A Systematic Review of Gait Analysis in the Context of Multimodal Sensing Fusion and AI

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***Abstract*—Background: Neurological diseases are a leading cause of disability and mortality. Gait, or human walking, is a significant predictor of quality of life, morbidity, and mortality. Gait patterns and other kinematic, kinetic, and balance gait features are accurate and powerful diagnostic and prognostic tools. Objective: This review article focuses on the applicability of gait analysis using fusion techniques and artificial intelligence (AI) models. The aim is to examine the significance of mixing several types of wearable and non-wearable sensor data and the impact of this combination on the performance of AI models. Method: In this systematic review, 66 studies using more than two modalities to record and analyze gait were identified. 40 studies incorporated multiple gait analysis modalities without the use of artificial intelligence to extract gait features such as kinematic, kinetic, margin of stability, temporal, and spatial gait parameters, as well as cerebral activity. Similarly, 26 studies analyzed gait data using multimodal fusion sensors and AI algorithms. Results: The research summarized here demonstrates that the quality of gait analysis and the effectiveness of AI models can both benefit from the integration of data from many sensors. Meanwhile, the utilization of EMG signals in fusion data is especially advantageous. Conclusion: The findings of this review suggest that a smart, portable, wearable-based gait and balance assessment system can be developed using multimodal sensing of the most cutting-edge, clinically relevant tools and technology available. The information presented in this article may serve as a vital springboard for such development.**

***Index Terms*—Gait analysis, artificial intelligence, multimodal sensing fusion.**

I. Introduction

HUMAN walking or gait involves intricate coordination and interplay between cortical and subcortical areas, the cardiorespiratory system, and the musculoskeletal system resulting in reflex or controlled movement. While normal gait can be defined as a series of rhythmic, systematic, and coordinated movements of the limbs and trunk, which results in the change in position of the body's center of mass, individual gait patterns are unique and influenced by age, personality, mood and sociocultural factors [1]. The period between one heel strike and the following heel strike when measuring forwards motion is defined as a gait cycle [2] (as shown in Fig.1, [3]).

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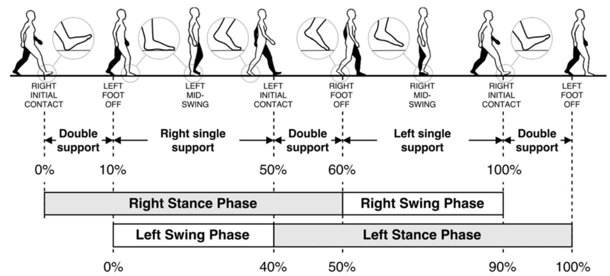

Fig. 1. Human gait cycle with stance and swing phases [3].

In addition to providing the key means for mobility, gait is a sensitive indicator of overall health status that can reveal the status and progression of underlying health challenges including neurological conditions (e.g., sensory or motor impairments and cognitive impairments) and musculoskeletal/orthopedic problems (e.g., osteoarthritis and skeletal deformities), to cardiovascular and metabolic conditions (e.g., heart failure, respiratory insufficiency, peripheral arterial occlusive disease, and obesity), and to ageing-associated ambulatory dysfunction and trauma [4], [5]. In the elderly, gait disorders are also linked to impaired proprioceptive function associated with polyneuropathy, frontal gait disorder associated with vascular encephalopathy, poor vision, as well as osteoarthritis [6]. As precursors of falls, gait deficits are considered as the most common cause of severe injuries in the aging population, while slow gait correlates with mild cognitive impairment (MCI) and future occurrence of dementia [7].

Gait analysis has emerged as a quantitative method for investigating a wide range of walking challenges and gait irregularities [4]. Gait analysis, supported by modern sensing technology and computational algorithms, can be used in clinical and research laboratory investigations, security, and everyday living contexts, allowing for the identification, monitoring, and intervention.

Instrumented gait analysis (IGA) is considered the gold standard for gait assessment [8]. IGA measures and analyzes different aspects of human gait applying spatiotemporal, kinematic, and kinetic measures. Traditional IGA systems consist of motion capture cameras, force plates, instrumented walk-ways, and treadmills, whereas contemporary IGA systems consist of miniaturized peripheral sensing systems, computational platforms, and modalities [8]. IGA-based quantitative assessment can improve the diagnosis, outcome prediction, and rehabilitation of different gait impairments [9], [10], [11], [12]. Smart wearable technologies, multi-modal physiological network sensors, sensor fusion techniques, and AI-driven computational platforms are becoming the center of interest when it comes to evaluating human mobility and gait. Such cutting-edge movement analysis technologies allow for gait and balance assessment to be more objective, accurate, quantifiable, and sensitive to alterations brought on by age, illness, or trauma [13]. These technologies provide synchronous monitoring of spatiotemporal gait parameters (swing, stance, cadence, step width, step length, etc.), as well as upper/lower limb dynamics, including kinematics (angular positions, velocities, and accelerations), kinetics (forces, moments, plantar pressure and center of pressure), in conjunction with associated musculoskeletal, cardiorespiratory and neurological changes [14]. Currently, there are two main types of modalities used for gait acquisition: sensor-based (SB) and vision-based (VB) [15]. Although SB gait capture demands more complicated sensing technology, it has the capability of providing precise quantitative data using either floor sensors or wearable sensors in addition to utilizing either marker free or marker-based recording [15], [16].

Although the importance of the role that cortical areas play in normal gait is well known, decoding the precise relationship between cortical activity and gait characteristics remains elusive. Numerous studies indicate that cortical involvement is essential in human gait [17], [18]. In the last two decades, evidence for cortical involvement in human locomotion has been provided by neuroimaging studies based on position emission tomography [19], electroencephalography (EEG) [20] and functional near-infrared spectroscopy (fNIRS) [21]. EEG and fNIRS are increasingly gaining acceptance in the scientific community owing to their non-invasiveness, mobility, and ease of use [22], [23]. EEG is one of the first methods developed for capturing cortical activity and has several applications in gait analysis [24]. fNIRS is a relatively new technique which effectively captures brain hemodynamic [25]. A large amount of multimodal data is, however, difficult to interpret and requires a computational system to describe and connect the many variables. Proprietary algorithms or models of artificial intelligence (AI) are computational systems that are currently being intensely investigated for prediction, as well as the diagnosis or prognosis of different clinical pathology [26].

Researchers in the field of gait analysis are utilizing AI techniques including machine learning (ML), support vector machine (SVM), and neural network (NN). These techniques have the potential to provide ways for obtaining, storing, and evaluating multifactorial complicated gait data, capturing its non-linear dynamic variability, and giving the crucial advantages of predictive analytics. ML models are a subset of AI models, comprising supervised and unsupervised learning. Both have advantages and disadvantages with supervised learning models being time-consuming, and labels for input and output variables need specialized knowledge. In contrast, unsupervised learning algorithms might provide radically erroneous outcomes [27]. Sensor data collection, pre-processing, feature extraction, feature selection, classification, and result interpretation are all becoming standard procedures for gait classification, prediction, and analysis based on AI [28], [29], [30].

Several systematic reviews have evaluated the viability of utilizing wearable and non-wearable sensors individually as unimodal detectors for gait features associated with various neurological disorders [15], [16]. Furthermore, while studies like [31] and [32] conducted in-depth examinations of deep gait recognition techniques and related privacy and security issues, they predominantly concentrated on the analysis of gait patterns using vision sensors. This analysis, however, omitted the exploration of the potential benefits stemming from multimodal data integration, including the fusion of cerebral activity and kinematic data. Moreover, the clinical implications of their findings remained less apparent, lacking investigations into the gait characteristics of individuals afflicted by neurological conditions like Parkinson's disease, as well as the impact of exoskeleton-assisted rehabilitation on gait dynamics. In contrast, our review paper specifically addresses these unexplored aspects, shedding light on the synergistic potential of sensor fusion, AI models, and clinical relevance in the realm of gait analysis. To the best of our knowledge, there has been no comprehensive evaluation of the efficacy of multimodal sensor fusion and AI prediction models for gait analysis. In this context, the overarching research question guiding this systematic review is: How does the integration of multiple gait analysis modalities through fusion techniques, coupled with AI models, impact the quality of gait analysis and the effectiveness of AI models for diagnosing and prognosing neurological diseases, with a focus on wearable and non-wearable sensor data?

In particular, this review highlights:

1. the need to integrate several gait analysis methods in order to extract kinematic, kinetic, margin of stability, temporal, and spatial gait parameters, as well as brain activity, in order to assess the pace and intensity of movement.

