that all instances related to a single subject were present in the train or test set, to avoid biasing classification results. For this reason, techniques such as cross-validation should be avoided, as it could not be guaranteed that instances of the same participants would be limited to the train or test set.

Another limitation is represented by the statistical features derived from the original kinematic features. With the performed statistical feature extraction, the conducted analysis moved from a time series classification problem to a standard classification problem. These problems are easier to address because they require less computing power, making it possible to use tools such as WEKA for the testing part. On the other hand, working with derived features reduces the explicability of the models making them less interpretable for clinicians. Instead of extracting statistical features, in Liew et al. (2020a,b) the authors deal with time series data by making them all the same lengths and then applying functional data boosting (FDboost) (Brockhaus et al., 2017).

From a computational point of view, all the proposed ML algorithms could be deployed on devices with reduced computational power, including commercial PCs or microcontrollers. This makes deploying the

Table 8
Machine learning libraries available for microcontroller.

Framework	Web site	Brief description
uTensor	https://utensor.ai/	A lightweight version of TensorFlow designed specifically for microcontrollers, which supports a variety of hardware platforms and is optimised for memory and computational efficiency
Edge Impulse	https://www.edgeimpulse.com/	An open-source deep learning inference framework designed for microcontrollers, which provides a simple and flexible API for building and deploying ML models on microcontrollers
Arm CMSIS-NN	https://developer.arm.com/ip-products/processors/machine-learning/cortex-m/cmsis-nn	A platform for building, training, and deploying machine learning models on edge devices, including microcontrollers. Edge Impulse provides a range of pre-built ML models and supports a variety of hardware platforms
TinyML	https://www.tinyml.org/	A collection of optimised neural network kernels for Arm Cortex-M processors, which provides a set of low-level functions for implementing neural networks on microcontrollersc
ELL	https://microsoft.github.io/ELL/	An open-source platform for building ultra-low-power machine learning applications on microcontrollers, which includes a range of pre-trained models and tools for developing custom models
Keras for Microcontrollers	https://www.tensorflow.org/lite/microcontrollers/library/overview	A lightweight version of the Keras deep learning framework designed specifically for microcontrollers. Keras for Microcontrollers includes support for a range of microcontroller architectures and provides a simple API for building and deploying ML models
OpenMV	https://openmv.io/	An open-source platform for machine vision and deep learning on microcontrollers, which includes a range of pre-trained models and tools for developing custom models

entire computational chain very close to the sensors possible, following the so-called "AI on the edge" approach. There are several ML libraries available online for microcontrollers (Table 8).

5. Conclusions

This paper investigated the classification performance of different ML classifiers in discriminating PAL from motion data. It was shown that reducing the feature space increased performance for most of the considered classifiers. Analysis of the best-performing classifiers (KNN, Random Forest, and RSesLib KNN) showed the behaviour of accuracy by varying the number of features considered, suggesting that some of the features are redundant.

Future work should focus on extending the proposed results by comparing NCA with other feature selection techniques and analysing and testing additional ML classifiers based on time-varying data. In addition, a more in-depth analysis of performance behaviour concerning the number of features considered is needed. To this end, shuffling the features to find the best minimum set of relevant features will be executed.

CRediT authorship contribution statement

Svonko Galasso: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Visualization. **Renato Baptista:** Conceptualization, Methodology, Resources. **Mario Molinara:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision. **Serena Pizzocaro:** Conceptualization, Methodology, Resources. **Rocco Salvatore Calabrò:** Investigation, Data curation. **Alessandro Marco De Nunzio:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Svonko Galasso reports financial support was provided by National Research Fund.

Data availability

Data will be made available on request.

Acknowledgements

Many thanks to the participants who contributed to this study, which was fully supported by the Luxembourg National Research Fund (FNR) under the project **MEMENTO** – **M**achine l**E**arning-based **M**arker-l**E**ss gait analysis system for clinical assessment of huma**N** mo**T**i**O**n [16749075].

Funding

This work was supported by the Luxembourg National Research Fund (FNR) [16749075].

References

Ailisto, H.J., Lindholm, M., Mantyjarvi, J., Vildjiounaite, E., Makela, S.-M., 2005. Identifying people from gait pattern with accelerometers. Biom. Technol. Hum. Identif. II 5779, 7. http://dx.doi.org/10.1117/12.603331.

