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Research Article

Human lower-extremity movement classification based on biomechanical sensor data: Machine learning approach

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ABSTRACT

Wearable biomechanical sensor signals can be used to precisely recognize human lower extremity movements based upon gait parameters such as walking speed, which is an increasingly important field with a significant role in biomedical studies. In this study, human walking patterns were classified using wearable biomechanical sensors and machine learning and time series analysis techniques. Accurate classification of level-ground gait patterns of IMU, digital goniometer (GON) and electromyography (EMG) sensor data is of great importance in informing physicians and medical device innovators working in this discipline. For this study, an open access dataset recorded from four unilaterally placed IMUs, three GONs and eleven EMG sensors in 22 subjects at different walking speeds was used. The sliding time window method was used to extract features in the first part of biomedical signal processing. Then, the effects of various window lengths and single or multiple sensor models on machine learning classification performance are compared. The results of this study showed that the QSVM classifier and IMU-based sensor with a window length of 1000 (5s) had the highest classification accuracy of 0.954 to classify human gait at different walking speeds based on the proposed method. In addition, it is seen that the classifiers have different classification accuracy for the seven sensor models used. QSVM has higher accuracy in gait recognition compared to WNN and ESKNN classifiers. In particular, the accuracy (0.961) in the experiment using the IMU and GON multiple sensor and QSVM classifier is the highest among other sensor combinations and classifiers. When QSVM classification and gait recognition were compared, the accuracies were found as IMU (0.954), GON (0.827) and EMG (0.735) sensor models, respectively. Then, in dual sensor combination models, the highest accuracy was achieved in IMU-GON (0.961), IMU-EMG (0.895) and GON-EMG (0.776) sensor models, respectively. Finally, the accuracy of the IMU-GON-EMG model, in which all three sensors are included, is 0.919. The findings of this study showed that IMU sensor models improved the classification performance in level-ground gait pattern recognition, and their use together with GON sensor models contributed positively to this performance. It has been found that EMG sensor models show lower classification performance compared to IMU sensor modelsg the necessary precautions were beneficial in terms of protecting the health of the employees.

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INTRODUCTION

Between 2015 and 2050, the World Health Organization (WHO) and United Nations (UN) estimated that the proportion of the global population over 60 years old will approximately double from 12% to 22% [1]. In recent years, the concept of developing novel methods and technologies that recognize daily human activities using data from wearable biomechanical sensors has gained popularity because of an increased older population. This approach has emerged because of the potential applications of such methods in various fields, including sports science, physical therapy, rehabilitation and assistive robotic device design [2-4].

In this study, we address recent studies that have classified human lower-extremity movements based on biomechanical sensor data using machine learning (ML) algorithms and highlight the benefits and drawbacks of these approaches. Initially, we provide a brief overview of the biomechanical sensors frequently used to collect information on lower-extremity activities in humans. Secondly, the sliding time window method and feature extraction methods used in human activity recognition studies are introduced and then machine learning applications in related work are presented. Finally, we focus on previous work that makes use of wearable sensor combination in studies of human movement recognition.

Wearable biomechanical sensors can be utilized to classify multiple movement patterns including walking speed (WS) in addition to estimating significant movement metrics such spatiotemporal parameters [5, 6] or comparing gait variability between healthy and pathological gait [7, 8]. Several wearable biomechanical sensors, such as accelerometers, gyroscopes, magnetometers, electromyography (EMG) and goniometers (GON) have been employed to record information about human movement pattern classification. A common combination of these sensors is the inertial measurement unit (IMU), which can provide a more comprehensive view of movement by tracking both angular and linear motions. Because of their mobility, affordability, and ability to supply precise measurements of human movement in practical settings, IMUs have grown in popularity as tools for gathering biomechanical data [9-11]. The effectiveness of movement and muscle activation during lower-limb activity depends on how a person maintains their posture. Kinematic data are gathered through motion capture cameras and digital goniometers, which measure joint angles and distance [12-14].