2. the utilization of multimodality AI analysis of the patient's walking pattern to compensate for the one-sidedness of single modality gait recognition systems that only learn gait alterations in a single measurement parameter.

II. Review Methodology

Finding studies, vetting them for inclusion, and extracting data for this review were all completed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement recommendations (Fig.2) [33].

A. Search Strategy

A total of 660 articles were collected from Google Scholar, PubMed, Scopus, and IEEE Xplore databases. The term "gait analysis" was combined with at least two of the following search words/terms: Electroencephalography (OR EEG); Electromyography (OR EMG); Inertial Measurement Unit (OR IMU); Functional near-infrared spectroscopy (OR FNIRS);

Hear rate (OR HR); Electrodermal activity (OR EDA); and Ground reaction force (OR GRF). In addition to scanning databases, the reference lists of all chosen papers were examined to identify any relevant research that may have been missed during the first search.

B. Inclusion and Exclusion Criteria

Articles published between January 2000 and July 2023 were considered. In the first stage of screening, duplicated articles were excluded, leaving English journal papers. In subsequent steps, abstracts only were excluded and full texts were evaluated in order to include only publications that utilized multi-modal sensors for analyzing gait and to exclude articles with animal experimentation and those pertaining to upper limb prostheses. To prevent the inclusion of unreliable gray literature, we implemented stringent selection criteria. We prioritized publications from reputable journals that had undergone peer review and evaluated author credibility, methodological rigor, and consistency of findings. These measures were implemented to ensure that only credible, high-quality sources were included in our study (Fig.2). While a comprehensive quality assessment for all 66 articles was not feasible, this stringent selection process was instrumental in upholding study quality, contributing to the overall integrity of our review's findings.

C. Data Extraction

Data was gathered from articles that employed multimodal sensing to analyze gait (without the use of AI): (1) Author and year of publication; (2) Aim of study; (3) Acquired data type; (4) Number of sensors; (5) Sensors placement; (6) Sampling frequency; (7) Gait features; (8) Assessment methodology; and (9) Main findings. However, the reports that examined gait with multimodal sensing and AI had eight main variables extracted from them: 1) Author and year of publication; (2) Aim of study; (3) Number of subjects; (4) Number of features; (5) Input features; (6) Acquired data type; (7) Assessment methodology; and (8) Performance.

III. Gait Analysis Using Multimodal Sensing Fusion

Fusion of multimodal data is a potential advancement for human movement research, such as enhanced activity detection and more accurate gait assessment [34]. By quantifying the spatiotemporal, kinematic, kinetic, muscular, and physiological features of people, a fusion method provides a more complete understanding of gait impairment [16] and rehabilitation opportunities [35]. The current review identified one study that recorded cortical and kinematics data from EEG and IMU, respectively, while 19 studies examined gait by integrating EEG and EMG sensor data. Eight research papers used EMG data with HR data, seven studies combined EMG with IMU data, and two studies combined EMG with fNIRS data. Fig.3 presents a clustered bar chart showing the several combined gait analysis approaches. Several widely used fusion approaches are also described in this overview (Table I).

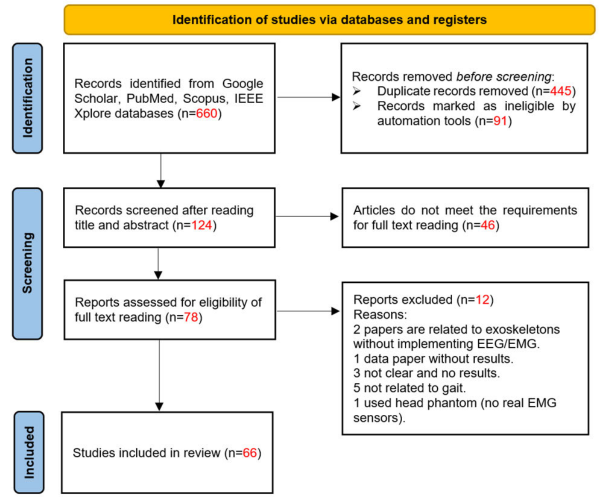

Fig. 2. Diagram illustrating the PRISMA article selection process.

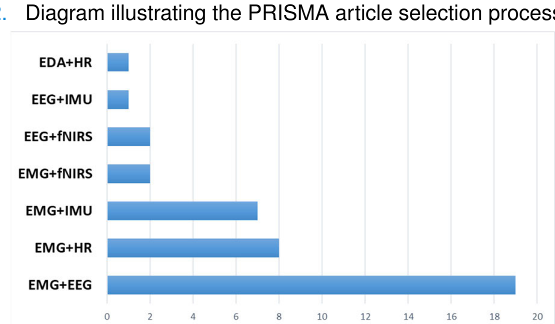

Fig. 3. Graph depicting the results of 40 studies utilizing multimodal sensing fusion for gait analysis.

A. EMG & EEG

Twenty research studies employed EEG and EMG together, six of these focused on Parkinson's disease (PD). Time-frequency analysis of electrophysiological data reported by Roeder et al. [23] indicated substantially reduced cortico-muscular coherence (CMC) and EMG power at low beta frequencies in older and PD individuals, whereas shorter swing time was noted for PD patients compared to healthy ones. Günther et al. [36] explored muscle and EEG activity during the freezing of gait associated with Parkinson's disease and how it varies from both walking and deliberate halting. At the outset of halt and freeze of gait events, they observed an increase in EEG-EMG coupling [37], [38]. Venuto et al. [39] evaluated a non-invasive wearable embedded cyber-physical system for PD monitoring and discovered that the system can extract changes in walking pattern between PD and healthy patients. Alterations in central common drive to ankle muscles in response to visually directed foot positioning was reported by Jensen et al. [40], who noted that the corticospinal tract is involved in the modification of gait when visually directed foot placement is necessary.

Furthermore, several researchers investigated hybrid EMG-EEG data collected during walking of healthy individuals in order to explore the contribution of the motor cortex to muscle activation. In study [41], coherence and directionality analyses were utilized to determine if the motor cortex contributes to plantar flexor muscle activity during the stance phase and push-off phase of gait. There was substantial EEG–EMG and EMG–EMG coherence in the beta