Akhtaruzzaman, M., Shafie, A.A., Khan, M.R., 2016. Gait analysis: systems, technologies, and importance. p. 16. http://dx.doi.org/10.1142/S0219519416300039.

Alton, F., Baldey, L., Caplan, S., Morrissey, M.C., 1998. A kinematic comparison of overground and treadmill walking. Clin. Biomech. 13, 434–440. http://dx.doi.org/10.1016/S0268-0033(98)00012-6.

Aminian, K., Najafi, B., 2004. Capturing human motion using body-fixed sensors: outdoor measurement and clinical applications. Comput. Animat. Virtual Worlds 15, 79–94. http://dx.doi.org/10.1002/CAV.2.

Aminian, K., Najafi, B., Büla, C., Leyvraz, P.F., Robert, P., 2002. Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. J. Biomech. 35, 689–699. http://dx.doi.org/10.1016/S0021-9290(02)00008-8.

Auvinet, B., Berrut, G., Touzard, C., Moutel, L., Collet, N., Chaleil, D., Barrey, E., 2002. Reference data for normal subjects obtained with an accelerometric device. Gait Posture 16, 124–134. http://dx.doi.org/10.1016/S0966-6362(01)00203-X.

Ayachi, F.S., Nguyen, H.P., Lavigne-Pelletier, C., Goubault, E., Boissy, P., Duval, C., 2016. Wavelet-based algorithm for auto-detection of daily living activities of older adults captured by multiple inertial measurement units (IMUs). Physiol. Meas. 37, 442–461. http://dx.doi.org/10.1088/0967-3334/37/3/442.

Bauman, A., Ainsworth, B.E., Bull, F., Craig, C.L., Hagströmer, M., Sallis, J.F., Pratt, M., Sjöström, M., 2009. Progress and pitfalls in the use of the international physical activity questionnaire (IPAQ) for adult physical activity surveillance. J. Phys. Act Health 6, S5–S8. http://dx.doi.org/10.1123/JPAH.6.S1.S5.

Begg, R.K., Palaniswami, M., Owen, B., 2005. Support vector machines for automated gait classification. IEEE Trans. Biomed. Eng. 52, 828–838. http://dx.doi.org/10.1109/TBME.2005.845241.

Bonato, P., 2003. Wearable sensors/systems and their impact on biomedical engineering. IEEE Eng. Med. Biol. Mag. 22, 18–20. http://dx.doi.org/10.1109/MEMB.2003.1213622.

Bottou, L., 2012. In: Montavon, G., Orr, G.B., Müller, K.R. (Eds.), Neural Networks: Tricks of the Trade. In: Lecture Notes in Computer Science, 7700, Springer, Berlin, Heidelberg, http://dx.doi.org/10.1007/978-3-642-35289-8_25.

Brockhaus, S., Rügamer, D., Greven, S., 2017. Boosting functional regression models with fdboost. J. Stat. Softw. 94, 1–50. http://dx.doi.org/10.48550/arxiv.1705.10662.

Chen, B., Liu, H., Chai, J., Bao, Z., 2009. Large margin feature weighting method via linear programming. IEEE Trans. Knowl. Data Eng. 21, 1475–1488. http://dx.doi.org/10.1109/TKDE.2008.238.

Cho, Y., Cho, H., Kyung, C.M., 2016. Design and implementation of practical step detection algorithm for Wrist-Worn devices. IEEE Sens. J. 16, 7720–7730. http://dx.doi.org/10.1109/JSEN.2016.2603163.

Chockalingam, N., Chatterley, F., Healy, A.C., Greenhalgh, A., Branthwaite, H.R., 2012. Comparison of pelvic complex kinematics during treadmill and overground walking. Arch. Phys. Med. Rehabil. 93, 2302–2308. http://dx.doi.org/10.1016/J.APMR.2011.10.022.

Dua, S., Acharya, U.R., Dua, P. (Eds.), 2014. Machine Learning in Healthcare Informatics, Vol. 56. Intelligent Systems Reference Library, http://dx.doi.org/10.1007/978-3-642-40017-9.

Engin, M., Demirel, A., Engin, E.Z., Fedakar, M., 2005. Recent developments and trends in biomedical sensors. Measurement (Lond) 37, 173–188. http://dx.doi.org/10.1016/J.MEASUREMENT.2004.11.002.

Fawcett, T., 2006. An introduction to ROC analysis. Pattern Recognit. Lett. 27, 861–874. http://dx.doi.org/10.1016/J.PATREC.2005.10.010.