In terms of multiple movement patterns and gait phases, biomechanical study [15] have demonstrated considerable biomechanical variances in how human muscles and joints work. Based to this context, a wearable system's perception of the human body is its most fundamental capability to carry out the assigned task [16, 17], making human movement recognition systems comprehensive and integrated systems. The signal processing methods and sensor combinations applied must be compatible to clearly recognize human movement. Nagaraj et al. applied the EMG signal and angular acceleration from motion cameras as input to the ANN model for the estimation of the lower extremity joint angle of the athletes during exercise and compared it with the experimental results measured with a digital goniometer [13]. Lencioni et al. statistically analyzed the human movement during straight walking and stair climbing at different speeds with the biomechanical parameters calculated from the force plate, motion capture camera and EMG data, and compared the results [15].

A popular time series analysis method for recognizing lower extremity activity is the sliding window method. The length of the selected window affects how well this method recognizes the human movement. While processing takes more time when a wider window length is used, recognition success declines because the motion pattern is not adequately recognized for narrower window lengths. The length of the sliding window was chosen to range from 0.08 seconds to 2.5 seconds and even 30 seconds in the motion recognition tests that have been published in the literature [18]. Noor et al. proposed an adaptive method for selecting the temporal frame length for activity recognition using IMU sensors [19]. Wang et al. evaluated different window lengths for recognizing human motion patterns and observed that pattern recognition was acceptable at lengths of 0.5 s and 2.5 s–3.5 s [20].

One of the main challenges in developing such methods are selecting appropriate features from sensor data that can accurately represent different types of human movements. Machine learning algorithms that can easily learn from appropriate extracted features by ML engineers and classify activities based on them, have been used to overcome this challenge [9-11]. Huynh and Tran, in their study on human fall detection, proposed to apply frequency domain features using FFT (Fast Fourier Transform) of IMU sensor data [21]. Shawen et al., in their machine learning classification study of Parkinson's disease detection, suggested using the time domain and frequency domain mean, standard deviation, skew, kurtosis features of IMU sensor data [22]. In another study, in which continuous-time walking speed determination algorithms and sensors for robotic knee and ankle prosthesis were evaluated, 8 time series features of each gait phase including minimum, maximum, mean, standard deviation, start value, end value, signal magnitude area, and signal energy has been used [23].

Recent studies have used machine learning algorithms including Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Artificial Neural Networks (ANN) to classify human lower-extremity movements using information gathered from biomechanical sensors [23-26]. One study classified ambulatory activities of daily living using a SVM algorithm based on information gathered from IMU and EMG sensors. The SVM algorithm's classification accuracy of 0.943 demonstrates the promise of machine-learning methods [27]. Another study analyzed the importance of several sensor types and locations. Camargo et al. observed that biomechanical sensors such as IMU, GON, and EMG are crucial for classification, goniometers provide the majority of accuracy for estimation of stair/ramp, and a single IMU for speed estimation on the level ground dramatically reduced the need for all additional sensor types and locations [28]. In addition, Dong et al. have classified the gait phase and pattern with high accuracy using multi-channel EMG and IMU sensor data and machine learning algorithms [29].

Human movement recognition studies using wearable sensor data and machine learning tools are a very popular new research area. The most difficult issues for many applications are the precise classification and prediction of human lower-extremity movements. While understanding the user experience can improve the adaptability of rehabilitation devices to changing environments during the design phase, it can also considerably help physicians in clinical practice monitor patient activities in-depth. A few related works present studies such as fall detection [21], classification of patients with balance disorders such as Parkinson's disease [22], the development of robotic motion assist devices [23]. Bhakta et al. evaluated the machine learning models they developed to readily predict walking speed on the data of subjects walking on a robotic knee-ankle prosthesis. They showed that using machine learning models provides high accuracy with low error rate, by applying the performance of their proposed model in various static walking speeds and dynamic speed trials [23].