TABLE I
RECENT RESEARCH ON GAIT ANALYSIS WITH MULTIMODAL FUSION SENSORS

Ref	Year	Purpose / Pathology	Acquired data	# of sensors	Sensors placement	Fs	Gait features	Methodology	Results
[56]	2019	Removing EEG artifacts for gait analysis	EEG	64	Whole brain regions	1000Hz	- Forehead acceleration - ERSP	Using IMU data to update the parameters of the non-linear projection from the acceleration to each EEG channel separately	ERSP analysis for walking showed that the gait dependency of artifact contamination was eliminated on all target frequencies.
			IMU	3	Forehead, right foot, left foot	128Hz			
[51]	2023	Simplified markerless gait event detection	EMG	12	TA, GM, VL, RF, SM, BF	1000Hz	-Step duration -acceleration	Statistical analysis	sMaSDP extracted muscle activity in healthy walking and identified heel-strike events in PD patient data.
			IMU	1	Right foot	60Hz			
[52]	2023	Gait analysis for CSM patients	IMU	1	Lumbar 5	148Hz	-Walking -Speed -Cadence -Stride time -Step length -EMG peak	Statistical analysis	cadence, step length and walking speed were statistically significantly lower in CSM patients than healthy control. EMG amplitude for TA and RF was significantly lower for CSM patients.
			EMG	8	TA, LG, RF, BF	148Hz			
[53]	2019	Analyze variability between subjects and activities differs across IMUs, EMG, and goniometers modalities	IMU	5	Bilateral thigh and shank and waist	-	- Shank velocity and acceleration - RI, SI and DS between activities and subjects	mean, standard deviation, maximum, minimum, initial and final values. MAV, waveform length, number of zero crossings and slope sign changes and the coefficients of a sixth-order autoregressive model	SI & RI were lowest for the features of the multimodal and highest for the single modal.
			Goniometers	4	Bilateral knee and ankle	-			
			EMG	14	TA, GM, SOL, VL, RF, BF, ST	-			
[49]	2021	Test new prototype (MGTR) for gait rehabilitation	IMU	2	Front of the thigh and shank of the right leg.	150Hz	- Hip and knee joints angle - Angular velocity - Anterior-posterior acceleration - RoM - MVC	Kinematic analysis by comparing the hip and knee joints and the muscle activity between the normal gait and MGTR.	Knee joint angle showed a high correlation between the MGTR and normal gait. There was no correlation between TA and BF, a low correlation with GM, and a high correlation with RF.
			EMG	4	RF, BF, TA, GM.	1112Hz			
[84]	2022	Remodel the step's physical features for optimal performance	IMU	1	Between S1 and S2 vertebrae	1000Hz	Global symmetry index, symmetry index, quality index of the gait cycle, pelvic kinematics, and muscle activation	Analysis of specific parameters of the gait cycle before and after an aerobic fatigue test	Loss of equilibrium of the subjects examined under stress/fatigue conditions. Global index of symmetry decreased.
			EMG	8	TA & GM	1000Hz			
[85]	2021	Gait analysis for five different terrains	FSR	4	Below the heel and the toe position	100 Hz	- Shank angular rate - Foot pressure - Muscle's activities	Python-based graphical user interface to analyze and display the processed data.	Using a single IMU attached to the shank is more favourable to collect gait data in real-time. IMUs are advantageous over FSRs.
			EMG	4	TA & GM	-			
			IMU	2	Right leg's lateral side (shank)	-			
[50]	2019	Examine how self-reported walking difficulty and limb dynamics may influence neuromuscular strategies observed among patients with knee OA	EMG	16	MQ, LQ, LH, MH, MG, LG	1000Hz	- 3D angular velocity - Linear acceleration - Gait intervals and speed - MVC	Frontal and sagittal plane knee angles were calculated via Visual 3D using Euler angles and used to determine gait intervals. Co-contraction index.	Limb dynamics were largest among those with knee OA and walking difficulty and smallest among the control group.
			IMU	6	Bilateral tibial tuberosities, bilateral superior patellas, and the pelvis at S2	100Hz			
			FP	2	-	1000Hz			
[57]	2021	Effects of load carrying techniques on gait parameters	HR	8	Wrist	64 Hz	- Gait parameters: gait speed, cadence, double support time, step duration, stance duration, and swing duration. - Gait symmetry ratio: step, stance, and swing time symmetry. - Dynamic balance: CoP displacement and velocity.	Repeated measures analyses of variance (ANOVAs) with Bonferroni correction were used to compare the effects of different load carrying conditions (no load, hand load, shoulder load, and head load) on gait, dynamic balance, HR, and EDA.	Carrying load close to the body with both hands is recommended. Head load causes neck and spine injuries. Carrying loads in both hands, improved gait symmetry and dynamic balance and lowered risk of falls.
			EDA	13	Right foot, left foot	4 Hz			
[22]	2014	Concurrent monitoring of both blood flow changes in the brain and actual movements of the body	EMG	3+	GM, TA, RF, VL, BF, ECR, FCR.	1000 Hz	- Skeletal model and joint angles. - Hemoglobin concentration.	Using EMG, fNIRS and OMC during bilateral lower extremity cycling and gait tasks	Increased fNIRS activity on the left brain region during right hand squeezing.
			fNIRS	16	Whole Brain region	50 Hz			
			OMC	3+	Medial and lateral malleolus, medial and lateral knee joint, ASIS, PSIS.	100 Hz			
[54]	2020	Use fNIRS to delineate brain activation differences between 'Active' and 'Passive' overground gait in a robotic exoskeleton	IMU (Xsens)	2	Sacrum, mid-thigh, mid-shank, and lateral feet	100 Hz	- Joint angles. - Muscle activity. - Hemodynamic response.	Walking trials in a robotic exoskeleton for Passive and Active conditions, with fNIRS and EMG. Using inertial measurement units (Xsens) to examine knee kinematics	Increased oxyhemoglobin in the right frontal cortex for Passive compared with Active gait.
			EMG	2	RF, BF	1000Hz			
			fNIRS	16	Whole Brain region	4.35 Hz			
[23]	2020	Parkinson's disease	EEG	10	P3, P4, C3, Cz, C4, F7, F3, Fz, F4, F8	2 kHz	- Walking speed. - Stride time. - Step time. - EEG power. - ITC EEG/EMG. - CMC.	Independent component analysis (ICA). Hilbert transform. Statistical analysis.	CMC and EMG power at low beta frequencies (13–21 Hz) was significantly decreased in older and PD participants. Shorter swing time for PDC/older comparing to healthy/young.
			EMG	2	TA	2 kHz			
[24]	2022	Relationship between NKC and NMC	EEG	128	Whole brain	1 kHz	- Velocity envelopes. - EMG envelopes. - Gait events.	Comodulations between EEG power envelopes with myogenic/velocity envelopes. eLORETA algorithm.	1- Myogenic body signals are more discriminative than kinematic data in analyzing gait-related brain-body connectivity. 2- The gait-related brain-body connectivity dependent on the body sensor used to extract kinematic more than the frequency of the neural oscillations measured by EEG.
			EMG	8	VM, BF, TA, GM	2 kHz			
			3-axis acceleration signals	2	Left and right ankles	148 Hz			