Gilad-Bachrach, R., Navot, A., Tishby, N., 2004. Margin based feature selection-theory and algorithms. Proc of the 21th Int Conf on Machine Learning. doi:http://dx.doi.org/10.1145/1015330.1015352.

Goetz, C.G., Tilley, B.C., Shaftman, S.R., Stebbins, G.T., Fahn, S., Martinez-Martin, P., Poewe, W., Sampaio, C., Stern, M.B., Dodel, R., Dubois, B., Holloway, R., Jankovic, J., Kulisevsky, J., Lang, A.E., Lees, A., Leurgans, S., LeWitt, P.A., Nyenhuis, D., Olanow, C.W., Rascol, O., Schrag, A., Teresi, J.A., van Hilten, J.J., LaPelle, N., Agarwal, P., Athar, S., Bordelan, Y., Bronte-Stewart, H.M., Camicioli, R., Chou, K., Cole, W., Dalvi, A., Delgado, H., Diamond, A., Dick, J.P., Duda, J., Elble, R.J., Evans, C., Evidente, V.G., Fernandez, H.H., Fox, S., Friedman, J.H., Fross, R.D., Gallagher, D., Goetz, C.G., Hall, D., Hermanowicz, N., Hinson, V., Horn, S., Hurtig, H., Kang, U.J., Kleiner-Fisman, G., Klepitskaya, O., Kompoliti, K., Lai, E.C., Leehey, M.L., Leroi, I., Lyons, K.E., McClain, T., Metzer, S.W., Miyasaki, J., Morgan, J.C., Nance, M., Nemeth, J., Pahwa, R., Parashos, S.A., Schneider, J.S., Sethi, K., Shulman, L.M., Siderowf, A., Silverdale, M., Simuni, T., Stacy, M., Stern, M.B., Stewart, R.M., Sullivan, K., Swope, D.M., Wadia, P.M., Walker, R.W., Walker, R., Weiner, W.J., Wiener, J., Wilkinson, J., Wojcieszek, J.M., Wolfrath, S., Wooten, F., Wu, A., Zesiewicz, T.A., Zweig, R.M., 2008. Movement disorder society-sponsored revision of the unified parkinson's disease rating scale (MDS-UPDRS): scale presentation and clinimetric testing results. Mov. Disorders 23, 2129–2170. http://dx.doi.org/10.1002/MDS.22340.

Goldberger, J., Roweis, S., Hinton, G., Salakhutdinov, R., 2004. Neighbourhood components analysis. Advances in Neural Information Processing Systems (NIPS 2004) Vancouver Canada: Dec.. 17.

Guo, G., Wang, H., Bell, D., Bi, Y., Greer, K., 2003. KNN model-based approach in classification. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Vol. 2888. pp. 986–996. http://dx.doi.org/10.1007/978-3-540-39964-3_62/COVER.

Hagströmer, M., Oja, P., Sjöström, M., 2006. The international physical activity questionnaire (IPAQ): a study of concurrent and construct validity. Public Health Nutr. 9, 755–762. http://dx.doi.org/10.1079/PHN2005898.

Muro-de-la Herran, A., García-Zapirain, B., Méndez-Zorrilla, A., 2014. Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications. Sensors (Basel) 14 (3362), http://dx.doi.org/10.3390/S140203362.

Hollman, J.H., McDade, E.M., Petersen, R.C., 2011. Normative spatiotemporal gait parameters in older adults. Gait Posture 34, 111–118. http://dx.doi.org/10.1016/J.GAITPOST.2011.03.024.

Hua, A., Chaudhari, P., Johnson, N., Quinton, J., Schatz, B., Buchner, D., Hernandez, M.E., 2020. Evaluation of machine learning models for classifying upper extremity exercises using inertial measurement unit-based kinematic data. IEEE J. Biomed. Health Inform. 24, 2452–2460. http://dx.doi.org/10.1109/JBHI.2020.2999902.

Hutabarat, Y., Owaki, D., Hayashibe, M., 2021. Recent advances in quantitative gait analysis using wearable sensors: A review. IEEE Sens. J. 21, 26470–26487. http://dx.doi.org/10.1109/JSEN.2021.3119658.

Jayalath, S., Abhayasinghe, N., Murray, I., 2013. A gyroscope based accurate pedometer algorithm. In: International Conference on Indoor 178 Positioning and Indoor Navigation.

