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Review Article

The Use of Spatiotemporal Gait Analysis in Diagnosing Pathologies: A Review

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Abstract

Background: Gait, particularly walking speed (WS), has emerged as an essential indicator of health. WS is indicative of current health and predicts future health trends, especially in older adults. Notably, a 0.1 m/s WS increase corresponds to a 12% rise in survival among this demographic, establishing WS as a powerful prognostic tool. This has resulted in the designation of WS as the "6th vital sign", which is applicable to a broad spectrum of medical conditions. Additionally, computerized gait analysis reveals nuanced differences in movement patterns across age groups. This review provides a detailed insight into the multifaceted nature of gait and its health implications.

Purpose: This review's primary objective is to underscore the significance of gait and WS as pivotal health markers. By framing WS as the "6th vital sign" and delving into gait's complexities using digital analysis, the review aims to elucidate how gait metrics inform health trajectories in diverse medical scenarios.

Methods: Our analysis employed laboratory-based three-dimensional gait techniques. Kinematic data were obtained using infrared markers on the body and triangulated with multiple cameras. Concurrently, force plates within electronic pathways captured kinetic data, such as ground reaction forces. Data collection was guided by a pre-established checklist encompassing specific conditions (including Parkinson's Disease, Lumbar disk herniation, Chronic Mechanical Lower back pain, Lumbar Spinal Stenosis, Depression, Hip Osteoarthritis, COPD), analysis tools (e.g., type of cameras, force plates), kinematic and kinetic parameters (e.g., support moments, momentum), and potential psychological impacts on participants (e.g., Hawthorne and "white-coat" effects). The clinical significance of our data was validated against existing research on gait pattern variations in mentioned conditions, ensuring quality through stringent research standards.

Conclusion: Spatiotemporal gait analysis, especially with machine learning application, is nascent. Although there's potential in its diagnostic capability, extensive research is needed for clinical use. Our focus was primarily on Parkinson's Disease, aiming to gauge machine learning's role in discerning pathological from normal gait using spatiotemporal metrics. Future investigations should explore this approach for different gait-related conditions.

Keywords: gait; walking speed; health status; ageing demographics; computerized gait analysis; 6th vital sign; kinematic data; spatiotemporal metrics

Introduction

Gait as a measure of health

Gait refers to the way a person or animal walks or runs and is a simple yet informative measure of overall health. Most patterns of movement inevitably slow and deteriorate with age not only for humans, but across various species [1]. Deteriorations in gait, and in particular walking speed (WS), have been associated with a plethora of ageing-associated conditions such as cognitive impairment, arthritis, cardiovascular disease and sarcopenia, and has emerged as an important measure of overall health in ageing human populations [1]. According to a meta-analysis by Studenski et al, WS is positively associated with survival in older adults. For each increment of 0.1 m/s, a 12% increase in survival was observed (HR 0.88, 95% CI, 0.87- 0.90; P<0.001) [2]. This shows that WS is not only a measure of current health but also a predictor of survival and therefore future health. These findings have reasonably high external validity in the ageing population as they recruit community-dwelling older adults.

Importantly, other studies have led WS, to be dubbed as the "6th vital sign" [3] as it has proven to be a valid,

reliable and sensitive [4,5] measure of health outcomes restricted not only to the context of ageing, but also various pathology groups including neurological, cardiovascular, orthopedic and psychiatric conditions [6-10]. Gait, however, is remarkably complex and is not restricted to the metric of walking speed. Computerized gait analysis with kinematic and kinetic parameters (for example cadence, reaction forces) can highlight more interesting and robust differences [1] between normative and pathological gait in the young and old

[11]. This in turn, has sparked great interest in the computerized analysis of gait with the gait metrics explored below.

