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RESEARCH ARTICLE

Assessing Pediatric Gait Symmetry Through Accelerometry and Computational Intelligence

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ABSTRACT This paper focuses on the use of wearable sensors to acquire and process motion data, which is essential for monitoring physiological movement and identifying gait disorders. It is particularly relevant in pediatrics, neurology, and rehabilitation. The research evaluates body motion symmetry in children using accelerometric data, taking into account factors such as age, diagnosis, and gender. Signals were recorded from 35 children (average age 10.8 years) using mobile sensors and were analyzed using digital signal processing techniques and classification methods. The proposed methodology includes data acquisition by smartphone sensors, wireless data export to a remote drive, and data processing through a graphical user interface. The highest classification accuracy of walking features, at 92.0%, was achieved with a two-layer neural network. The findings underscore the effectiveness of these tools in rehabilitation, fitness monitoring, and neurological studies.

INDEX TERMS Computational intelligence, mobile sensors, accelerometers, physical activity monitoring, gait symmetry, pediatric motion disorders.

I. INTRODUCTION

The classification of pediatric gait symmetry involves a detailed analysis and comparison of various gait parameters to identify the extent of symmetry or asymmetry in a child's walking pattern. Symmetry is considered a sign of physiological and healthy movement, while pronounced asymmetries often signal underlying pathological issues [1]. Gait and balance assessments typically rely on data from accelerometric sensors, which have proven effective in evaluating gait disorders and concussion symptoms [2], [3], [4], [5]. In some studies, this involves examining differences in muscular activity between the left and right legs during walking [6].

The process of detecting gait irregularities in children using wearable accelerometric sensors centers around extracting key features from the data. These features may include step length, step width, durations of stance and swing phases, stride time, cadence, among others. The significance of these studies is underscored by rapid advancements in sensor

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technology [7], which have broad applications in physical activity analysis [8], [9], [10], rehabilitation, sports [11], [12], and health monitoring [13], [14], [15]. Computational intelligence techniques, including machine learning algorithms and neural networks, are frequently employed to classify and understand gait disorders. These algorithms are trained on labeled datasets where gait symmetry has been established, enabling them to recognize patterns and predict outcomes in new data.

Evaluating gait irregularities involves interpreting data to understand gait symmetry patterns in pediatric subjects across different physiological measures. The effectiveness of the classification models is assessed using metrics such as accuracy, sensitivity, specificity, and F1-score. Cross-validation and testing on independent datasets are essential for ensuring the model's robustness and generalizability. This analytical process can highlight potential gait anomalies or asymmetries that may require further examination or intervention.

Assessing gait symmetry in children requires a thorough examination and comparison of various gait parameters to determine the level of symmetry or asymmetry in their walking patterns. Symmetry typically reflects normal, healthy movement, while notable asymmetries may indicate underlying health issues. Gait and balance evaluations often use data from accelerometric sensors [16], which have been effective in diagnosing gait abnormalities and concussion symptoms. In some research contexts, this evaluation includes a detailed analysis of variations in muscular activity [6] between the left and right legs during walking.

The application of computational intelligence to process gait features, alongside data from accelerometric sensors, has become an increasingly important tool for efficiently classifying pediatric gait symmetry. This approach yields critical insights that are instrumental in clinical diagnosis and the formulation of treatment strategies. Additionally, gait assessments can be enhanced by three-dimensional, anatomically-based measurements of joint motion, providing a more comprehensive understanding of gait dynamics [17]. This multidimensional approach to gait analysis enables a more nuanced and accurate identification of gait irregularities, offering significant benefits for both clinical and research applications in pediatric healthcare.

The assessment of gait symmetry in pediatric populations involves a nuanced approach that considers various gait parameters and the use of microelectromechanical (MEMS) sensors [18], [19]. The determination of gait symmetry is not standardized and can vary depending on the research or clinical context, as well as the specific gait parameters being evaluated. This variability requires a tailored approach in which researchers and clinicians select gait parameters based on their relevance to the particular condition under investigation or the clinical needs for accurate diagnosis and effective treatment planning. In-depth studies often focus on the analysis of joint angles, using data gathered during walking on force plates and employing motion capture systems. These studies typically involve both direct and inverse kinematics to evaluate differences in the kinematic parameters of pediatric gait [20], [21]. Some studies utilize inertial measurement units (IMU) for motion analysis, focusing on the dynamic detection of joint angles during walking and stair climbing. These methods involve attaching sensors at specific locations on the body to measure movements and calculate symmetry indices after reducing tissue artifacts.

Advancements in wearable technology for human motion and posture recognition are now widely studied. The review [22] highlights progress in sensor monitoring indicators, system design, and the importance of factors such as data security, wearing comfort, and durability. An extensive survey of the state-of-the-art in wearable sensor technology for gait, balance, and range of motion analysis is presented in [23]. These studies emphasize the importance of quantitative methods for assessing patient progress and early diagnosis of movement disorders, showcasing various algorithms and evaluation metrics used in wearable sensor systems.