TABLE I

(Continued.) RECENT RESEARCH ON GAIT ANALYSIS WITH MULTIMODAL FUSION SENSORS

[86]	2020	Parkinson disease	EEG	32	Entire scalp	512 Hz	- Step length. - EMG envelopes. - Power spectra and ERSP.	Detect EEG changes around SMA using ERSP. Gain model. Statistical analysis.	1- Enhanced alpha/theta synchronization around the auditory cue. 2-Instructed arm swing improves Parkinson's gait initiation.
			EMG	8	TA, soleus, RF, BF	512 Hz			
			Tri-axial accelerometers	3	Both ankles and over the L3 lumbar spine segment	512 Hz			
[87]	2020	Unilateral Cerebral Palsy	EEG	64	Whole brain	1000 Hz	- Muscle synergies. - Power spectra.	ERSP, NNMF, ICA	1-Children with CP have higher cortical activation during walking. 2-The gamma-activity in children with CP is higher in the frontal and parietal areas.
			EMG	16	TA, GM, SOL, PL, RF, VL, MH and HL	1000 Hz			
			Motion capture	10	Pelvis and lower extremities	100 Hz			
[88]	2005	The effect of direction on MRP	EMG	4	SOL, TA	2000 Hz	- COP displacement. - Resultant force. - Cycles duration.	Statistical analysis	Backward-oriented tasks are more positively associated to increases in MRPs. Gait tasks were mainly differentiated in early MRPs, while stepping tasks were more differentiated in late MRPs.
			EEG	24	Whole brain	500 Hz			
			GRF	2	Underneath the heels	500 Hz			
[36]	2019	FOG in Parkinson's disease	EEG	32	motor cortex	2048 Hz	- EMG amplitudes and frequencies. - Phase synchronization indices. - EEG relative power.	Statistical analysis. Cross correlation.	Increase in EEG-EMG coupling at the beginning of stop and FOG episodes.
			EMG	4	TA, gastrocnemius muscles	2048 Hz			
[41]	2019	Motor cortex contribution to plantar flexor muscle activity during gait	EMG	4	MG, SOL	1000 Hz	- Average autospectra. - Cross-spectra.	Spectral correlation analysis. Discrete Fourier transform.	Significant EEG–EMG and EMG–EMG coherence in the beta and gamma frequency bands.
			EEG	64	Whole brain	1000 Hz			
[40]	2018	Corticomuscular coherence related to visually guided foot placement.	EEG	64	Whole brain	2000Hz	- Average autospectra. - Cross-spectra. - Step cycles.	Time-frequency analysis of coherence Pooled coherence estimates.	Corticospinal tract is involved in modifying gait when visually guided placement of the foot is required.
			EMG	8	TA, SOL, GM	2000Hz			
			Motion capture	14	-	-			
[42]	2015	Brain role in controlling gait stability	EEG	64	Bilateral premotor cortices	2048Hz	- CoP - heel strikes - toe-offs	-Independent component (IC) analysis - Beamforming analysis	Trunk movements and step width decrease. Stability increase. Increased beta activity during stabilized walking.
			EMG	4	Trapezius	2048Hz			
[37]	2012	Efficacy of rTMS in Parkinson disease	EEG	13	Motor cortices	-	- Walking time. - MEP	Statistical analysis	50-Hz rTMS did not improve gait. No pathological increase of cortical excitability or epileptic activity.
			EMG	6	ECR, BB, DEL	-			
[17]	2012	Synchrony between EEG and EMG	EEG	28	Sensorimotor cortex	2000Hz	- Time of heel strike. - Power spectra.	- ICA. - Coherence. - Statistical analysis.	Motor cortex and corticospinal tract contribute directly to the muscle activity observed in steady-state treadmill walking.
			EMG	2	TA	2000Hz			
[38]	2011	Efficacy of iTBS in Parkinson disease	EEG	13	Motor cortices	-	- Walking time. - MEP	Statistical and power analysis	Beneficial effects of iTBS on mood, but no improvement of gait. EEG/EMG monitoring recorded no pathologic increase of cortical excitability or epileptic activity.
			EMG	6	ECR, BB, DEL	-			
[89]	2008	Rhythmic foot movements	EEG	64	Whole brain	1000Hz	- Power spectra. - Corticomuscular delay.	Coherence. Statistical analysis. Isocoherence maps.	Corticomuscular coherence at the stepping frequencies in the central midline region.
			EMG	-	TA	1000Hz			
[90]	2021	Quantify neuromuscular plasticity induced by an exoskeleton	EEG	64	Whole brain	250Hz	- MRCP. - Foot-strike/off. - EMG amplitude & CoA.	- Time-frequency analysis. - Graph analysis - Statistical analysis.	**Expected results:** -Less regular timing of foot-strike and foot-off events between pre- and post-training session. -Antagonist's muscles show a larger co-contraction with consequent stiffening of lower limb joints during the free walking post-training.
			EMG	4	VL, BF, TA LG	2000Hz			
			IMU	3	Fifth lumbar vertebra, lateral aspect of both shanks	250Hz			
[91]	2017	Cortical contribution to locomotion	EEG	64	Whole brain	2048Hz	- ERSP. - IC dipolarity. - Mean power.	ICA & PCA. Source localization. EMG decoding. Effective connectivity	Unidirectional brain-to-muscle connectivity for proximal and distal muscles, rhythmically related to stride phases.
			EMG	6	TA, BF, VM	1000Hz			
[43]	2018	Corticospinal involvement in the human gait	EMG	4	TA	2 kHz	- EEG power. - CMC. - ITC. - Gait time points.	- Time lag and phase offset. -Spectral analysis. -ICA analysis.	- Increases in power and ITC. - Evoked responses at spinal and cortical populations. -A positive time lag between EEG and EMG.
			EEG	10	Sensorimotor cortex	2 kHz			
[92]	2000	Involuntary movements associated with streptococcal infection	EEG	-	-	-	- Cortical evoked potentials. - EMG discharging time/frequency.	SEP LLR	Unilateral rhythmic involuntary movements occur secondary to streptococcal infection. EEGs show continuous delta activity predominant in the left frontocentral region.
			EMG	2	Brachioradialis, gastrocnemius.	-			
[93]	2016	Alexander technique & knee osteoarthritis	EEG	64		500Hz	- MVIC. - Net joint torque. - Moments. - WOMAC pain score	ERP. Statistical analysis.	Decrease in medial co-contraction at the end of the intervention. WOMAC pain score reduced from 9.6 to 4.2.
			EMG	4	VL, VM, BF, semimembranosus	3000Hz			
			GRF walkway	2	-	1500Hz			
[39]	2018	Testing non-invasive wearable embedded CPS for PD monitoring.	EEG	8	Motor cortex	500Hz	- Bereitschafts potential (BP). - μ-rhythm. - β-rhythm. - Haste rate (HR).	MRP. Statistical analysis.	The system can extract walking pattern differences between PD and healthy subjects. MRPs increase during the voluntariness recovery.
			EMG	8	RF, BF GM, TA	500Hz			

TABLE I

(Continued.) RECENT RESEARCH ON GAIT ANALYSIS WITH MULTIMODAL FUSION SENSORS

[94]	2014	Different forms of bodyweight supported locomotion with incomplete spinal cord injury (SCI)	HR	1	wrist	-	- Oxygen uptake. - Beats per minute.	Statistical analysis.	Lokomat is better for isolated hip extension strength. ZeroG and Manual Treadmill sessions eliciting greater oxygen consumption comparing to the Lokomat. High HR values for SCI comparing to CON.
			EMG	8	TA, BF, RF, GM	1000Hz			
[48]	2012	The effect of load position on gait	HR	2	Chest, wrist	50 Hz	- Joints angle. - Joints range of motion. - Stride length.	RPE. Statistical analysis. Muscle burst intensity	No significant effects of load position for HR or joints angle. Less EMG intensity for GM with high position load. Vertical GRF impact peak was greater in the high load position.
			EMG	5	TA, GM, VL, SM, BF	1000Hz			
			GRF	8	-	1000Hz			
			Motion capture	9	Left lateral aspect	100 Hz			
[95]	2011	Gait analysis for walk-run transition	HR	1	Wrist	1000Hz	- Muscle activity. - RERmax. - Beats per minute.	Linear regression. Statistical analysis.	Speed corresponding to WRT is more related to mechanical than to metabolic factors.
			EMG	4	GM, VL, RF, TA	1000Hz			
[47]	2018	Nordic walking analysis.	HR	1	Wrist	1 Hz	- Energy expenditure. - RERmax. - MVC. - Pole force.	Statistical analysis.	EMG in the lower limbs significantly decreased with Nordic walking.
			EMG	6	BB, VL, BF, TA, GM	1000Hz			
[46]	2007	Age-related differences during walking in water.	EMG	5	VM, RF, BF, TA, LG	1000Hz	- %MVC. - Stride frequency. - Walking speeds.	Statistical analysis.	Older subjects had increased hip musculature activity and decreased ankle plantar flexor activity while walking in water. No significant difference in the HR response between older and young subjects.
			HR	-	-	-			
[96]	2007	Analysing backward and forward walking on an underwater treadmill	EMG	-	VM, BF, TA, LG, RA, gluteus medius, paraspinal muscles.	1000Hz	- %MVC. - HR responses.	Statistical analysis.	Muscle activities and HR were significantly greater when walking backward than when walking forward
			HR	-	-	-			
[44]	2010	The effects of age, gender and walking speed on the gait.	EMG	8	BF, RF, TA, GM.	1000Hz	- Joint angles. - MVC.	Pearson correlations. Duncan's multiple range test.	Females exhibited higher GRF in the heel-strike and toe-off stages, as well as higher TA muscle activity. Older subjects had significantly higher RF muscle activity than younger adults.
			HR	1	Wrist	-			
			GRF	2	-	400Hz			
			Motion capture	37	Lower body segments	120Hz			
[45]	2005	Analyze running in hypergravity conditions	EMG	4	TA, GM, VM, BF	1kHz	- Oxygen consumption. - ROM. - Dynamic knee angle.	Statistical analysis.	LBNP increased the HR, GRF. No changes were seen on the EMG and RoM.
			HR	1	-	-			
			GRF	2	-	1kHz			
[55]	2021	Effects of dopaminergic medication on people with PD	EEG	32	Motor cortex	500 Hz	- EEG absolute power. - HbO2 concentration. - Step length. - Step duration. - Velocity.	Statistical analysis. Spectral analysis. Partial correlation.	PD compromises PFC activation during obstacle avoidance. Dopaminergic medication increased step length, step velocity, and β and γ power in the CPz channel.
			fNIRS	8	Prefrontal cortex	10 Hz			
			FP	-	-	200 Hz			
[25]	2020	Influence of PD motor subtypes on cortical activity	EEG	32	Motor cortex	500Hz	- EEG absolute power. - HbO2 concentration. - Step length. - Step duration. - Velocity.	Statistical analysis. Spectral analysis.	Postural instability gait disorder patients presented higher PFC activity than tremor dominant patients. Both patients reduced alpha and beta power in FCz and CPz channels.
			fNIRS	8	Prefrontal cortex	10 Hz			
			FP	-	-	200 Hz			