Types of gait analysis

Under quantitative and qualitative gait analysis, three broad categories exist, including observational gait analysis, kinematic analysis, and kinetic analysis (see Figure 1).
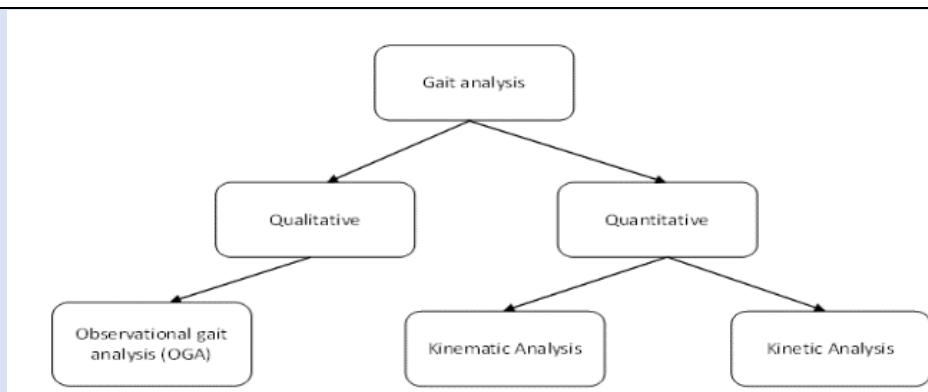

Figure 1: Types of gait analysis

Gait analysis can be categorized into qualitative methods, which refers to observation by clinicians, and quantitative methods which can be further categorized into kinematic and kinetic analysis.

Observational gait analysis

Observational gait analysis methods are qualitative and are useful in the differentiation of pathological gait patterns in clinical practice. For example, a clinician may distinguish Parkinsonian gait from myopathic gait (for example positive Trendelenburg sign) or neuropathic gait (for example foot drop) [12]. However, observational methods are highly subjective, and their accuracy depends on the skill of the clinician and their knowledge of both normal and pathological gait. A study measuring the gait disturbances after stroke found poor correlation between validated foot-force sensors and clinician measurements (mean r=0.55) [13].

Kinematic Data

Kinematics describes the way in which objects move without regard for the forces which cause them to move. In contrast to observational methods, data is quantitative and includes both spatiotemporal metrics such as gait velocity, cadence, step time, step length etc. as well as descriptive components of gait

such as angles of joint rotation, pronation and supination as well as range of motion [14].

Kinetic Data

Kinetic data is also quantitative in nature, but rather aims to understand why objects move the way they move i.e., regarding the forces behind the actions. As such, it includes metrics such as ground reaction force, support moment, power and energy [14].

Laboratory methods

Laboratory-based three-dimensional gait analysis has long been regarded as the "gold standard" in measuring quantitative gait parameters in both clinical and non-clinical (sport) applications [14]. The use of infrared markers placed at points around the body allow researchers to use cameras to triangulate the body in 3D space and gather highly accurate kinematic data [14]. In addition, force plates in electronic walkways can reveal kinetic data such as ground reaction forces, support moments and momentum [15]. The literature strongly suggests the clinical relevance of both kinematic and kinetic data as statistically significant differences in gait patterns have been observed in patients with lumbar spinal stenosis [16], recovering from total knee arthroplasty (TKA) [17], Parkinson's disease [18] and obesity [19].

However, there are several drawbacks with laboratory-based analysis. Firstly, it requires expensive equipment and technicians which are not feasible in the clinical setting [20]. Secondly, these methods are susceptible to the psychological Hawthorne and "white-coat" effects as individuals are more likely to be conscious of their gait when observed by a clinician and fail to capture 'free-living gait' which refers to the way people walk in everyday life [20]. One study by Brodie et al. highlights this well, finding that lab-based technologies tend to overestimate parameters such as cadence (8.91%, p< 0.001) whilst underestimating the variability in gait (81.55%, p<0.001) [21]. These drawbacks may limit the validity of the study and decrease the generalizability of the findings.