The mathematical analysis of motion data encompasses a broad methodology that includes general signal processing [24], [25], machine learning, and both time-frequency and time-scale analyses of signals. A particular emphasis is placed on the use of computational intelligence for the extraction, evaluation, and classification of signal features. This approach allows for a more detailed and precise understanding of gait patterns, facilitating better diagnosis and treatment of gait abnormalities in children. The integration of these advanced methodologies enhances clinicians' and researchers' ability to discern subtle variations in pediatric gait, thereby contributing to more effective and individualized patient care.

This paper outlines the use of accelerometers [26], [27], [28], [29] and the Global Navigation Satellite System (GNSS) [30] for analyzing the walking symmetry of children across various ages and those with walking disorders. These analyses are performed using wearable sensors embedded within mobile phones [31], [32], [33], which are positioned on the body as illustrated in Fig. 1, along with the proposed settings for data acquisition and implementation of wireless communication links. The focus of this project is to monitor pediatric walking patterns [34], [35], [36], [37], assess their symmetry, and identify potential gait disorders in a diverse group of children, differentiated by age, gender, and Body Mass Index (BMI). The advantage of the proposed methodology lies in the use of common smartphone sensors and the ability to conduct walk analyses in natural conditions. However, drawbacks include the need for an internet connection, access to a remote Matlab drive, and the possible requirement for detailed gait analysis in specialized laboratories equipped with more sophisticated sensors.

The examination of gait patterns has been used to diagnose many health conditions in clinical environments and gait laboratory settings. Symmetry is often considered a sign of physiological and healthy movement, although there

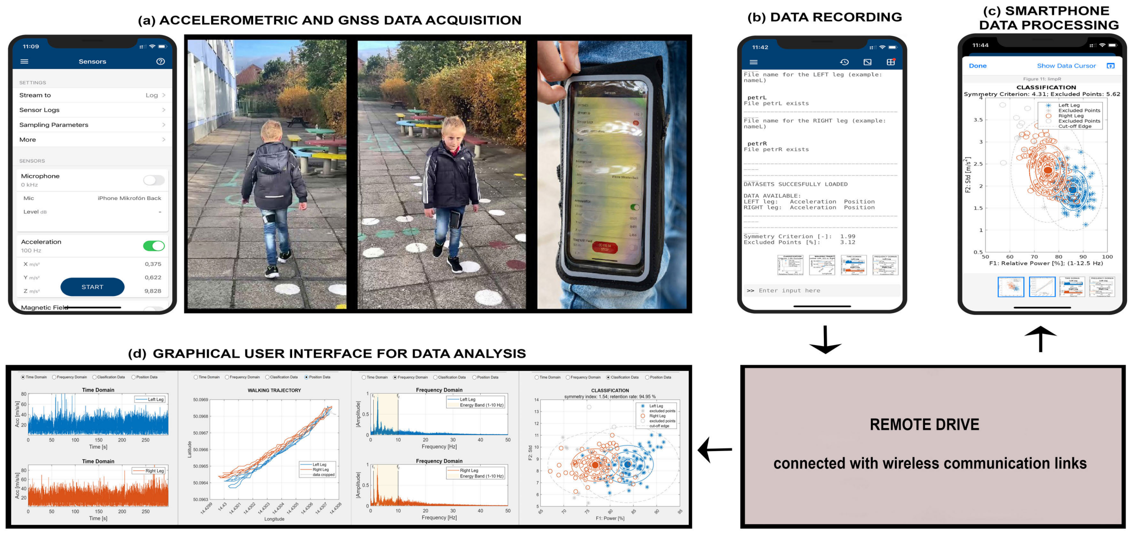

FIGURE 1. Principle of motion data acquisition during walking tests presenting: (a) initialization of sensors and conducting a walking experiment with the recording of accelerometric and GNSS positioning data, (b) the use of mobile Matlab on a smartphone for data recording and wireless export to a remote drive, (c) evaluation of the symmetry coefficient on the smartphone using the remote drive, and (d) a graphical user interface for detailed data analysis, which allows for the presentation of time-domain accelerometric data, a GNSS record of walk positioning, evaluation of gait frequency components, and the distribution of gait features evaluated separately from the left and right legs using data stored on the remote drive.

is no commonly accepted method for quantifying gait symmetry [1]. This study contributes to research in the use of portable systems and remote data processing for near-clinical or community-based assessments. The paper's objectives include (i) the computational analysis of frequency components recorded on the left and right legs during walking in real-world conditions and the proposal of a combined symmetry coefficient, (ii) the implementation of smartphones, communication links, and the mobile Matlab computational environment, (iii) immediate data processing by the proposed algorithms using remote access to data on the Matlab Drive, and (iv) the implementation of the proposed graphical user interface (GUI) for detailed data analysis. The current study aims to quantify walking patterns using accelerometric data from both healthy and unhealthy children.

The results highlight a synergy between traditional diagnostic methods and mathematical techniques for processing signals obtained from appropriate sensors. These sensors are effective in both clinical settings and real-world conditions [38], [39]. This innovative approach to gait analysis offers pediatric neuropsychologists a variety of metrics for the quantitative assessment of gait in spectral and spatial domains [40].