MAV	Mean absolute value	**RAGT**	Robot-aided gait training	**ITC**	Intertrial coherence	**FPGA**	Field-programmable gate array
RI	Repeatability index	**SI**	Separability index	**DS**	Desirability score	**PIGD**	Postural instability gait disorder
ROM	Range of motion	**RF**	Rectus femoris	**RA**	Rectus abdominis	**BF**	Biceps femoris
TA	Tibialis anterior	**GM**	Gastrocnemius medial	**SMA**	Supplementary motor area	**MGTR**	Machine of gait training and rehabilitation
MVC	Maximum voluntary contraction	**MQ**	Medial quadriceps	**CPS**	Cyber-physical system	**ERSP**	Event related spectral perturbation
LQ	Lateral quadriceps	**LH**	Lateral hamstring	**CON**	Able-bodied controls	**MH**	Medial hamstrings
LG	Lateral gastrocnemius	**ECR**	Extensor carpi radialis	**CMC**	Corticomuscular coherence	**MARG**	Magnetic, angular rate, and gravity
VL	Vastus lateralis	**VM**	Vastus medialis	**TD**	Tremor dominant	**ELORETA**	Exact low-resolution brain electromagnetic tomography
ASIS	Anterior superior iliac	**PSIS**	Posterior superior iliac spine	**VGRF**	Vertical ground reaction force	**ITC EEG**	Inter-trial coherence of EEG
CMC	Corticomuscular coherence	**NKC**	Neurokinematic connectivity	**LLR**	Long latency EMG responses	**NMC**	Neuromuscular connectivity
OMC	Optical motion capture	**OA**	Knee osteoarthritis	**ERPS**	Event-related potentials	**MVIC**	Maximal voluntary isometric contractions
HL	Hallucis longus	**PL**	Peroneus longus	**sMaSDP**	Simplified Markerless Stride Detection Pipeline	**NNMF**	On-negative matrix factorization
PSD	Power spectral density	**MRPS**	Movement-related potentials	**COA**	Center of activity	**CSM**	Cervical Spondylotic Myelopathy
COP	Centre of pressure	**MCS**	Motion Capture system	**FSR**	Force-sensitive resistor	**FOG**	Freezing of gait
iTBS	Intermittent theta-burst stimulation	**FCR**	Flexor carpi radialis	**MVC**	Maximal voluntary contraction	**rTMS**	Repetitive transcranial magnetic stimulation
BB	Biceps brachii	**DEL**	Deltoid	**ST**	Semitendinosus	**MEPS**	Motor evoked potentials
ICA	Independent component analysis	**SM**	Semitendinosus	**SEP**	Somatosensory evoked potentials	**MRCP**	Movement related cortical potential
MSL	Multi-scale learning	**SOL**	Soleus	**MRP**	Movement-related potential	**PPWS**	Percentage of preferred walking speed
RPE	Ratings of perceived exertion	**WRTS**	Walk-run transition speed	**LBNP**	Lower body negative pressure	**RERMAX**	Maximal respiratory exchange ratio

and gamma frequency ranges. Similarly, the beta band activity was shown to originate mostly in the bilateral pre-motor cortices when a beamforming analysis was performed [42]. Examining changes in cortical power and CMC during the gait cycle, Roeder et al. [43] reported evoked responses at spinal and cortical populations as well as positive time lag between EEG and EMG during human walking.

B. EMG & HR

The association of HR and EMG with gait has been reported by eight studies. The objective of these was to examine muscle activation, heart rate, and oxygen consumption in a variety of gait scenarios including walking at different walking speeds and the impact of age, and gender. The magnitude of the vertical ground response force during the toe-off phase varied significantly as a function of gender and gait speed [44]. However, only HR was affected in the study by Groppo et al. [45] when applying negative pressure to the lower body and recreating a hypergravity condition. Similarly, Masumoto et al. [46] investigated the effect of walking in water on muscle activity, stride frequency, and HR and EMG responses with respect to age. While walking in water, older participants had greater hip musculature activity and reduced ankle plantar flexor activation. Nordic walking was also employed to investigate the relationship between pole force and physiological reactions [47]. Furthermore, Simpson et al. [48] developed backpack load position recommendations for hikers following the observation higher load positions resulted in weaker EMG activity in the gastrocnemius medialis muscles.

C. EMG & IMU

Integrating wearable EMG and IMU sensors provides granular gait metrics including kinematics and muscle activation. Seo and Kim [49] tested a novel phenotype for gait rehabilitation (machine of gait training and rehabilitation - MGTR). The MGTR was found to have a strong association with knee angle during normal gait. In addition, IMU and EMG data demonstrated ability to discriminate between limb kinematics and muscle co-contraction strategies to appropriately diagnose gait deficiencies by segmenting EMG signals via IMU data [50], [51], [52]. In addition to these features, Krausz et al. [53] recommended the incorporation of an eye movement tracker that might improve the performance of the EMG and HR models.

D. fNIRS & EMG, fNIRS & EEG

Quantitative information of gait has the potential to significantly advance our understanding of cortical control of movement in both normal and abnormal gait patterns. In four publications, the assessment of the hemodynamic response using fNIRS was paired with EMG and EEG separately to detect cortical hemodynamic body movements. Peters et al. [54] utilized fNIRS and EMG to distinguish between active and passive overground locomotion when using a robotic exoskeleton. Here passive walking was associated with higher levels of oxyhemoglobin in the right frontal cortex than active gait. Two studies combined fNIRS and EEG and focused on gait analysis for PD patients [25], [55]. Orcioli-Silva et al. [55], looked into how dopaminergic drugs affected cortical activity in PD patients as they walked freely and avoided obstacles. They found a promising effect on the β and γ power in the EEG CPz channel with dopaminergic medication and an increase in step length and step velocity. The same group investigated how tremor dominant (TD) and postural instability gait disorder (PIGD) motor subtypes of PD affected cortical activity during free walking and obstacle avoidance indicated that individuals with postural instability gait condition have more pre-frontal brain activity than tremor dominating patients [25].

E. EEG & IMU, EDA & HR

To reduce movement noise in EEG recordings during gait, Kilicarslan and Vidal [56] collected EEG and IMU data. IMU sensors were used to analyze the total head movement and segment the gait, while an adaptive de-noising framework was built to describe and manage the motion artifact contamination in EEG readings. Using EDA and HR data, Anwer et al. [57] investigated the impact of load bearing strategies on gait metrics, which indicated that carrying burdens with both hands increased gait symmetry, dynamic balance, and decreased the chance of falling.

IV. Gait Analysis Using Multimodal Sensing Fusion and AI

Statistical characteristics and frequency domain features are typically generated for use with AI models. Recent gait analysis research employing AI and multimodal fusion sensors are outlined in Table II. Twenty-six publications have utilized AI models to analyze multimodal fusion sensing data for gait analysis. The majority of these focused on combining EMG data either with IMU (12 studies) or EEG (7 studies).

A. Feature Extraction

Several studies retrieved statistical characteristics from processed raw time-series data using a sliding window approach, which was particularly prominent for EMG data, such as mean, median, entropy, standard deviation, root mean square variance, etc., [58] and [59]. The frequency-domain characteristics represent yet another set of feature extraction. Hasan et al. [60] employed wavelet synchro squeezed transform (WSST) to recover EEG alpha and beta event-related desynchronization from the data epochs. Mezzina and De Venuto [61] analyzed the brain signal patterns using fast Fourier transformation (FFT). The EMG power spectrum along with waveform length, median and mean frequency, and modified mean frequency were the most frequently employed techniques for transforming original EMG temporal sequences into the frequency domain [58], [59].

With its ability to standardize the process of automated extraction of features, deep learning algorithms such as long short term memory (LSTM) and convolutional neural network (CNN) have become more prominent in the field of gait analysis. While EMG data are closely correlated with muscle force, they are collected with a substantial phase delay due to filtering, which makes accurate prediction difficult. To overcome this issue, artificial neural network algorithms

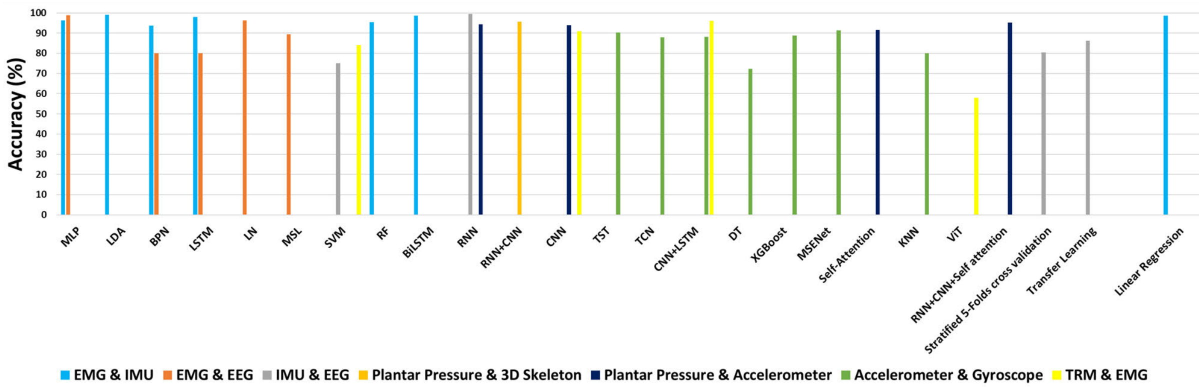

Fig. 4. Performance of several AI models in gait analysis using sensing fusion data. Figure shorthand is listed in Table II's footnotes.