Wearable sensors

In contrast, inertial measurement units (IMU's) are wearable single-point devices with an accelerometer, magnetometer, and a gyroscope. Measurements made with IMU's have shown to be largely consistent with that of the laboratory analysis techniques (r >0.83). These are very promising as they can capture free-living gait in community and home environments as they are small, portable, and unobtrusive to the activities of daily living [22-24]. The potential of IMU's to gather kinematic data is well established in the literature with a many papers documenting the accurate measurement of spatiotemporal metrics and overall agreement with that obtained from laboratory-based techniques [25-30]. Other descriptive kinematic data such as joint angles are also possible with IMU's, yet they often require multiple sensors and extensive calibration [31]. which again, is not feasible in the fast-paced clinical environment. However, the literature is relatively scarce when it comes to gathering clinically relevant kinetic data using IMU's. A possible reason for this is that it is difficult to measure forces accurately without expensive electronic walkways [32]. A select few studies seek to validate use of IMU's in the form of smart-insoles and tendon-tensiometry devices which measure kinetic parameters such as ground reaction forces and muscle work and power

output respectively [32,33]. These, however, not only have limited reliability due to minimal repetition, but are also more popular in the realm of high-performance sports and rehabilitation where the real focus of gait analysis is not to identify disease states but rather to maximize the efficiency of locomotion [34]. For example, several studies have explored how GRF relates to the optimal cadence, stride length and gait velocity values for runners to minimize energy expenditure and maximize efficiency [35-37].

Whilst several studies have shown that there are clinically significant differences in kinetic metrics between various pathology groups [16-19], the literature is undecided regarding its clinical utility and indicates that kinematic parameters such as spatiotemporal data are sufficient whilst having the additional benefit of being efficiently obtained using single-point wearable IMU's. In addition, models created by Verghese et al. and Lord et al. which used spatiotemporal data alone were able to explain up to 80% of gait variance between healthy and pathological gait using only five factors: pace, rhythm, variability, asymmetry and postural control [38,39] showing that spatiotemporal parameters are more than adequate in clinical gait analysis. Whilst the above arguments strengthen the case for the use of wearable IMU's, they suffer from drift errors and noise due to interference with the magnetic fields of other electronic devices. According to one study, these errors can render up to 20% of data unusable. Fortunately, these entries can be manually identified and removed in data processing stages [40,41].

Spatiotemporal gait metrics

A normal gait cycle for each leg involves a stance and a swing phase. Stance (also known as support) phase describes the entire period during which a foot is on the ground, and swing describes the time this same foot is in the air as the limb advances in space. When one limb is instance, the contralateral limb is in swing, except for an overlapping period where both feet are on the ground, known as the double support time, as seen in Figure 2.
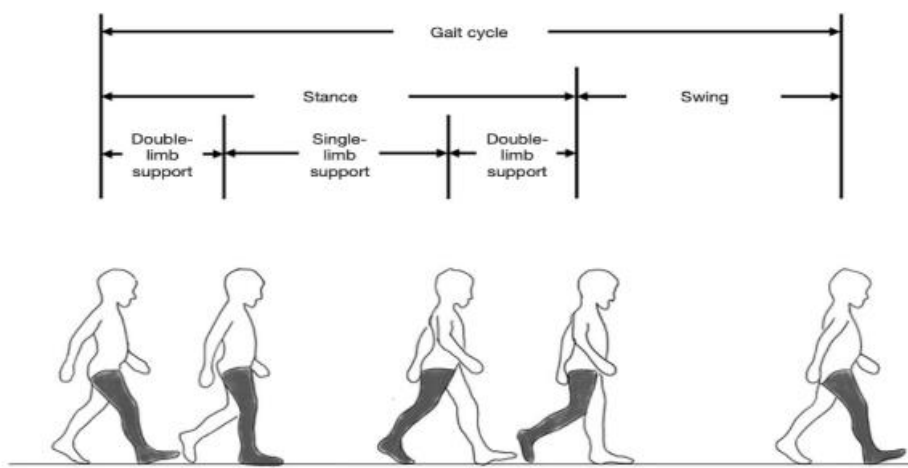
Figure 2: Gait cycle for right leg (shaded).

The figure shows that the gait cycle for any one leg is comprised of a stance and a swing phase. The right-leg is shaded and used as an example. Figure taken [83], The single support time is the period during which only one limb is on the ground. Several other spatiotemporal gait metrics exist and are shown below in Figure 3.