Jiménez-Grande, D., Farokh Atashzar, S., Martinez-Valdes, E., Marco De Nunzio, A., Falla, D., 2021. Kinematic biomarkers of chronic neck pain measured during gait: A data-driven classification approach. J. Biomech. 118, http://dx.doi.org/10.1016/J.JBIOMECH.2020.110190.

Kalmegh, S., 2015. Analysis of WEKA data mining algorithm REPTree, simple cart and randomtree for classification of Indian news. IJISET-Int. J. Innov. Sci. Eng. Technol. 2.

Katsiaras, A., Newman, A.B., Kriska, A., Brach, J., Krishnaswami, S., Feingold, E., Kritchevsky, S.B., Li, R., Harris, T.B., Schwartz, A., Goodpaster, B.H., 2005. Skeletal muscle fatigue, strength, and quality in the elderly: the health ABC study. J. Appl. Physiol. 99, 210–216. http://dx.doi.org/10.1152/JAPPLPHYSIOL.01276.2004, (1985).

Khaksar, S., Pan, H., Borazjani, B., Murray, I., Agrawal, H., Liu, W., Elliott, C., Imms, C., Campbell, A., Walmsley, C., 2021. Application of inertial measurement units and machine learning classification in cerebral palsy: Randomized controlled trial. JMIR Rehabil. Assist. Technol. 8, http://dx.doi.org/10.2196/29769.

Kleinbaum, D.G., Klein, M., 2010. Logistic regression. Stat. Biol. Health http://dx.doi.org/10.1007/978-1-4419-1742-3.

Lawal, M.O., 2021. Tomato detection based on modified YOLOv3 framework. Sci. Rep. 11, 1–11. http://dx.doi.org/10.1038/s41598-021-81216-5, 2021 11:1.

Li, Q., Young, M., Naing, V., Donelan, J.M., 2009. Walking speed and slope estimation using shank-mounted inertial measurement units. In: 2009 IEEE International Conference on Rehabilitation Robotics, ICORR 2009. pp. 839–844. http://dx.doi.org/10.1109/ICORR.2009.5209598.

Liew, B.X.W., Rugamer, D., Abichandani, D., de Nunzio, A.M., 2020a. Classifying individuals with and without patellofemoral pain syndrome using ground force profiles - development of a method using functional data boosting. Gait Posture 80, 90–95. http://dx.doi.org/10.1016/J.GAITPOST.2020.05.034.

Liew, B.X.W., Rugamer, D., Stocker, A., de Nunzio, A.M., 2020b. Classifying neck pain status using scalar and functional biomechanical variables - development of a method using functional data boosting. Gait Posture 76, 146–150. http://dx.doi.org/10.1016/J.GAITPOST.2019.12.008.

Luinge, H.J., Veltink, P.H., Baten, C.T.M., 2007. Ambulatory measurement of arm orientation. J. Biomech. 40, 78–85. http://dx.doi.org/10.1016/J.JBIOMECH.2005.11.011.

M, S., C, H., A, S., J, M., G, G., D, A., B, N., 2014. Frailty and technology: a systematic review of gait analysis in those with frailty. Gerontology 60, 79–89. http://dx.doi.org/10.1159/000354211.

Macellari, V., Giacomozzi, C., 1996. Multistep pressure platform as a stand-alone system for gait assessment. Med. Biol. Eng. Comput. 34, 299–304. http://dx.doi.org/10.1007/BF02511242.

Macellari, V., Giacomozzi, C., Saggini, R., 1999. Spatial–temporal parameters of gait: reference data and a statistical method for normality assessment. Gait Posture 10, 171–181. http://dx.doi.org/10.1016/S0966-6362(99)00021-1.

Mahoney, J.M., Rhudy, M.B., 2019. Methodology and validation for identifying gait type using machine learning on IMU data. 43, 25–32. http://dx.doi.org/10.1080/03091902.2019.1599073.

Mannini, A., Genovese, V., Sabatini, A.M., 2014. Online decoding of hidden Markov models for gait event detection using foot-mounted gyroscopes. IEEE J. Biomed. Health Inform. 18, 1122–1130. http://dx.doi.org/10.1109/JBHI.2013.2293887.

Mannini, A., Trojaniello, D., Cereatti, A., Sabatini, A.M., 2016. A machine learning framework for gait classification using inertial sensors: Application to elderly, post-stroke and huntington's disease patients. Sensors (Basel) 16, http://dx.doi.org/10.3390/S16010134.