were suggested to automatically extract signal characteristics in order to circumvent a possible bottleneck. LSTM was differentiated from other artificial neural networks by its capacity to ignore irrelevant information [62]. To efficiently extract the inhibition and excitation mechanisms among EMG data and to emphasize the association between combined efforts of muscle activations and movements, LSTM with its power of forgetting unnecessary information, jointly analyses the signals of all the channels [63], [64]. Similarly, Duan et al. [65] used CNN-based deep learning to efficiently extract walking-related characteristics from multimodal inputs after converting them into a 2D matrix. CNN is an end-to-end algorithm that offers superior learning capabilities since it bypasses the need for feature extraction. Local features on both temporal and spectral scales can be extracted via convolutional layers, which is useful for signal classification and motion detection. Moreover, to efficiently extract characteristics from disparate data sources, Jun et al. [66] supplied sequential skeleton and average foot pressure data into recurrent neural network (RNN)-based encoding layers and CNN-based encoding layers, respectively. Likewise, Zhao et al. [35] proposed a novel hybrid model for learning the locomotion disparities between PD patients. A spatial feature extractor (SFE) was built to understand the spatial information of multiframe time-series data and to output spatial features following dimensionality reduction. In the meantime, a novel correlative memory neural network (CorrMNN) architecture was created to measure the correlation in bimodal gait data and extract the dynamic gait variations to generate temporal features [35]. Similar neural network was developed to capture the changes in multimodal PD handwriting data using a novel Spatio-temporal Siamese neural network [67]. Meanwhile, the Multiview gait identification problem was addressed by proposing a spiderweb graph neural network (SpiderNet) to deal with visual gait data appropriately. By constructing a multi-view active graph convolutional neural network, it outperformed other methods in representing the Spatio-temporal and structural knowledge underlying the gait data [68]. As well, the associated Spatio-temporal capsule network (ASTCapsNet) utilized by Zhao et al. [69] demonstrated significant results when combining multiple independent datasets that rely on unimodal data, such as vision data, force-sensitive data, and ground reaction force data. The common spatial pattern (CSP) neural network was also used to extract characteristics from EEG brain signals. CSP technique relies on the computation of a collection of spatial filters that increases the variance of one class of EEG signals and decreases the variance of another class [70].

B. EMG & IMU

Assistive devices, such as exoskeletons, play a significant role in rehabilitation, leading Su et al. [71] to suggest a framework for machine learning that uses two multilayer perceptrons (MLP) to forecast locomotor modes and recognize gait events. Likewise, a deep RNN was employed as an intention prediction model for powered prosthesis based on knee joint motion prediction [72]. Wang et al. [73] also made accurate predictions for the continuous joint angle using a hierarchical planner, however, according to research conducted by [74], bidirectional long short term memory (BiLSTM) generates the most accurate predictions of lower limb joint angles throughout the entire locomotion cycle. Donahue's study confirmed these findings by showing that kinetic waveforms can be estimated using machine learning from real-world running data without the need for feature engineering using the BiLSTM architecture [75]. Exoskeleton control and user activity monitoring might be improved with more precise estimates of joint moment [76]. In addition, the end-to-end training made it possible for LSTM predictor to be used for continuous kinematics prediction through the regression process, when transmission delay is introduced by exoskeletons [63]. Also, multiple linear regression yielded an F1 score of 0.9 for approximating IMU angular velocity profiles and subsequently locomotion events using EMG data [77].

C. EMG & EEG

In the categorization of walking patterns [65], the combination of EEG and EMG data offers better performance compared to employing a single modality of EEG or EMG. Tortora et al. [64] designed and tested a hybrid human-machine interface (hHMI) for deciphering leg walking phases using a Bayesian fusion of EEG and EMG inputs. hHMI performed considerably better than its single-signal inputs. In addition, during the time-frequency domain analysis of the brain signal changes, logic networks primarily handled differentiating an unexpected loss of balance event from typical movements [61], [78]. MLP was employed to assess brain and muscle health in the earliest stages of PD. This aided prescribing the correct medication to limit the progression of the disease, as well as identifying the various phases of PD and distinguishing PD from non-PD

TABLE II
RECENT STUDIES THAT EMPLOYED AI AND MULTIMODAL FUSION SENSORS FOR GAIT ANALYSIS

Ref	Year	Pathology/ Purpose	# of Subjects	# of features	Input features	Acquired data	Algorithm/model	Performance	Limitations
[60]	2021	Prediction of gait acceleration intention	1	20 features for each 1-second epoch.	Alpha and beta band ERDs.	EEG IMU GRF	SVM with radial basis kernel	Offline scenario: accuracy85.9±2.9%. Real-time scenario: 9 out of 12 acceleration events were predicted successfully with average latency of -741ms.	Low subjects number. Requires advanced computational methods.
[81]	2020	Multimodal biometric authentication system	7	-	EEG power Kinematics	EEG IMU	RNN	Accuracy=99.57%	Small sample size.
[80]	2023	FoG prediction for PD patients	8	Data windows 32 samples.	EEG and IMU statistical features	EEG IMU	Stratified 5-Folds cross validation.	Accuracy=80.4%	The performance of the model was only validated for offline applications and on a single dataset.
							Transfer learning	Accuracy=86.2%	
[77]	2023	Gait event prediction for PD patients	6	Ninety-three minutes of gait activity and 5253 full gait cycles. 210 EMG features.	Swing peak velocity, heel contact, and toe-off events	IMU EMG	Multiple linear regression	Median F1-score of ~0.9	IMU data are not considered the "gold standard" for defining ground-truth gait parameters. Small sample size. The proposed approach was not tested on healthy control data.
[74]	2023	Predicting future joint angles during various phases of gait	30	14 EMG features. 144 IMU features.	Statistical features from EMG and IMU	IMU EMG	LSTM BiLSTM Random forest	BiLSTM is the most robust performer across the gait cycle, with a mean prediction RMSE of 1.42-5.71 degrees.	-
[99]	2023	Estimating lower extremity muscle activity from IMU data	22	5440 gait cycles	Acceleration, Angular velocity EMG envelope	IMU EMG	FNN LSTM	LSTM outperformed the conventional FNN in predicting muscle activity. RMSE (FNN) < 15% RMSE (LSTM) < 10%	NN couldn't accurately estimate muscle behavior because of secondary or minor peak contractions.
[75]	2023	Estimate gait events and GRF waveforms from IMU	16	10 footfalls for a combination of velocity and grade	Angular velocities. Resultant accelerations.	IMU GRF	BiLSTM	Average RMSE of 0.030 for contact time with foot-mounted IMUs	Unconstrained running environment of this study. Using 13 LOOCV
[100]	2023	Select the optimal sensor site for GED and GRF prediction using IMU data.	27 Healthy 18 MKOA	-	5 synchronized IMU acceleration in 3 directions	IMU GRF	Reservoir computing RNN	For GRF prediction, the best sensor location was top of the shoe for 72.2% and 41.7% of individuals in the healthy and MKOA populations, respectively.	The findings are limited to the shank and the foot segments only. Results are only based on the data collected in a lab setting condition.
[71]	2021	Locomotion mode transition prediction based on gait-event identification	8	MLP1: 42-element vector MLP2: 62-element vector	- Linear acceleration. - Angular velocity. - EMG & IMU signals.	IMU EMG	Two MLPs: - MLP1 detected the gait event using IMU data. - MLP2 predict the locomotion mode transitions.	MLP1: accuracy of 100% and 98% for FC and TO events respectively. MLP2: accuracy of 96.3%, 90.1%, and 90.6% for walking, ramp ascent, and ramp descent transitions.	Did not consider a feature selection procedure. Dealing with only healthy subjects.
[72]	2019	Knee joint motion prediction	11	7 channels signals	- Roll angles. - Angular velocities. - Sampled EMG signals.	IMU EMG	RNNs	Prediction error = ±2.93 degrees. Better than SVR and traditional ANN.	The reference data for knee joint angle was determined by two IMUs mounted on lower limb. It was calculated as the difference of roll angle between segments (shank and thigh), which is not the gold standards of biomechanics
[76]	2022	Predict biological joint moment	12	675 features for each data window	Autoregression coefficients. Slope Sign Changes.	IMU EMG GRF GON MCS	NN and XGBoost	Lower error in anticipating hip moment comparing to knee and ankle. MAE is 0.06 Nm/kg for XGBoost, and 0.07 Nm/kg for NN.	The models were trained on a subject-by-subject basis per ambulation mode.
[73]	2022	Motion intention prediction and joint trajectories generation	8	264-dimensional feature vector	EMG: 6 temporal features and 4 spectral features. IMU: 4 temporal features.	IMU EMG	LDA and Quadratic SVM	Accuracies of 99.13% and 99.39% for standing and swing phases. RMSE of the walking frequency estimate was 2.3%.	-
[58]	2021	Using a classifier to identify the movements of lower limbs to verify the correctness of the muscles selected by SPSS statistical mathematics method and human anatomy principles.	10	6000 eigenvalues for each action/gait	- EMG temporal features: iEMG, RMS, VAR. - EMG frequency features: MF, MPF.	IMU EMG	Backpropagation neural network	- Average recognition rate is 86.49% for seven gradients, 93.76% for five kinds of gait and 86.07% for four kinds of movements. - EMG signals of muscles selected by correlation analysis can identify different gaits and road slopes.	-
[63]	2021	Continuously prediction of lower-limb kinematics	10	Each window: 37-element feature vector	EMG temporal features. Knee angles.	IMU EMG MCS	LSTM + SVR	Average RMSE = 3.98° Prediction time is in the interval of 27ms and 108ms.	Multiple motion patterns should be added.