The study elucidates the efficacy of utilizing wearable sensors during natural walking as a feasible substitute for conventional treadmill-based exercises typically employed in gait monitoring. Healthcare professionals can conduct various tests to ascertain the nature of gait abnormalities. Such abnormalities, manifesting as alterations in walking patterns, may arise from injuries and various medical conditions. Factors impacting the brain, spinal cord, legs, or feet can influence gait, altering its patterns and symmetry.

This research contributes to the field of accelerometric signal analysis, aiming at the detection of walking disorders. It plays a crucial role in enhancing the diagnosis and treatment of the underlying causes of gait abnormalities. The applications of this methodology can be extended and generalized across various fields, including neurology, rehabilitation, engineering, and robotics [41], [42], [43].

The rest of the paper is organized as follows: Section II describes the proposed methodology, comments on data acquisition, and summarizes the signal processing methods. Section III presents the proposed graphical user interface and the results of walk symmetry analysis. Section IV contains the discussion, and Section V concludes with remarks on possible future research.

II. METHODS

The dataset consists of data captured by wearable sensors within a smartphone, including a GNSS receiver and a three-axis accelerometer. The GNSS receiver records terrestrial data such as longitude, latitude, and altitude. All procedures involving human participants complied with the ethical standards of the institutional research committee and adhered to the 1964 Helsinki Declaration and its subsequent amendments.

The proposed research flowchart for classifying gait symmetry in pediatric walking using wearable accelerometric sensors, as presented in Fig. 1, involves the following steps:

(a) Initialization of the sensors within the smartphone.
(b) Wireless export of accelerometric data recorded by the smartphone to a remote drive using internet communication links.

(c) Evaluation of the symmetry coefficient on the smartphone using data recorded on the remote drive.
(d) Detailed processing of accelerometric signals stored on the remote drive using the proposed graphical user interface.

This methodology employs wearable sensors and implements them through smartphone technology.

TABLE 1. Description of individuals (*Ind.*), their diagnosis (*Diag.*), and the symmetry index evaluated in the time (*Sym1*) and frequency (*Sym2*) domains from accelerometric signals for a group of 35 children.

Ind.	*Diag.*	*Age* [year]	*Gender* *m / f*	*Height* [cm]	*Weight* [kg]	*BMI* [kg/m^2]	*Sym1* [-]	*Sym2* [-]
W01	0	12	f	152	36	15.6	0.59	0.9
W02	1	12	f	145	45	21.4	4.62	4.44
W03	0	8	m	131	27	15.7	4.38	4.27
W04	1	7	m	123	21	13.9	4.49	4.23
W05	1	3	m	104	17	15.7	3.8	3.9
W06	0	13	m	150	35	15.6	2.02	1.67
W07	0	9	f	142	34	16.9	0.73	1.82
W08	0	12	f	130	26	15.4	2.29	2.37
W09	0	11	f	148	35	16.0	1.60	1.45
W10	0	8	f	130	26	15.4	0.49	0.79
W11	1	6	m	121	23	15.7	3.10	5.81
W12	1	12	m	167	60	21.5	0.92	3.55
W13	0	13	m	153	36	15.4	2.14	1.77
W14	0	13	f	141	27	13.6	0.12	0.09
W15	1	4	m	100	15	15.0	4.44	3.67
W16	0	4	f	110	20	16.5	0.26	0.96
W17	0	10	m	148	35	16.0	1.29	2.98
W18	1	4	m	100	19	19.0	1.87	3.44
W19	0	9	m	140	33	16.8	0.51	0.50
W20	0	6	m	110	19	15.7	0.23	0.59
W21	1	9	m	154	38	16.0	3.19	3.04
W22	0	13	m	167	77	27.6	2.06	1.87
W23	0	11	m	157	83	33.7	1.54	1.25
W24	0	11	m	144	55	26.5	4.04	4.05
W25	0	15	m	177	137	43.7	3.02	2.97
W26	0	6	m	130	44	26.0	0.50	1.75
W27	0	11	m	167	112	40.2	2.16	1.87
W28	0	10	m	145	68	32.3	0.83	1.37
W29	0	14	f	174	115	38.0	0.55	1.20
W30	1	9	f	139	64	33.1	3.28	3.41
W31	0	14	f	170	106	36.7	2.69	2.58
W32	0	11	f	166	93	33.7	2.53	1.95
W33	0	13	f	152	84	36.4	1.23	1.16
W34	0	13	f	162	97	37.0	0.65	1.11
W35	1	11	f	159	76	30.1	2.22	2.47

A. DATA ACQUISITION

The study included 35 children, consisting of 20 boys and 15 girls, ranging in age from 3 to 15 years. The mean age of the participants was 10.8 years, with a standard deviation of 2.78 years. Detailed information is presented in Table 1, which includes data for both the 25 healthy children and the 10 children diagnosed with various types of motion disorders by experienced medical specialists. The experiments were not constrained by time limits; however, the walking trajectory for all participants was approximately 400 meters in length to maintain consistency across the study.