Matkovic, F., Ivasic-Kos, M., Ribaric, S., 2022. A new approach to dominant motion pattern recognition at the macroscopic crowd level. Eng. Appl. Artif. Intell. 116, 105387. http://dx.doi.org/10.1016/J.ENGAPPAI.2022.105387.

McGrath, J., Neville, J., Stewart, T., Cronin, J., 2021. Upper body activity classification using an inertial measurement unit in court and field-based sports: A systematic review. Proc. Inst. Mech. Eng. P 235, 83–95. http://dx.doi.org/10.1177/1754337120959754/ASSET/IMAGES/LARGE/10.1177_1754337120959754-Fig.1.JPEG.

Namar, M.M., Jahanian, O., Koten, H., 2022. The start of combustion prediction for methane-fueled HCCI engines: Traditional vs. Machine learning methods. Math. Probl. Eng. 2022, http://dx.doi.org/10.1155/2022/4589160.

Niang, A.E.S., McFadyen, B.J., 2005. Effects of physical activity level on unobstructed and obstructed walking in young male adults. Gait Posture 22, 75–81. http://dx.doi.org/10.1016/J.GAITPOST.2004.07.003.

Noble, W.S., 2006. What is a support vector machine? Nature Biotechnol. 24, 1565–1567. http://dx.doi.org/10.1038/nbt1206-1565, 2006 24:12.

Nowlan, M.F., 2009. [PDF] human identification via gait recognition using accelerometer gyro forces | semantic scholar [WWW document]. Yale Comput. Sci. 8, URL https://www.semanticscholar.org/paper/Human-Identification-via-Gait-Recognition-Using-Nowlan/a63e04fefd2be621488646ae11bfe66c98d9649e (accessed 3.25.22).

O'Connor, C.M., Thorpe, S.K., O'Malley, M.J., Vaughan, C.L., 2007. Automatic detection of gait events using kinematic data. Gait Posture 25, 469–474. http://dx.doi.org/10.1016/J.GAITPOST.2006.05.016.

Pappas, I.P.I., Keller, T., Mangold, S., Popovic, M.R., Dietz, V., Morari, M., 2004. A reliable gyroscope-based gait-phase detection sensor embedded in a shoe insole. IEEE Sens. J. 4, 268–274. http://dx.doi.org/10.1109/JSEN.2004.823671.

Pogorelc, B., Gams, M., 2013. Detecting gait-related health problems of the elderly using multidimensional dynamic time warping approach with semantic attributes. Multimed. Tools Appl. 66, 95–114. http://dx.doi.org/10.1007/S11042-013-1473.

Ramchoun, H., Amine, M., Idrissi, J., Ghanou, Y., Ettaouil, M., 2016. Multilayer perceptron: Architecture optimization and training. Int. J. Interact. Multimed. Artif. Intell. 4 (26), http://dx.doi.org/10.9781/IJIMAI.2016.415.

Rhudy, M.B., Mahoney, J.M., 2018. A comprehensive comparison of simple step counting techniques using wrist- and ankle-mounted accelerometer and gyroscope signals. J. Med. Eng. Technol. 42, 236–243. http://dx.doi.org/10.1080/03091902.2018.1470692.

Rokach, L., 2009. Ensemble-based classifiers. Artif. Intell. Rev. 33, 1–39. http://dx.doi.org/10.1007/S10462-009-9124-7, 2009 33:1.

Roy, A.M., 2022. Adaptive transfer learning-based multiscale feature fused deep convolutional neural network for EEG MI multiclassification in brain–computer interface. Eng. Appl. Artif. Intell. 116, 105347. http://dx.doi.org/10.1016/J.ENGAPPAI.2022.105347.

Semaan, M.B., Wallard, L., Ruiz, V., Gillet, C., Leteneur, S., Simoneau-Buessinger, E., 2022. Is treadmill walking biomechanically comparable to overground walking? A systematic review. Gait Posture 92, 249–257. http://dx.doi.org/10.1016/J.GAITPOST.2021.11.009.

Shahbazi, M., Farokh, A.S., Ward, C., Talebi, H.A., Patel, R.v., 2018. Multimodal sensorimotor integration for expert-in-the-loop telerobotic surgical training. IEEE Trans. Robot. 34, 1549–1564. http://dx.doi.org/10.1109/TRO.2018.2861916.