TABLE II
(Continued.) RECENT STUDIES THAT EMPLOYED AI AND MULTIMODAL FUSION SENSORS FOR GAIT ANALYSIS

[62]	2020	Ahead-of-motion prediction of lower-limb kinematics and kinetics.	10	10-element feature vectors	EMG features. Joint angles	IMU EMG MCS	LSTM + SVM	LSTM predictor processes a better performance than the SVM predictor. R-value of 0.9 for LSTM extractor with predictor.	Multiple motion patterns should be added.
[79]	2023	Detecting and alerting freezing of gait symptom	12 PD patients	Public dataset with multi-modal sensory data	EEG to detect FoG Patch sensor to measure muscle activity and movement data	4 EEG channels EMG with accelerometers	Deep learning (DL) model trained on FoG dataset. CNN in parallel using time-domain signals as input.	The DL model achieves a high detection sensitivity of 0.81 and a specificity of 0.88.	Size of DL model limited by memory and computational resources of selected microcontroller module.
[61]	2019	Early detection of balance losses	6	-	Time-frequency linearization of reactive cortical responses	EEG EMG MCS	Logic network classifier	Accuracy= 96% Discrimination time= 370.6 ms	-
[65]	2022	Gait pattern classification	30	Wavelet transformed maps of size channels×frequency	Multi-scale tensors decomposed from EEG and EMG signals using Wavelet transform.	EEG EMG	MSL	Accuracy= 89.33% Classification accuracy of the 62-channel EEG setting is always better than the 20-channel EEG setting, regardless of whether the EMG signal is used or not.	- only male subjects took part in the Experiment. - relationship between brain regions and classification accuracy was not explored
[70]	2019	Control wearable walking exoskeleton by EEG classification	3	2 dimensional CSP feature vector	CSP projection matrix	EEG EMG	4-layer back propagation neural network	The ERA about two different imagery tasks is over 80%.	-
[64]	2020	Hybrid human-machine interface for gait decoding through Bayesian fusion of EEG and EMG classifiers	6	Single EEG/EMG features per channel.	Segmented and block averaged EEG/EMG time series.	EEG EMG	-LSTM networks -Bayesian Belief Fusion	hHMI significantly outperforms its single-signal counterparts. Fusion of EEG and EMG keeps a stable recognition rate of each gait phase of more than 80%.	-The approach weights the classifier decision based on the performance estimated on the validation set without considering the classifier's confidence in that decision. -The data were for healthy subjects only
[78]	2020	Multisensing architecture for the balance losses detection	6	-	Energy of EEG PSD. Neuromuscular parameters.	EEG EMG	Logical network	Detection time= 370.62 ± 60.85 ms. Accuracy= 96.21%.	-
[59]	2019	Quantification of Parkinson's disease using EEG-EMG correlation	60	3 from EEG. 9 from EMG.	EEG: Lyapunov and inverse Lyapunov exponent. Shannon entropy. EMG: Power. Variance. RMS.	EEG EMG	ANN	Accuracy= 98.8%. The rise in Shannon entropy in PD indicates that their brain complexity contributes to their poor coordination and disordered gait.	-
[82]	2021	Human gait speed classification	50	Spatial / Temporal 156 / 585 24 / 585 12 / 8985 8 / 8985	 3D TRM 3D GRF Forces and moments EMG	TRM GRF EMG	Fusion Modality Hybrid CNN+LSTM Multi-stream CNN Single Modality Single stream CNN ViT Single stream SVM	F1 score = 96% F1 score = 97% F1 score = 91% ±0.6% F1 score = 58% ±0.3% F1 score = 84% ±1.1%	Limited to gait speed prediction
[97]	2023	Activity-based person identification	81	nine vectors of 128 values. 450 features from each sample.	Statistical Temporal Spectral	Accelerometer Gyroscope	MSENet, TST, TCN, CNN-LSTM, ConvLSTM, XGBoost, DT, KNN	Accuracy MSENet=91.31% TST=90.22% TCN=87.89% CNN-LSTM=88.15% ConvLSTM=82.71% XGBoost=88..73% DT=72.20% KNN=80.00%	Data collected from a single session (less model robustness).
[83]	2022	User identification from gait pattern	40	dataset consists of 6303 unit steps and about 158 unit steps per subject.	Pressure Acceleration Rotation	Pressure sensor Accelerometer Gyroscope	CNN RNN Self-Attention Ensemble	Accuracy= 94.00% Accuracy= 94.63% Accuracy= 91.64% Accuracy= 95.32%	-
[66]	2021	Abnormal gait classification	12	1,440 skeleton and foot pressure instances	1 channel image of average foot pressure 14 joints and time steps	Plantar Pressure 3D skeleton	RNN CNN	Multimodal hybrid accuracy=95.66%	Few subjects, and the datasets were collected by simulation

ERD	Event related desynchronization	**hHMI**	Hybrid human-machine interface	**SVM**	Support vector machine	**FC**	Foot contact	**FPGA**	Field-programmable gate array
TO	Toe off	**PSD**	Power spectrum density	**MLP**	Multilayer perceptron	**IMU**	Inertial measurement unit	**ERA**	EEG recognition accuracy
EMG	Electromyography	**LSTM**	Long Short-Term Memory	**GRF**	Ground reaction force	**RNN**	Recurrent neural network	**CSP**	Common spatial pattern
SVR	Support vector regression	**BOI**	Bands of interests	**ANN**	Artificial neural networks	**RMS**	Root mean square	**MPF**	Mean power frequency
MAE	Mean absolute error	**PIFD**	Pre-impact fall detection	**GON**	Electrogoniometer	**MCS**	Motion Capture system	**MF**	Median frequency
NN	Neural network	**MSL**	Multi-scale learning	**RMSE**	Root mean square error	**LDA**	Linear discriminant analysis	**SRF**	Spatial Feature Extractor
CorrMNN	Correlative Memory Neural Network	**LOOCV**	Leave One Out Cross Validation	**FNN**	Feedforward Neural Network	**ViT**	Vision Transformer	**DT**	Decision Tree
BiLSTM	Bidirectional Long Short Term Memory	**MSENet**	multivariate squeeze-and-excitation network	**TST**	Timeseries Transformer	**TCN**	Temporal convolutional network	**KNN**	k-nearest neighbor
TRM	Trajectories of Reflective Markers	**GED**	Gait Event Detection	**ESN**	Echo State Network	**MKAO**	Medial Knee Osteoarthritis	**LN**	Logistic Network
BPN	Backpropagation network								

[59]. Similarly, Hou et al. [79] obtained high sensitivity and specificity for real-time FoG detection utilizing a CNN deep learning model and an adaptable, wireless sensor network.