Gait variable	Definition	Units	Type
Step length	Average distance between two consecutive contacts of any foot with the ground	Metres (m)	Spatial
Stride length	Average distance between two consecutive contacts of the same foot with the ground	Metres (m)	Spatial
Step time	Average time between two consecutive contacts of any foot with the ground	Seconds (s)	Temporal
Stride time	Average time between two consecutive contacts of the same foot with the ground	Seconds (s)	Temporal
Walking speed (or gait velocity)	Average distance travelled per second	Metres/second (m/s)	Spatiotemporal
Cadence	Average rate (or frequency) of steps	Steps/minute	Spatiotemporal
Step time variability	Step-to-step variability of step time	Standard deviation (SD) coefficient of variance (cov = SD/mean)	Gait variability
Step length variability	Step-to-step variability of step length	Standard deviation (SD) coefficient of variance (cov = SD/mean)	Gait variability
Walking speed (or gait velocity) variability	Step-to-step variability of walking speed	Coefficient of variance (cov = SD/mean)	Gait variability
Step time asymmetry	Average difference in time taken for successive steps on left and right foot	Seconds (s)	Gait asymmetry
Step length asymmetry	Average difference in length for successive steps on left and right foot	Metres (m)	Gait asymmetry

Figure 3: Common spatiotemporal gait metrics.

The figure above summarizes the most common spatiotemporal metrics. Spatial parameters such as step and stride length can be considered alongside temporal metrics of step and stride time to calculate spatiotemporal data pertaining to gait velocity and cadence. Furthermore, more complex 'derived' metrics such as variability and asymmetry in step time, step length and gait velocity can also be calculated. Figure taken from Natarajan et al. [83]

Using gait to distinguish pathologies

As aforementioned, several studies have demonstrated the potential for spatiotemporal gait metrics to differentiate healthy and pathological gait sig-natures. A comprehensive literature search of four databases (Medline, Embase, PubMed, Web of Science) was conducted, after which 1476 records were identified and 21 articles included after screening. These studies investigated the spatiotemporal gait metrics in various conditions and compared them to healthy age-matched controls. Findings from these articles are summarized in Table 1.

Table 1: Summary of gait alteration in various conditions.

Gait Velocity	Cadence	Stride Length	Stride Time	Stride time variability	Double support time
Parkinson's Disease [43-49,84]					
-(8-11) %	-6%	-(7-17) %	+(6-8) %	+76%	+24%
Lumbar Disc Herniation[50]					
-76%	-66%	×	×	×	+53%
Chronic Mechanical Lower Back Pain [50,55,56]					
-(13-26) %	-19%	×	×	×	+(14-16) %
Lumbar Spinal Stenosis [51-53,85,86]					
-(12-37) %	-(10-14) %	×	×	×	×
Depression [87]					
-3%	×	×	×	×	+0.03%
Hip Osteoarthritis [88]					
-14%	-5%	-10%	×	×	+13%
COPD [89,90]					
-7%	-(7-13) %	×	+15%	×	+(16-17) %