Figure 1 illustrates the system setup and the placement of the accelerometric sensor on the body. The smartphone, serving as both the GNSS receiver and the accelerometric data acquisition sensor, was attached in a vertical position on the left or right leg, with the display facing forward [29]. Accelerometric data were captured using mobile Matlab 2024a, recording at a sampling frequency of 100 Hz.

This analysis encompasses 35 experiments, all conducted in real-world settings. The data recorded during each experiment were promptly transmitted to Matlab Drive after each walk. The algorithm, operating via remote Matlab cloud computing, then displayed preliminary results on the mobile phone's screen, as shown in Fig. 1(c). These methods facilitated the immediate verification of the experiments and a preliminary evaluation of the symmetry coefficient.

Detailed descriptions of the observations can be found on IEEE DataPort (dx.doi.org/10.21227/f0hc-bw59) for further investigation. This repository contains (i) all positioning and accelerometric signals used in the present study, (ii) algorithms for wireless data acquisition using the smartphone sensors and their recording on Matlab Drive through communication links, (iii) a graphical user interface for detailed data analysis and classification, and (iv) a graphical video abstract of the paper.

B. SIGNAL PROCESSING

Data processing procedures are intrinsically linked to the characteristics of the sensors used for data acquisition. The database of records was composed of both accelerometric and GNSS signals captured by sensors within the mobile phone. This data served two primary purposes: the immediate analysis of body motion and the visualization of walking positions in real-world environments. Additional analyses were conducted to identify turning points, allowing for a more comprehensive examination of all records. Generally, signal de-noising and the extraction of features in both time and frequency domains are common challenges encountered during the detailed processing stage.

Accelerometric data for each experiment, denoted as l, were captured by tri-axial sensors positioned on specific parts of the body (left leg and right leg). This data generated three sequences $\{s_x(l,n), s_y(l,n), s_z(l,n)\}_{n=0}^{L(l)-1}$ for each location. Typically, the modulus of these sequences for $n = 0, 1, \cdots, L(l) - 1$ was calculated using the following relation:

$$s(l,n) = \sqrt{s_x(l,n)^2 + s_y(l,n)^2 + s_z(l,n)^2} \tag{1}$$

to eliminate inaccurate positions of the accelerometric sensor, and to refine data for further processing.

Signals in the time domain were analyzed using statistical methods to describe $M1$ features $\{F_L(l,r), F_R(l,r)\}_{r=1}^{M1}$ associated with the left and right legs, respectively, for each experiment l. In this instance, $M1 = 2$, and the two features analyzed were the mean and the standard deviation.

An alternative analysis was conducted in the frequency domain. The mean value of the observed signal for each experiment l was calculated using the following relation:

$$\bar{s}(l) = \frac{1}{L(l)} \sum_{i=1}^{L(l)} s(l, i) \tag{2}$$

and the short-time discrete Fourier transform was then applied to evaluate:

$$S(l, k) = \sum_{n=0}^{L(l)-1} (s(l, n) - \bar{s}(l))\, e^{-j\,k\,n\,2\,\pi/L(l)} \tag{3}$$

for $k = 0, 1, \cdots, L(l) - 1$. The proposed GUI in Fig. 2 present spectrograms of the accelerometric signals for the left and right legs, respectively, for the selected individual.

The use of spectral-domain features required the evaluation of the relative power $E(l)$ for experiment l in the frequency band $\langle fc_1, fc_2\rangle$:

$$E(l) = \frac{\sum_{k\in\Phi_w} |S(l, k)|^2}{\sum_{k=0}^{L(l)/2} |S(l, k)|^2} \tag{4}$$

where Φ_w represents the set of indices for the frequency components f_k within the range $\langle fc_1, fc_2\rangle$. In cases where $M2 = 2$ frequency features are considered, the relative power in two frequency bands, specifically $\langle 1, 10\rangle$ Hz and $\langle 10, 20\rangle$ Hz, can be selected to determine additional spectral features $\{F_L(l, r), F_R(l, r)\}_{r=M1+1}^{M1+M2}$ associated with the left and right legs, respectively. The frequency-domain features include relative power within the same frequency bands, chosen individually for both the left and right legs.

The symmetry index, based on the commonly used methodology, can then be calculated for each experiment l and feature r using the following relation:

$$C1(l, r) = \frac{1}{2}\,\frac{F_L(l, r) - F_R(l, r)}{F_L(l, r) + F_R(l, r)}\, 100 \tag{5}$$

For each pair of gait parameters, this is done to quantify the similarity between the left and right sides of the body. To incorporate all features, where $M = M1 + M2$, for each experiment l, a new criterion was proposed. The alternative criterion for a single experiment l, encompassing all features r, was evaluated using the proposed relation:

$$C(l) = \sqrt{\frac{1}{M} \sum_{r=1}^{M} (C1(l, r))^2} \tag{6}$$

Signal features were assessed for the entire duration of experiment l as well as for its Q subwindows to facilitate a more detailed analysis of each experiment.

There is potential to integrate time-domain and frequency-domain features, as illustrated in Fig. 1(c), which displays immediate preliminary results on the smartphone screen. Various statistical features and functional transforms, including wavelet transforms [44], can be employed for more advanced classification approaches.