Wearable biomechanical sensors, whose resolution and usage requirements have increased, are still limited in application because the algorithms used in human motion pattern recognition systems increase the computational load. This study proposes a machine learning approach-based method for human gait pattern recognition with features extracted from single and multiple combinations of IMU, GON and EMG wearable sensor signals. The sliding windows method approach was used in feature extraction and the effects of different window sizes on the classification performance were examined in the experiments. The primary aim of our study was to investigate the performance of widely used machine learning classifiers to recognize human gait pattern of single and multiple wearable biomechanical sensor signals. Our objective was to determine the appropriate temporal gait features from wearable sensors subject to machine learning algorithms:

i) build signal processing methods for multiple biomechanical sensor channels,
ii) observe sliding window length impacts on human movement pattern classification,
iii) compare ML classification performance of single and multiple wearable sensor models.

MATERIALS AND METHODS

A graphical representation of the proposed methodology is shown in Figure 1. Initially, the open-source dataset of Camargo et al. was used in this study, which included lower-extremity biomechanical and wearable sensor signals [30]. Then, biomedical signal processing and feature extraction methods are outlined for classifying the data from wearable sensors. Finally, machine learning techniques were presented to classify human lower-extremity activities.

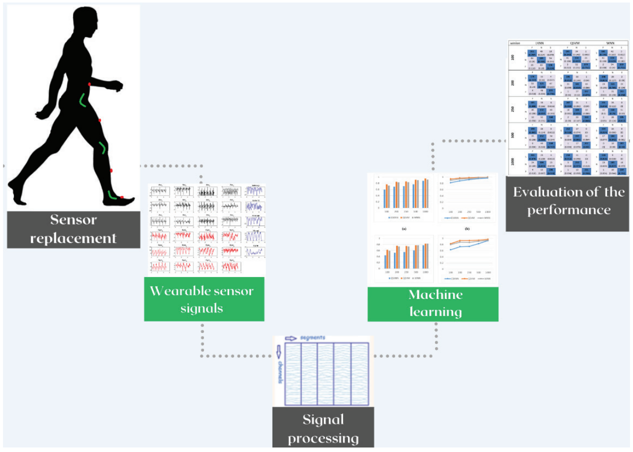


Figure 1. The overall procedure for the classification of human gait.

In this dataset, level-ground locomotion of the human lower extremity was performed at three distinct walking speeds using data from four IMU, three goniometer, and eleven EMG wearable sensors. Demographic information of 22 healthy individuals in this dataset is shown in Table 1. With respect to each subject's preferred speed, a total of thirty repetitions of level-ground walking have been performed at each of three self-selected speeds: fast (F), normal (N), and slow (S). Fast, normal, and slow walking speeds (mean ± standard deviation) have been calculated using the average pelvic velocities of the subjects and were observed to be 1.45±0.27 m/s, 1.17±0.21 m/s, and 0.88±0.19 m/s, respectively.

The wearable biomechanical sensors have been placed unilaterally on the right side of the subjects when dataset was created. At a sampling frequency of 200 Hz, IMU