Studies included in this summary tables reported mean values of gait parameters in patients with relevant pathologies as well as their age-matched controls. The percentage difference was calculated and reported above. A range was included where results were derived from multiple studies. Table 1 is merely a snapshot of the unique gait 'signatures' of various pathologies which illuminates the diagnostic potential of spatiotemporal gait metrics. For example, appreciable differences can be noted between Parkinson's disease [42-49] and Lumbar disc herniation [50] in terms of cadence (-6% vs -66%) and double support time (+24% vs +53%) whilst those with Lumbar spinal stenosis [20,51-54] present with a more modest decrease in cadence (10-14%). Moreover, the large ranges observed in the decrease in gait velocity in chronic mechanical back pain [50,55,56] (13-26%) and Lumbar spinal stenosis (12-37%) may indicate that gait metrics can diagnose the severity of a condition, or that methods used to measure gait velocity are simply imprecise. Additionally, there are many blank cells in Table 1, showing that the literature has not comprehensively addressed spatiotemporal gait changes in all gait-altering pathologies. Parkinson's disease [42-49] is the most studied gait pattern in the literature, with studies on other pathologies being relatively scarce. Certainly, this field is still largely in its infancy and a many more research papers comparing the gait metrics of pathological and normative gait of age-matched controls of various pathologies are necessary before the diagnostic utility of gait metrics can be considered. There is a single meta-analysis of spatiotemporal gait changes associated with Parkinson's disease (PD) [57]. Its findings have very low external validity as only two studies screened in the review contained data gathered from "free-living contexts" and even these were excluded from the final meta-analysis as they were found to be largely heterogenous with laboratory data. A 2016 study by Del Din et al. [58] found statistically significant differences between laboratory and free-living gait in PD patients as can be seen in Figure 4 which demonstrates the overwhelming need for studies documenting 'free-living' gait and strengthens the case for the use of wearable IMU's.
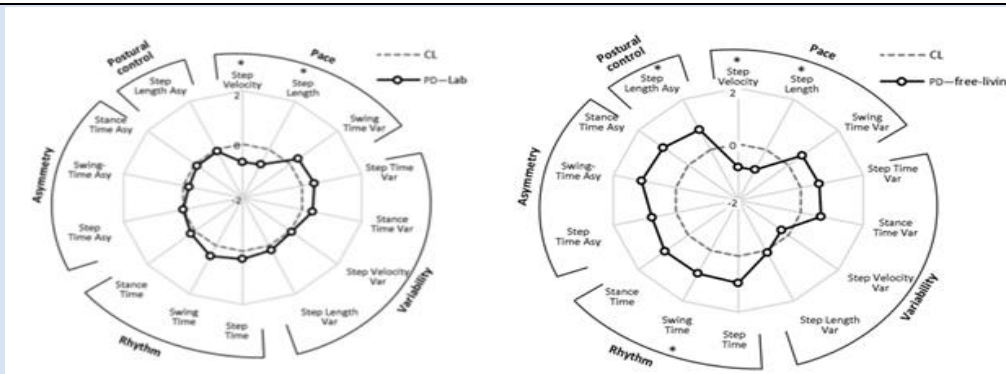
Figure 4: Radar plot illustrating 14 spatiotemporal gait metrics for patients with Parkinson's Disease (PD) and controls (CL) as evaluated in the laboratory (left) and in free-living contexts (right). Central dotted line represents CL data and bolded line represents PD data measured in standard deviations from CL values (range $\pm 2SD$). Figure taken from Del Din et al. [58]

The same study also found that gait signatures varied significantly with the duration of the ambulatory bout as shown in Figure 5. Longer ambulatory bouts (ABs) were more discriminative of pathological gait in PD.

This calls into question a large portion of the current literature and the short (<10 seconds) ABs used to obtain gait metrics as summarized by Table 2.
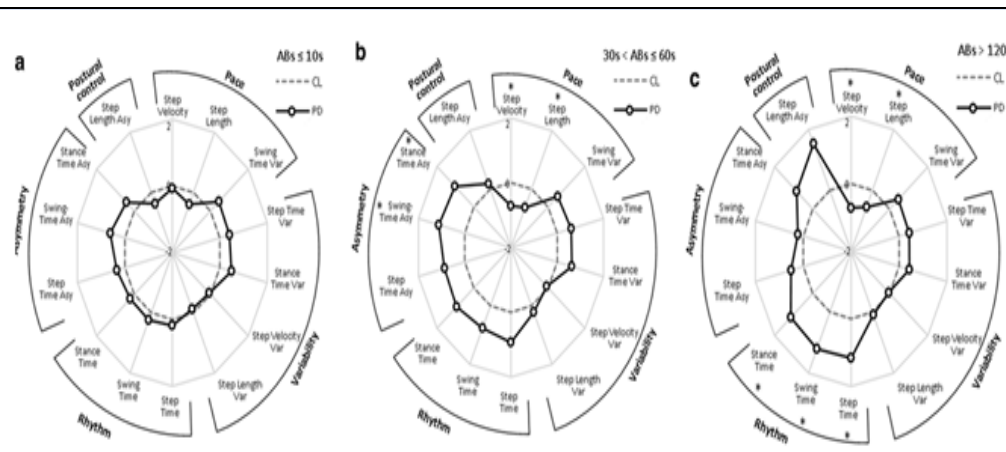

Figure 5: Radar plot illustrating 14 spatiotemporal gait metrics for patients with Parkinson's Disease (PD) and controls (CL) as evaluated ambulatory bouts (ABs) in free-living contexts. Central dotted line represents CL data and bolded line represents PD data measured in standard deviations from CL values (range $\pm 2SD$). (a) represents Abs<10s, (b) represents 30s<Abs<60s and (c) represents Abs>120s. Figure taken from Del Din et al. [58].