Common computational tools used for data analysis include specifying pattern vectors, associated target values, and optimizing the proposed mathematical model for the segmentation and classification of (multichannel) signal components. The classification of Q signal segments requires the creation of pattern and target matrices during the learning phase to enhance the mathematical model. Analyzing its coefficients facilitates the model's application in the subsequent classification of unknown pattern vectors, with the probability of class membership being precisely calculated.

All signal segments correspond to sets of column feature vectors $\{\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_j, \ldots, \mathbf{p}_Q\}$ and associated target classes $\{T_1, T_2, \ldots, T_j, \ldots, T_Q\}$, which are either determined by a medical expert or derived from measurement conditions (for example, specifying measurements on the right and left legs, respectively, in this particular case). Each feature vector $\{\mathbf{p}_j\}_{j=1}^{Q}$ comprises R features $\{p(i, j)\}_{i=1}^{R}$, forming the feature matrix $\mathbf{P}_{R,Q}$.

Common algorithms used for signal segment classification include support vector machines, Bayesian methods, and neural networks. The mathematical model, optimized for the training dataset, is then tested to assess its generalization capabilities and effectiveness in classification during practical implementation.

The k-fold cross-validation method is frequently employed to validate the final model and to determine the proportion of incorrectly classified target classes. In this method, one of the k folds of the original dataset forms the test set, while the remaining data is used for model optimization. In this paper, we used the 10-fold cross-validation method.

The evaluation of classification results involved analyzing the two-class receiver operating characteristic (ROC) curve, using TP, FN, FP, and FN to identify the number of true positives, false negatives, false positives, and false negatives. The ROC analysis is used to calculate the following metrics:

- The sensitivity (also known as the True Positive Rate or Recall), defined as the proportion of actual positives that are correctly identified by the model, indicating how well the model can identify true positives:

$$TPR = \frac{TP}{TP + FN} \tag{7}$$

- The specificity (also known as the True Negative Rate), defined as the proportion of actual negatives that are correctly identified by the model, indicating how well the model can identify true negatives:

$$TNR = \frac{TN}{TN + FP} \tag{8}$$

- Accuracy, defined as the proportion of total correct predictions (both true positives and true negatives) out of all predictions made by the model, providing an overall measure of how well the model performs across both classes:

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

III. RESULTS

Data acquisition was conducted using Mobile Matlab on a smartphone, utilizing its built-in sensors. The proposed algorithm enabled immediate preliminary processing of the data recorded on Matlab Drive, with results displayed as illustrated in Fig. 1(c). The implemented algorithm, designed as a general routine applicable both on the smartphone and on a personal computer, is accessible through the IEEE DataPort mentioned above. An internet connection was essential for this type of data acquisition and processing.

Figure 1(d) illustrates the route visualization for accelerometric data acquisition. Both GNSS and accelerometric data were captured using Mobile Matlab, and the developed algorithm assessed the symmetry coefficient for both time-domain and spectral-domain data after each experiment. This is presented in Fig. 1(c) for a selected individual. The proposed graphical user interface (GUI) for analyzing data recorded by mobile accelerometric sensors is shown in Fig. 2. It facilitates data processing in both the time and spectral domains, with features evaluated for the right and left sides of the body, including the calculation of the symmetry coefficient.

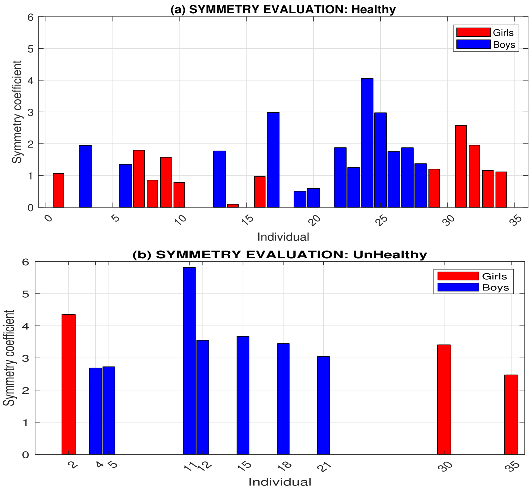

FIGURE 3. Symmetry coefficients of 35 individuals (comprising 20 boys and 15 girls) with its values (a) for 25 healthy children with prevailing symmetry walking patterns and (b) for 10 children with a medical diagnosis that may cause asymmetric walking.

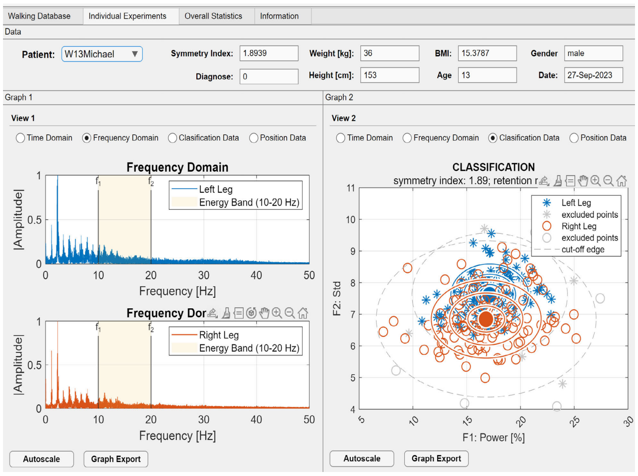

FIGURE 2. The proposed graphical user interface for analysis of data recorded by mobile accelerometric sensors and their processing both in the time and spectral domains showing features for the right and left side of the body.