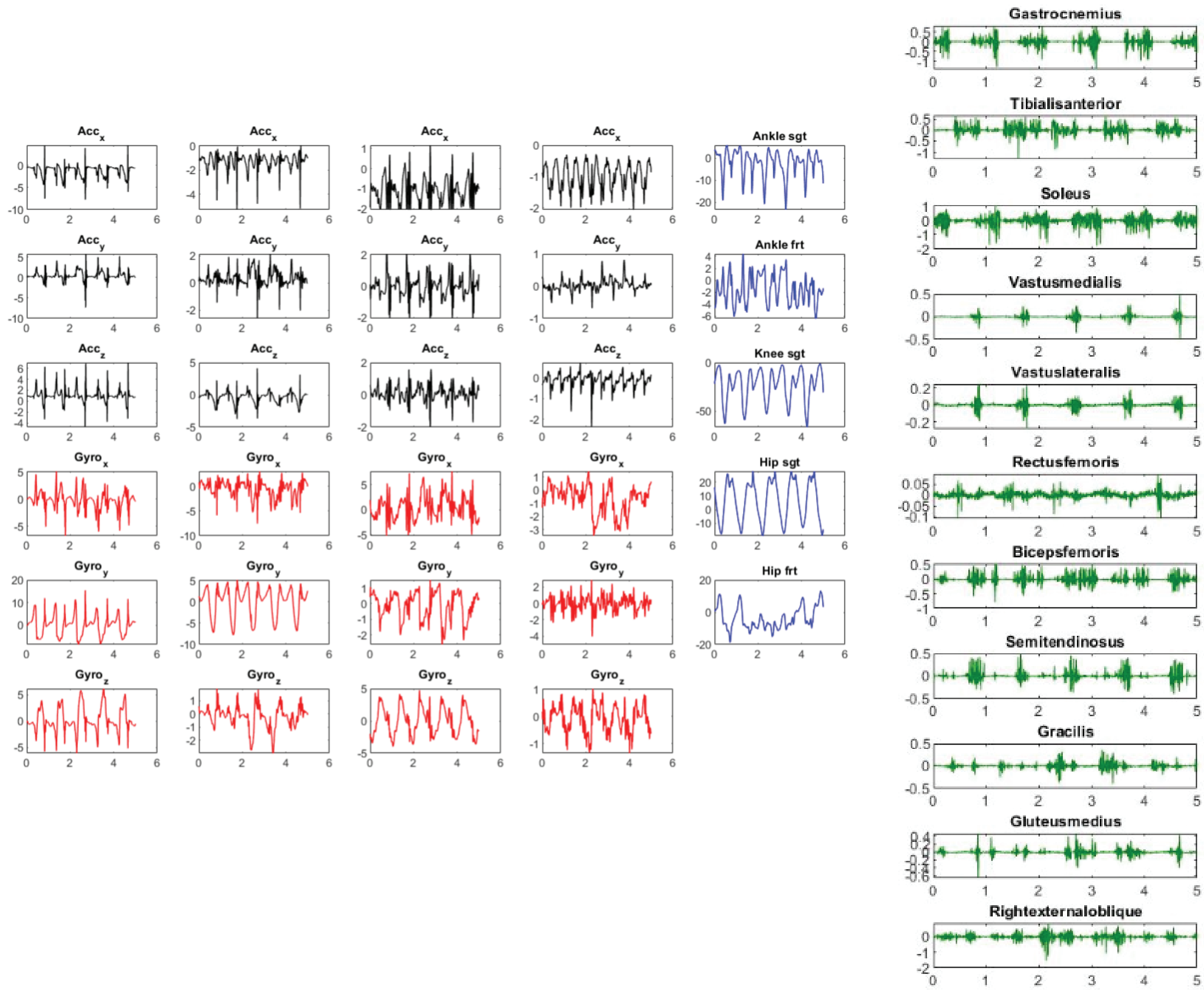
Table 1. Demographic information of subjects in this dataset

Gender	3 females and 19 males
Age	21±3.4 years
Height	1.70±0.07 m
Mass	68.3±10.83 kg

data has been collected from the foot, shank, thigh, and trunk sensors along with a 3-axis accelerometer (Acc_x, Acc_y, and Acc_z) and 3-axis gyroscope ($Gyro_x$, $Gyro_y$, and $Gyro_z$). Goniometer angle data has been collected from the ankle in sagittal and frontal planes, the knee in sagittal planes and, the hip in sagittal and frontal planes, at a sample frequency of 1000 Hz. EMG data has been recorded from Gastrocnemius, Tibialis anterior, Soleus, Vastus medialis, Vastus lateralis, Rectus femoris, Biceps femoris, Semitendious, Gracilis, Gluteus medius and Right external oblique lower extremity muscles with a sampling frequency of 1000 Hz. In signal preprocessing, down-sampling method was applied to balance the sampling frequency of GON and EMG signals with the sampling frequency of IMU, and the sampling frequency of all wearable signals used in the study was obtained as 200 Hz.

Each wearable sensor data varied in duration and also included redundant parts that were at the beginning and at the end of the signal without carrying any information. For this purpose, wearable biomechanical sensor signal processing steps were applied to the signals using MATLAB (The MathWorks, 2021b). As shown in Figure 2, raw wearable sensor signals to clipped with a 5 second (s) duration to standardize signal lengths collected from movement repetitions among different subjects.