Shaik, A.B., Srinivasan, S., 2019. A Brief Survey on RandOm Forest Ensembles in Classification Model. In: Lecture Notes in Networks and Systems, vol. 56, pp. 253–260. http://dx.doi.org/10.1007/978-981-13-2354-6_27/COVER.

Sokolova, M., Lapalme, G., 2009. A systematic analysis of performance measures for classification tasks. Inf. Process. Manag. 45, 427–437. http://dx.doi.org/10.1016/J.IPM.2009.03.002.

SR, S., 2004. Quantification of human motion: gait analysis-benefits and limitations to its application to clinical problems. J. Biomech. 37, 1869–1880. http://dx.doi.org/10.1016/J.JBIOMECH.2004.02.047.

Stojanovic, V., Nedic, N., 2016. Joint state and parameter robust estimation of stochastic nonlinear systems. Internat. J. Robust Nonlinear Control 26, 3058–3074. http://dx.doi.org/10.1002/RNC.3490.

Sun, Y., Todorovic, S., Goodison, S., 2010. Local-learning-based feature selection for high-dimensional data analysis. IEEE Trans. Pattern Anal. Mach. Intell. 32, 1610–1626. http://dx.doi.org/10.1109/TPAMI.2009.190.

Tao, H., Cheng, L., Qiu, J., Stojanovic, V., 2022. Few shot cross equipment fault diagnosis method based on parameter optimization and feature mertic. Meas. Sci. Technol. 33, 115005. http://dx.doi.org/10.1088/1361-6501/AC8368.

Tao, W., Liu, T., Zheng, R., Feng, H., 2012. Gait analysis using wearable sensors. Sensors (Basel) 12, 2255–2283. http://dx.doi.org/10.3390/S120202255.

Thin Swe, T., 2019. Analysis of tree based supervised learning algorithms on medical data thin thin swe. http://dx.doi.org/10.29322/IJSRP.9.04.2019.p8817.

Tong, K., Granat, M.H., 1999. A practical gait analysis system using gyroscopes. Med. Eng. Phys. 21, 87–94. http://dx.doi.org/10.1016/S1350-4533(99)00030-2.

Tudor-Locke, C.E., Myers, A.M., 2001. Methodological considerations for researchers and practitioners using pedometers to measure physical (ambulatory) activity. Res. Q. Exerc. Sport 72, 1–12. http://dx.doi.org/10.1080/02701367.2001.10608926.

Van Rossum, G., Drake, F.L., 2009. Python 3 reference manual.

Vanhees, L., Lefevre, J., Philippaerts, R., Martens, M., Huygens, W., Troosters, T., Beunen, G., 2005. How to assess physical activity? How to assess physical fitness? Eur. J. Cardiovasc. Prev. Rehabil. 12, 102–114. http://dx.doi.org/10.1097/01.HJR.0000161551.73095.9C.

Wang, F.-C., Chen, S.-F., Lin, C.-H., Shih, C.-J., Lin, A.-C., Yuan, Wei, Li, Y.-C., Kuo, Tien-Yun, Lin, C.-H., Shih, C.-J., Lin, A.-C., Yuan, W., Li, Y.-C., Kuo, T.-Y., Chang, S.-J., Prior, S.D., Ji, L.-W., 2021. Detection and classification of stroke gaits by deep neural networks employing inertial measurement units. Sensors 21, 1864. http://dx.doi.org/10.3390/S21051864, 2021, Vol. 21, Page 1864.

Whittle, M.W., 1996. Gait Analysis: an introduction. Butterworth-Heinemann.

Williamson, R., Andrews, B.J., 2000. Gait event detection for FES using accelerometers and supervised machine learning. IEEE Trans. Rehabil. Eng. 8, 312–319. http://dx.doi.org/10.1109/86.867873.

Witten, I.H., Frank, E., Hall, M.A., Pal, C.J., 2016. Data mining: Practical machine learning tools and techniques. pp. 1–621. http://dx.doi.org/10.1016/C2009-0-19715-5.

Yang, W., Wang, K., Zuo, W., 2012. Neighborhood component feature selection for high-dimensional data. J. Comput. (Taipei) 7, 162–168. http://dx.doi.org/10.4304/JCP.7.1.161-168.

Zhuang, Z., Tao, H., Chen, Y., Stojanovic, V., Paszke, W., 2022. An optimal iterative learning control approach for linear systems with nonuniform trial lengths under input constraints. IEEE Trans. Syst. Man Cybern. Syst. http://dx.doi.org/10.1109/TSMC.2022.3225381.