The experimental dataset consisted of 35 children, both boys and girls, and was utilized for a detailed study of gait symmetry disorders. The symmetry coefficient was calculated based on two features: the standard deviation of accelerometric data recorded on the right and left legs and the mean energy in the frequency range of $\langle 1, 10 \rangle$ Hz, as defined in Eq. (6). These values were assessed within a selected set of 50 subwindows.

The preprocessing stage included the detection and omission of segments containing significant errors. The criterion for exclusion was the distance of features from their mean values; segments where this distance exceeded three times the standard deviation were removed from further analysis. The iterative repetition of this process [33] resulted in the elimination of 6.77% of subwindows across all experiments.

The results of all experiments are summarized in Table 1, with symmetry coefficients evaluated by Eq.(5) presented in the last two columns. The values $Sym1$ are based on time-domain features (mean and standard deviation), while the values $Sym2$ utilize frequency-domain features evaluated by Eq. (4). Mean values of these symmetry coefficients are depicted in Fig. 3. Figure 3(a) shows the results for 25 healthy children, most of whom exhibited predominantly symmetric walking. In contrast, Fig. 3(b) presents the symmetry coefficients for 10 children with medical diagnoses that could lead to asymmetric walking. Most individuals in the group identified as having potential causes for asymmetric walking exhibited symmetry coefficients greater than 3.0. This observation was made even though some healthy children also displayed a higher coefficient of asymmetry. This variation can be attributed to natural factors and their uncoordinated walking patterns, underscoring the need for further medical investigation. In contrast, most healthy children had coefficients lower than this threshold, with 6 of them (24% of the healthy group) having coefficients below 1.

Figure 4 illustrates the relationship between the symmetry coefficient and BMI index for healthy boys and girls, as outlined in Table 1. Generally, there is a direct proportionality between the increasing BMI index and the symmetry coefficient for both boys and girls, with positive line slopes of 0.027 and 0.029, respectively. The average gait symmetry coefficient for healthy normosthenic children (W01–W21) with a BMI lower than 20 [kg/m^2] is 1.7, compared to healthy obese children (W22–W35) who have an average value of 2.7. These findings align with the observed connection between weight distribution and gait speed in children with motion disorders, as discussed in previous studies [45], [46].

The distribution of time and spectral domain features differs between symmetric and asymmetric walking. Figure 5

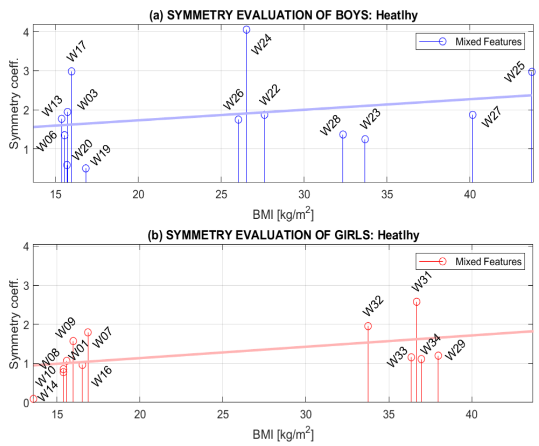

FIGURE 4. Correlation between the symmetry coefficient and BMI index in the set of (a) healthy boys and (b) healthy girls, as detailed in Table 1.

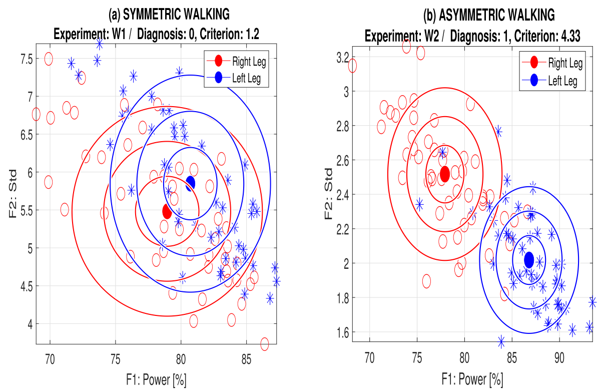

FIGURE 5. Comparison of the distribution of time and spectral domain features of (a) the predominantly symmetric and (b) predominantly asymmetric walk of the selected individual, along with the centers of both clusters and regions of c times the standard deviations for $c = \{0.5, 1.0, 1.5\}$.