Sliding window method, where window size and overlap size are the two main factors affecting segmentation performance, is very popular in the context of human activity recognition and aim to perform the sensor data segmentation preprocessing step. The length of the sliding time window will affect the movement recognition results. If the time window is too large, it may contain information from multiple activities, reducing the responsiveness of the recognition system and increasing the computational load. Conversely, if the time window is too small, some activities may be split into multiple consecutive windows, the



(a) (b) (c) (d) (e) (f)

Figure 2. Wearable biomechanical sensors time series signal channels. **(a)** Foot IMU sensor, **(b)** Shank IMU sensor, **(c)** Thigh IMU sensor, **(d)** Trunk IMU sensor, **(e)** Angles of GON sensor, (f) EMGs of lower extremity muscles.

Table 2. The pseudocode of proposed sliding window feature extraction method

Algorithm Sliding window feature extraction for IMU time series data.

Input: Fs, t, winlen, Wearable_Data

Output: Wearable _labels

```
Calculate nSeg = t / winlen
for i from 1 to nFiles
    Read Wearable _Data
    Store Wearable _ labels[i]= Wearable _Data.fileName for classfication labels
    Compute nChn = length(Wearable_Data(i,:))
    for j from 1 to nChn
      Compute Ct ={cj = Wearable_Data(:,j)}
        for k from 1 to nSeg
            Set segment ranges idx = k : k + winlen -1
            Compute segData = Ct(idx)
            Extract features of segData segfts (:, j, k) = [timeSeriesFts(segData), timeFreqFts(segData)]
            Store average of all segments based on features Wearable _labels{i,2} = mean(segfts)
        end
    end
end
```

recognition task is repeated too often but high recognition results are not obtained. As listed in Table 2, the sliding window algorithm calculates the number of segments (nSeg) by first dividing the signal time length (t) by the sliding window length (winlen). Each channel here represents the wearable sensor degrees of freedom shown in Figure 2. For each channel, time series and time-frequency domain features of each segment were then computed. These sequential tasks were processed for all segments in a channel, and then the average of the segments was determined. Several window lengths of between 100 (0.5s) and 1000 (5s) was analyzed using IMU and GON sensor signals in this study. In addition, in the study, EMG sensors were also included in the experiments to evaluate the motion recognition performance of wearable sensor combinations and the classification performances of the sensor combinations were compared.

The features were extracted from each signal segment segmented by the sliding windows method, and the average of these features obtained from the segments was applied as an input to machine learning. While mean, maximum (max), standard deviation (std), minimum (min), median absolute deviation (mad), interquartile range (iqr), and area of under curve (AUC) were used as the signal time series features, the time-frequency domain features were max, skewness, kurtosis and AUC calculating Fast Fourier Transform (FFT) of each wearable signal channel [21-23]. The degrees of freedom and number of extracted features for single and multiple wearable sensors are given in Table 3.

The extracted feature matrix and classification procedures compose the two sections of the ML classification procedure. Initially, the extracted feature matrices were constructed to the type of the wearable sensors based on

Table 3. Extracted feature matrix of wearable sensor signals for ML models

Sensor combination	Number of sensors	Degree of freedom of sensors	Number of extracted features
IMU	4	24	24*11 = 264
GON	3	5	5*11 = 55
EMG	11	11	11*11 = 121
IMU-GON	9	29	24*11 + 5*11 = 319
IMU-EMG	15	35	24*11 + 11*11 = 385
GON-EMG	9	16	5*11 + 11*11 = 176
IMU-GON-EMG	20	40	24*11 + 5*11 + 11*11 = 440

Table 4. Machine learning model training hyper parameters.