Table 2: Summary of ambulatory bouts used to measure spatiotemporal gait metrics in patients with Parkinson's disease. Certain studies provided the ambulatory bout in the methods section. Others specified the distance of the walkway only. When the average walking speed of patients was also given, an average ambulatory bout was calculated and reported in this table.

Study	Methods	Ambulatory bout (s)
Geroin et al. [47]	Use of GAITrite® electronic walkway	7.92
Muro-de-la-Herran et al. [46]	Timed 25-foot walk test	7.50
Hass et al. [91]	Use of a 5.8m x 0.9m pressure sensitive walkway	5.10
Din et al. [92]	Use of GAITrite® electronic walkway and Body worn monitory (BWM) concurrently.	7.0
Hausdorff [93]	Patients walking on level ground in the hallway outside a clinic	120-360
Schlachetzki et al. [43]	Self-selected speed on a 4x10m walkway. Patients asked to walk 10m, turn 180 degrees and repeat until a total of 40 meters were covered.	41.03

Therefore, it is evident that a large proportion of the current literature would struggle to present valid and accurate gait parameters for PD patients due to heterogeneity in ABs and the large proportion of shorter ABs. There is a need for research studies measuring gait parameters over longer ABs in free-living contexts. In summary, the field of spatiotemporal gait analysis requires a great deal of optimization with standardized testing methods. For example, studies which define minimum walking length or duration and a great volume of research studies which adhere to these regulations before data can be pooled and meta-analyzed.

Artificial intelligence

Distinguishing healthy and pathological gait has proven to be challenging and the literature shows that mathematical [59,60] and statistical techniques [61,62] are popular due to their simplicity. However, mathematical transforms provide limited insight as they rely solely on univariate signals and data processed from wavelets, whilst statistical techniques assume normal distributions which tend to oversimplify the complex non-linear relationships in gait data [63,64]. In contrast, recent applications of machine learning (ML) in gait analysis, a special subset of artificial intelligence (AI), have shown their ability to model non-linear multidimensional data whilst being versatile in incorporating new data to improve accuracy of predictions [65,66].

Use of AI in gait analysis

The workflow in classifying healthy and pathological gait can be broken down into 5 key stages as shown in Fig 6.
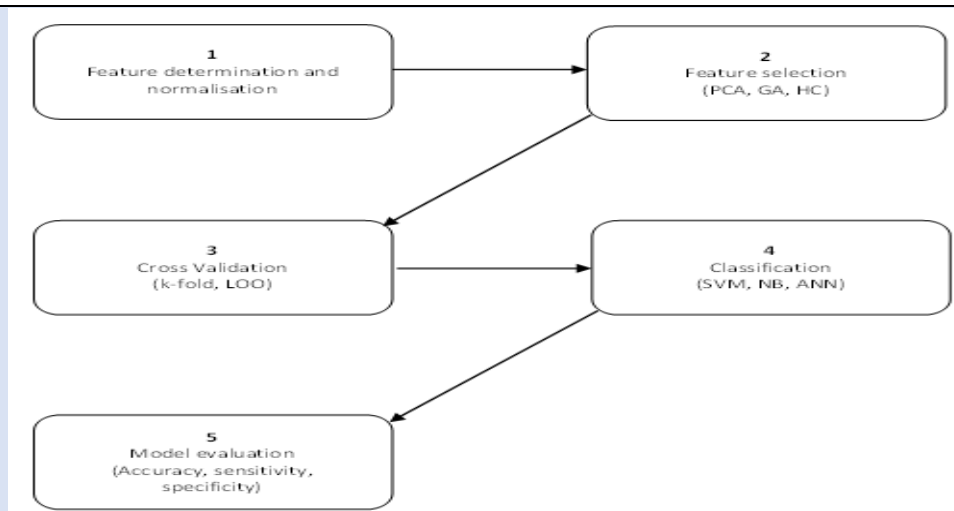

Figure 6: Summary of the workflow in classifying pathological and healthy gait. PCA = principal component analysis, GA=Genetic Algorithm, HC=Hill Climbing. SVM = Support vector machine, NB = Naïve Bayes, ANN = artificial neural network.