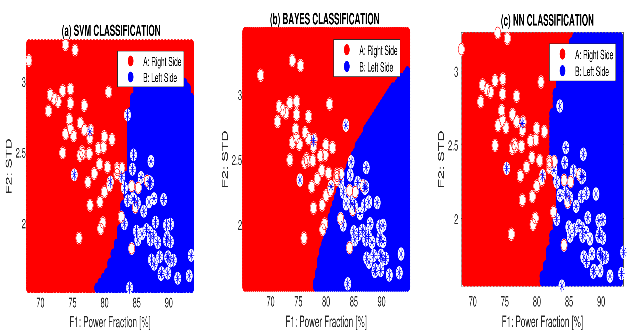

FIGURE 6. Classification of walking patterns for prevailing asymmetric walking by (a) the support vector machine method, (b) the Bayes method, and (c) the neural network method.

displays these features for a selected healthy individual with predominantly symmetric walking and an unhealthy individual with predominantly asymmetric walking. This figure also includes the centers of both clusters and regions corresponding to c times the standard deviation, where c takes values of 0.5, 1.0, and 1.5. Detailed information about all 35 individuals is summarized in Table 1. The features represent the relative power in the $\langle 1, 10 \rangle$ Hz range and the standard deviation of observed accelerometric data. Notably, the characteristics of asymmetric walking form more compact clusters that are significantly better separated than those associated with symmetric walking.

Figure 6 illustrates the classification of walking patterns for asymmetric walking using the support vector machine, Bayesian method, and a neural network with a two-layer structure that includes sigmoidal and softmax transfer functions. This classification is based on the frequency and time domain features of a selected individual. The results suggest that mathematical tools have the potential to detect asymmetric walking patterns. Both time-domain and frequency-domain features related to accelerometric data occupy distinct regions, facilitating their separation.

TABLE 2. The accuracy (AC [%]), the cross-validation error (CV), specificity (TNR [%]), and selectivity (TPR [%]) of symmetric and asymmetric walking classification by support vector machine (SVM), Bayesian, and two-layer neural network methods using two features specified as the power in the selected frequency band and the associated standard deviation of accelerometric data.

Method	*Symmetric Walk*				*Asymmetric Walk*			
	AC	*CV*	*TPR*	*TNR*	*AC*	*CV*	*TPR*	*TNR*
SVM	73	0.33	68.2	71.7	89	0.16	87.5	90.1
Bayes	68	0.40	62.0	74.0	89	0.17	88.0	90.0
NN	79	0.29	84.0	74.0	92	0.10	92.0	94.0

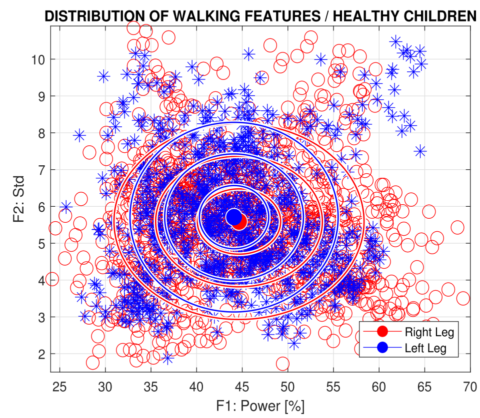

FIGURE 7. Distribution of time and spectral domain features of the set of 25 healthy children with centers of clusters standing for the right and left legs and areas of c multiples of standard deviations for $c = \{0.5, 1.0, 1.5\}$.

Table 2 provides a comparison of the classification of selected motion features using a support vector machine (SVM), Bayesian method [47], and a two-layer neural network with sigmoidal and softmax transfer functions, with 10 neurons in the first layer. All associated algorithms were developed in the computational and visualization environment of Matlab 2024a, utilizing its toolboxes. Cross-validation errors were calculated using the 10-fold cross-validation method.

The arrangement of time and spectral domain features for the set of 25 healthy children is depicted in Fig. 7. In this case, frequency domain features represent the relative power in the $\langle 0, 3 \rangle$ Hz range. The results indicate a similarity in the features of the left and right legs in cases of predominantly symmetric walking, with a global coefficient of symmetry equal to 0.71.

Figure 8 illustrates the distribution of cluster center means for the left and right legs, comparing 25 healthy children (primarily exhibiting symmetric walking) and 10 unhealthy children (primarily exhibiting asymmetric walking). This analysis employs both time-domain and spectral-domain features, which represent the standard deviation of accelerometric data and the relative power in the $\langle 0, 3 \rangle$Hz range, respectively. The notations of lines correspond to the individuals specified in Table 1. The mean distances for the first group of 25 children are 3.7 ± 3.9, whereas for the second group of 10 children, they are 7.4 ± 3.3. These results suggest a better separation of asymmetric walking, as evidenced by the higher distances between their cluster centers.

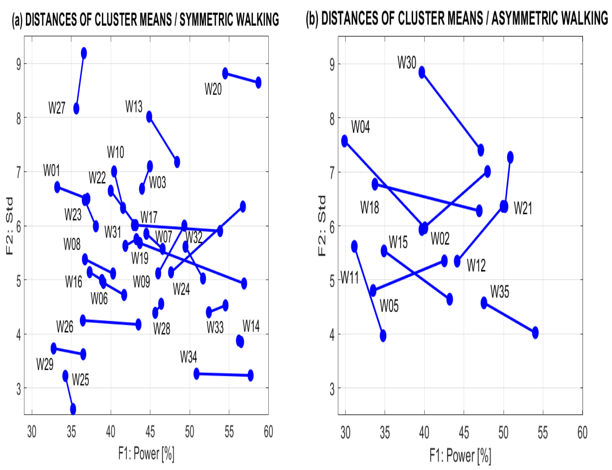

FIGURE 8. Distances of feature cluster means for (a) the prevailing symmetric and (b) prevailing asymmetric walking for the set of 25 healthy and 10 unhealthy individuals, respectively.