D. IMU & EEG

Using AI models while merging IMU and EEG data was reported in several research such as cortical changes associated with the intention of acceleration during self-paced walking, multimodal biometric authentication system, and FoG prediction for PD patients. Specifically, utilizing processed pre-acceleration EEG, a SVM classifier with radial basis kernel was developed to discriminate between the constant speed and accelerated speed conditions. This might be used to detect the intention to accelerate stride and then operate an associated assistive device adaptively [60]. In addition, Bajpai et al. [80] evaluated an ensemble model comprised of two neural Networks for clinical and personal applications. Transfer learning was used to learn user-specific FoG-related characteristics for personal use. Besides, Zhang et al. [81] designed a multimodal biometric authentication system based on RNN to protect against biometric authentication-related threats.

E. Other Multimodals

Multimodal gait analysis enhanced by AI also involved data from various sensors, like motion capture cameras, accelerometers, and pressure sensors, to comprehensively assess an individual's walking pattern. Alharthi and Ozanyan [82] investigated the integration of reflective marker trajectories, force-plates, and EMG sensors. They discovered that multimodality fusion produced more accurate predictions than single modality methods, such as single stream CNN, Vision Transformer, and statistical classifiers. Likewise, using data from pressure sensors, accelerometers, and gyroscopes, Moon et al. [83] demonstrated the same conclusion, showing the highest accuracy for gait recognition using a combination of CNN, RNN, and Self-Attention models. Meanwhile, the multivariate squeeze-and-excitation network proposed in [97] demonstrated 91.31% accuracy in the recognition of human locomotion. Fig.4 depicts the best performance of the various gait analysis models that have utilized EMG-IMU, EMG-EEG, IMU-EEG, and other multimodal sensing fusion data.

V. Discussion

Gait is not only necessary for human mobility, independence and everyday life functioning, but it is also a key predictor of quality of life, health status and mortality, as well as the progression of underlying pathophysiology [98]. Examining gait patterns, particularly spatiotemporal, kinematic, kinetic, and balance gait features, can shed light on the quality of gait in association with overall health status and functionality. In gait research, smart wearable technologies and artificial intelligence, such as machine learning and deep learning techniques, are gaining growing interest. Despite their limited use in clinical settings, these methods hold great potential for changing how gait is quantified by collecting, storing, and evaluating multifactorial complex gait data while also capturing its non-linear dynamic characteristics and variability. While neural networks have been used in a small number of research studies, the findings are encouraging and warrant more investigation. Several studies employed multimodal sensing fusion to design and improve lower limb prosthesis [39], [49], [53]. The results showed that the optimum separability, repeatability, clustering, and desirability across subjects and activities were achieved by integrating characteristics from vision, EMG, IMU, and goniometer sensors [53]. Hence, future applications of this sensing fusion in a forward predictor for powered lower-limb prostheses and exoskeletons might benefit from the incorporation of vision-based ambient data.

Promising results were also revealed by the EEG and EMG hybrid modality [24], [42], [55], [85], [87]. Chung and Wang [44] focused on the effects of age and gender. They discovered that females exhibit higher GRF during the heel-strike and toe-off phases, as well as more tibialis anterior muscle activation. On the other hand, Short et al. [87] investigated unilateral CP and found that children with CP had more cortical activity when walking. Research using the LDA classifier trained with fused IMU and EMG data achieved the highest accuracy compared to other types of classifiers trained with the same fusion of signals. However, this conclusion is not generalizable because of the wide variation of data collection settings and feature extraction strategies across investigations. LDA was mainly used for motion intention prediction and joint trajectory generation. In contrast, the single study that used the SVM classifier with EEG and EMG data had the lowest accuracy. Specifically, SVM was able to correctly predict 9 out of 12 acceleration events with a mean delay of −741ms. According to Huang et al. [72], RNN performs better than both support vector regression (SVR) and conventional artificial neural networks (ANN). Similarly, the LSTM predictor performed better than the SVM predictor [62]. On the other hand, gait events such as foot contact and toe-off were recognized accurately with MLP due to the meaningful IMU data that depicts these events clearly [71].

Higher number of electrodes with EEG also showed improved results in EEG-EMG multimodal classification [65]. Meanwhile, cortical and subcortical changes lead to PD patients poor coordination and abnormal gait [59]. Other factors that impact the performance of the models and lead to some variation in the findings include offline prediction that demonstrated superior model performance compared to online prediction. In addition, a number of models reported in the literature lacked modern computational methodologies and feature selection procedures or inadequately defined reference data such as knee joint angle. More research into the connectivity between cortical areas and classification accuracy is needed when EEG data is included into multimodal fusion AI.

Subject variability and label deficiency are intrinsic issues not just in gait assessment and staging, but in all healthcare settings. Therefore, future research might concentrate on loss design, data augmentation, or prototype learning methodologies to address this difficult but realistic topic. Similarly, creating unsupervised or semi-supervised approaches may lessen the need for time-consuming annotations and pave the way for more robust model creation. For this paradigm shift to be aligned with personalized gait abnormality assessment and rehabilitation, the loop must be closed with artificial intelligence models that include both static and dynamic features, as well as sophisticated data reduction and individualized feature selection of the most important gait characteristics.

The field of neurological disease assessment is undergoing notable trends that could reshape diagnostic approaches. A prominent trend involves integrating diverse gait analysis methods, encompassing kinematic, kinetic, and cerebral activity measurements. This holistic approach provides a more nuanced understanding of movement patterns, enhancing the diagnostic potential of gait analysis. Additionally, the rise of multimodal sensor fusion, which combines wearable and non-wearable sensor data through advanced techniques, is becoming increasingly prevalent. This trend significantly improves diagnostic accuracy by capturing data from multiple sources, contributing to more precise assessments. Moreover, artificial intelligence models are gaining traction, particularly when coupled with multimodal sensor fusion. This combined approach holds the potential to revolutionize neurological disease diagnosis, offering advanced predictive capabilities by processing complex datasets and identifying patterns that might not be discernible through individual modalities alone.

Despite the promising advancements, several open issues warrant careful consideration. Firstly, determining effective strategies to fuse various sensor data types optimally remains a challenge. This necessitates exploring fusion techniques that maximize the benefits of multiple data sources while ensuring robustness. Real-world validation of wearable systems across diverse settings and patient groups is imperative to establish their reliability and generalizability. Moreover, developing AI models that provide interpretable results is an ongoing concern, as comprehensible outcomes are vital for gaining clinicians' and patients' trust. Creating practical systems for long-term patient monitoring and disease tracking presents a technological challenge that requires attention to ensure usability and accuracy. Lastly, integrating gait analysis systems into clinical workflows and addressing adoption challenges remain key issues, emphasizing the importance of standardized practices and seamless incorporation into medical routines.

VI. Limitations

While this review did record the locations of the sensors and highlighted the most desired site by researchers, it was unable to draw any firm conclusions about the optimal number and placement of sensors. Even though all studies assessed gait, not all used the same experimental design, methodology, or conditions. This impacts both the obtained data and AI-based quantification of gait.

Different AI research groups also train their AI models with distinct datasets making it challenging to evaluate the performance of two AI models. Furthermore, software variation and its potential impact on algorithm efficacy were not considered due to lack of information in the included research studies. Likewise, there is also some uncertainty as to whether or not adding more sensors reduces or improves the reliability of the AI findings.

Certain machine learning models are known to be overfitting, and do not perform well on new datasets, making the scarcity of benchmark data all the more worrisome. The usefulness of an artificial intelligence model drops significantly if it lacks the ability to consistently generalize to novel, previously encountered situations.

VII. Conclusion and Future Work

This systematic review primarily discussed the relevance of gait analysis utilizing fusion approaches and AI models that have been developed for this purpose. Among the 66 research articles, 44 utilized EMG signals as part of the multimodal fusion data. The relevance of combining multiple forms of wearable and non-wearable sensor data and the influence of this combination on the performance of AI models might thus be investigated further. The significance of cortical activity in evaluating gait might also be investigated in future research utilizing EEG and fNIRS. This allows researchers to measure several forms of mental stress and cognitive processes along with a variety of aberrant gait patterns. While deep learning is only employed in a small number of gait analysis studies, the findings are encouraging and warrant more investigation. Consequently, this review article serves as a starting point for the design and validation of a smart portable wearable-based gait and balance assessment system employing current tools and technologies that have been specifically developed for clinical use.

Institutional Review Board Statement

Not Applicable.

Informed Consent Statement

Not Applicable.

Data Availability Statement

Not Applicable.

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Conflicts of Interest

The authors declare no conflict of interest.

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