Feature determination and normalization

Feature determination involves the extraction of gait 'features' such as gait velocity, cadence, step-time, and other spatiotemporal metrics. Variations in gait data due to patient height and weight can largely be corrected via normalization and has been shown to improve the classification accuracy in some ML models [67-69]. Normalization has been investigated as a function of height, stride time and body weight as seen in Table 3. However, there is no clear consensus in the literature regarding the most beneficial approach as the use of normalization is not necessarily correlated with greater classification accuracy. The highest accuracy with normalization is 97.9% whilst an accuracy of 100% was achieved without normalization (see Table 3). This could be because numerous factors are changing between models. For example, cross-validation, feature selection and machine learning techniques have changed. Further research where all other factors other than normalization methods are controlled variables, will allow researchers to determine its utility.

Table 3: Summary of the application of ML to clinical conditions in the current literature. PCA=Principal Component Analysis, LOO= Leave one out, SVM=Support vector machine, ANN = Artificial Neural Network, NB=Naïve Bayes. 'X' represents studies where normalization was not applied.

Study	Distinguishing Condition	Normalization	Feature selection	Cross-validation	Classification model	Model accuracy
Eskofier et al.[75]	Balance impairment	Stride time	PCA	LOO	SVM	95.8%
Khandoker et al.[80]	Falls	×	HC	LOO	SVM	100%
Begg et al.[81]	Young vs Old	×	HC	3-fold CV	SVM, ANN	83.3%, and 75% respectively
Begg and Kamruzzaman[69]	Young vs Old	Body weight	HC	6-fold CV	SVM	91%
Pogorelc at al.[82]	Back pain	Height	PCA	10-fold CV	SVM, NB	97.9% and 97.2% respectively
Study	Distinguishing Condition	Normalization	Feature selection	Cross-validation	Classification model	Model accuracy
Eskofier et al.75	Balance impairment	Stride time	PCA	LOO	SVM	95.80%
Khandoker et al.80	Falls		HC	LOO	SVM	100%
Begg et al.81	Young vs Old		HC	3-fold CV	SVM, ANN	83.3%, and 75% respectively
Begg and Kamruzzaman 69	Young vs Old	Body weight	HC	6-fold CV	SVM	91%
Pogorelc at al.82	Back pain	Height	PCA	10-fold CV	SVM, NB	97.9% and 97.2% respectively

Feature selection

Spatiotemporal gait analysis involves many features and produces a multitude of data. Feature selection aims to optimize the performance of the ML model by selecting the most relevant features with maximal separation between classes to ensure the model is both time and cost-efficient [70,71]. Methodologies fall under three main categories: filter, wrapper, and embedded methods. Filter methods are the least computationally intensive as they evaluate the dataset without evaluating the performance of the ML classification model [70]. Wrapper methods are the most computationally intensive as they evaluate the dataset and select features tailored to the performance of the ML model [70]. Embedded methods consider both the dataset and the performance of the model with the advantage of being much less computationally intensive than wrapper methods [70].

The most common feature selection methods used in gait analysis are Principal Component Analysis (PCA) a filter method, Genetic Algorithm (GA) a wrapper method, and Hill-climbing (HC) an embedded method [72-74]. Upon analysis of the literature, PCA which is the most basic and computationally simple technique, provides the most reliable results [75] (model accuracy >95%) (see Table 3). Theoretically speaking, HC is expected to be quite promising as an embedded method and has been highly successful (>96% accuracy) in heart monitors [76]. However, it still provides relatively low classification accuracy (75.5-83.3%) [69] with spatiotemporal gait data, showing that its use has not yet been optimized to gait analysis. Further research is recommended to realize its potential in clinical gait analysis.