The results indicate the potential for mathematical analysis of accelerometric data to detect walking disorders and assist in identifying motion asymmetry.

IV. DISCUSSION

The widespread availability of wearable sensors and smartphone technology is driving a rapid accumulation of human data, prompting the application of innovative computational and machine learning methods in clinical predictions.

This paper focuses on studying pediatric gait characteristics and asymmetrical walking patterns associated with gait disorders using smartphone sensors. The research utilizes the global navigation satellite system and selected wearable sensors for motion analysis. A diverse group of 35 children, varying in age, gender, and BMI, was analyzed, examining gait features in both the time and frequency domains. Various mathematical methods were employed to classify different walking patterns.

The classification of pediatric walking was based on signals recorded by the accelerometer within a smartphone placed at specific body positions. The average gait symmetry coefficient was found to be 37% better in healthy normosthenic children compared to healthy obese children.

Numerical analysis of accelerometric signals indicates a classification accuracy of 92% for distinguishing features of the left and right legs using a two-layer neural network for asymmetrical walking. The best classification accuracy for symmetrical walking was 79%, suggesting overlapping feature clusters and similar gait features in healthy individuals.

The relationship between the symmetry coefficient and body mass index shows that asymmetric walking tends to increase with higher BMI values in healthy children. This trend is consistent for both boys and girls, with positive line slopes indicating an association between BMI and asymmetric walking. Additionally, asymmetrical walking is more prevalent among boys than girls.

The potential applications of gait symmetry assessment methods in clinical practice include their impact on the diagnosis and rehabilitation of children with gait disorders. Gait asymmetry can reveal underlying functional deficits, such as muscle weakness, joint stiffness, or neurological impairments. By identifying these issues, rehabilitation can be tailored to address specific concerns. Asymmetrical gait can lead to poor balance and an increased risk of falls, so rehabilitation focused on correcting asymmetries can enhance overall stability and reduce the risk of injuries. Correcting gait asymmetry can also lead to smoother, more efficient walking patterns, improving mobility, especially for individuals recovering from injuries or dealing with chronic conditions like stroke or arthritis. Asymmetrical gait often results in the uneven distribution of forces across the body, contributing to pain in the hips, knees, or back. Rehabilitation aimed at promoting symmetry can help alleviate this pain by encouraging more balanced movement.

V. CONCLUSION

The paper addresses issues related to gait symmetry and the analysis of motion monitoring during walking experiments involving a group of 35 children. A specialized algorithm for smartphones was developed and utilized for acquiring accelerometric and GNSS data. This algorithm evaluates the coefficient of walking symmetry and visualizes the distribution of walking characteristics.

The results suggest that this method could be effective in distinguishing between the motion symmetry of normal walking and the movements of children with various walking disorders. Mathematical analysis of these motion patterns can inform the development of rehabilitation exercises and assist in monitoring the outcomes of their implementation. For more general studies and the evaluation of features in both healthy and unhealthy individuals, it may be necessary to balance individual groups using techniques like Synthetic Minority Over-sampling Technique (SMOTE) to create datasets of similar sizes.

Possible issues of overfitting that could affect the model's performance on new data should be addressed in future research. This can be achieved by increasing the training dataset to help the model generalize better, reducing the model's complexity, and closely monitoring the model's performance throughout the training process.

Applications of gait symmetry analysis extend to various fields, including motion monitoring in sports medicine, orthopedic care, and aiding individuals with neurological disorders in adjusting medications or therapies to better control symptoms and improve quality of life. Asymmetries in gait can also indicate balance problems or muscle weakness, leading to targeted interventions to prevent falls and enhance safety in daily activities. In academic and industrial research, gait symmetry analysis is utilized in the development of new medical devices and rehabilitation technologies.

A specific application includes the examination of rehabilitation exercises related to pre- and post-operative treatment during surgeries. Modifications of the proposed method can provide insights into the quality of exercises prescribed by rehabilitation specialists or medical doctors, thereby reducing the probability of complications after complex surgeries.

Future research should focus on the integration of more complex sensors, time-synchronized data acquisition, and advanced computational techniques. It is anticipated that sophisticated mathematical tools based on machine learning and computational intelligence will analyze complex patterns in the data, leading to improved diagnostics, motion monitoring, and personalized treatment plans. These advancements are closely linked with the progress of mathematical methods, deep learning strategies, and the application of augmented reality.

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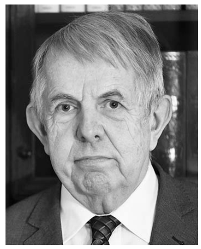

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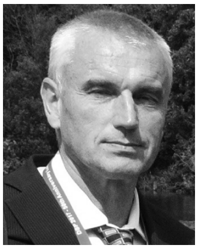

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