Cross-validation

Cross-validation (CV) is used to evaluate the generalizability and external validity of findings by ML

models by splitting data into training subsets used to train the ML model and a validation subset which seeks to validate the model [69,74,77]. Proper implementation of CV techniques is known to evaluate overfitting by measuring a quantity known as the root mean-squared-error in as it pertains to predictions made [73]. Most common CV techniques include the k-fold and leave one out (LOO) method. K-fold techniques randomly partition data into k subsets and k-1 subsets are used as training subsets, whilst the remaining one is used to validate the model [69]. LOO methodology uses the same concept as k-fold except that it is not random as data in each subset belongs to an individual participant.

Classification

Support vector machine (SVM), Naïve-Bayes (NB), and Artificial Neural networks (ANN) were by far the most common ML models used for classification purposes in the literature. SVM utilizes supervised learning methods to compute a hyperplane with greatest separability between the analyzed classes [69] whilst NB utilizes the Bayes theorem and assumes that all features are independent to create a probabilistic model [78]. Finally, ANN's feature a feed-forward networks where multiple nodes 'synapse' upon each other in a layered system, and rely on a 'transfer-function' for forward propagation and classification of pathological gait [79]. Clearly, SVM has shown the greatest success with model accuracies as high as 100% [75] (see Table 3). It is also the most used ML model [75,80-82]. NB has been featured sparingly in the literature, and more papers featuring this model are required before its utility can be determined.

Model evaluation

The literature has consistently used some or all of three metrics: accuracy, sensitivity, and specificity to evaluate the ML models and these are summarized in Figure 7.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$

$$Specificity = \frac{TN}{TP + FP} \times 100\%$$

Figure 7: Overview of metrics used to analyze machine learning models. TN = true negative, TP=true positive, FN=false negative, FP=false positive.

In summary, the combination of Principle Component Analysis and Support Vector Machine are the most reliable feature selection methods and ML models respectively when evaluated in terms of classification accuracy. Currently, k-fold CV is the most valid, with higher 'k' numbers indicating more iterations, culminating in greater accuracy [82].
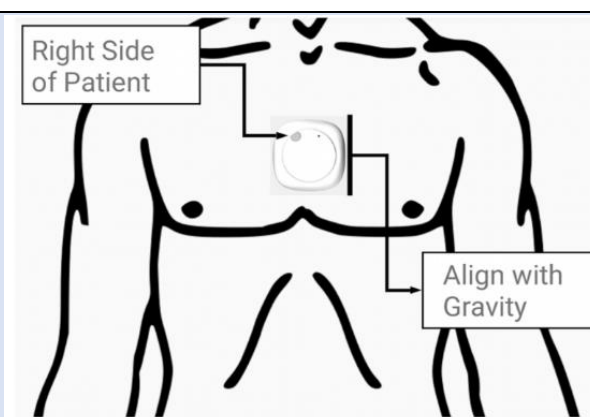

Figure 8: Metaemotion the MetaemotionC© (MMC) inertial measurement unit (IMU) developed by Mbientlab Inc. pictured as it will be fitted on the sternal angle of patients. Figure taken from Betteridge et al [94].

Conclusion and rationale

The field of spatiotemporal gait analysis is very much in its early days, and the application of ML models is even further in its infancy. Whilst the literature has shown that the combination of the two can produce a very powerful diagnostic tool, it requires significant further research so that it may be optimized for day-to-day clinical use. Current research is greatly heterogenous amongst the various pathologies explored and data-analysis techniques applied and lacks the repetitions required to make reliable conclusions. Furthermore, the use of ML models has not been optimized for any one pathology. As such, study aims to focus on a single pathology, Parkinson's Disease, and comprehensively explore the utility of machine learning in distinguishing healthy and pathological gait based on spatiotemporal gait metrics. Further studies should systematically repeat this type of investigation not only for Parkinson's disease but for other gait altering pathologies.

Declarations

Ethics approval and consent to participate
Not applicable

Consent for publication
Not applicable

Availability of data and materials
Not applicable

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(III): Provision of study materials or patients: VF. MM. RJM.
(IV): Collection and assembly of data: VF. RJM.
(V): Data analysis and interpretation: VF. MM. RJM.
(VI): Manuscript writing: All Authors
(VII): Final approval of manuscript: All authors

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