ESKNN	QSVM	WNN
Ensemble method: Subspace	Kernel function: Quadratic	Number of fully
Learner type: Nearest neighbors	Kernel scale: Automatic	connected layers: 1
Number of learners: 30	Box constraint level: 1	First layer size: 100
Subspace dimension: 132	Multiclass method: One-vs-One	Activation: ReLU
	Standardize data: true	Iteration limit: 1000

the sliding window length. In this study, there was a total of 675 class labels, consisting 225 'F', 221 'N', and 229 'S' labels. Then, ML classification section were evaluated using MATLAB (The MathWorks, R2021b) Classification Learner Toolbox. The classification process was performed using three different ML algorithms, which are frequently employed in human movement classification problems: Ensemble Subspace K-nearest neighbors (ESKNN), Quadratic Support Vector Machine (QSVM) and Wide Neural Networks (WNN). The K-Nearest Neighbors (KNN) non-hierarchical clustering approach detects input data characteristics based on likely similarity with their neighbors. A neighborhood has been set to contain k points, and the closest neighbors of a query point are determined using a distance metric such as the Euclidean distance. Support vector machine (SVM) is a supervised classifier that transforms human gait data, which is fundamentally nonlinear data, into a higher dimensional feature space via different kernel approaches including linear, polynomial, and Gaussian RBF. This classification is achieved by finding the most appropriate separating hyperplane that provides the balance between the maximum margin width and the minimum classification error between the predicted classes. A multilayer feed forward neural network known as an ANN consists of a collection of interconnected neurons, with connections between units occurring solely through hidden layers from input to output layers. All ML models were analyzed with the training hyper parameters included in Table 4 with repeated 10-fold cross-validation to avoid over-fitting.

Performance metrics such as accuracy, receiving operating curve-area under curve (ROC-AUC) and confusion matrix are used to determine how well the analyzed ML classifiers perform on the training, test and validation set. When a model correctly classifies positive and negative classes, the outputs are True Positive (TP) and True Negative (TN), respectively. Similarly, False Positive (FP) and False Negative (FN) are the model's outcomes when the positive and negative classes are misclassified, respectively. Classification accuracy is calculated by dividing the sum of the TP and TN by the total samples.

RESULTS AND DISCUSSION

The classification accuracies of the ML classifiers using different sliding window length based on IMU and GON sensor for gait classification are shown in Figure 3(a) and in Figure 3(c), respectively. Similarly, AUC-ROC scores of ML classifiers using IMU and GON sensor models are represented in Figure 3(b) and in Figure 3(d). The ML classification accuracies of IMU-based sensor and GON-based sensor were increasing with increased window lengths. The highest accuracies were 0.954 for IMU sensor and 0.828 for goniometer sensor using window length of 1000 (winlen-1000) and QSVM classifier. Similarly, the ROC-AUC score of IMU-based sensor and GON-based sensor were gradually increased with increased window lengths. In case of QSVM and window lengths of 1000, just as the ROC-AUC score of IMU-based sensor reached 0.99, the ROC-AUC score of GON-based sensor reached 0.97.

It can be seen from these graphs that the classifiers have different classification accuracy and ROC-AUC score for IMU and GON sensor models. QSVM has higher accuracy in gait speed recognition compared to other classifiers. In particular, the accuracy in the experiment using sliding window length of 1000 based on the IMU sensor and QSVM classifier is the highest. In IMU sensor, the accuracy was found to be higher than those with the GON sensor. In gait recognition with QSVM classifier using IMU sensor, winlen-1000 (0.954), winlen-500 (0.913) and winlen-250 (0.861) models are seen as the models showing the highest accuracy. Likewise, ROC-AUC scores were also ranked by the accuracy of the models. When the ML classification performance were evaluated using wearable sensors, the overall (all ML classifiers, sensor types and window lengths) accuracies and AUC-ROC scores were 0.954 and 0.99 for IMU sensor and 0.828 and 0.97 for goniometer sensor, respectively.

The number of samples for each walking speed predicted by the ML models was shown in the confusion matrices in Table 5 and Table 6. The true gait speed labels for the samples were also shown in the columns. The parenthesized numbers in the lower row of the table showed the TP percentage, while the blue cells in the top row of the table indicated the TP value for each WS class. The FN value for a certain WS class was the total of the values in all of the cells in a row except for the blue cell.

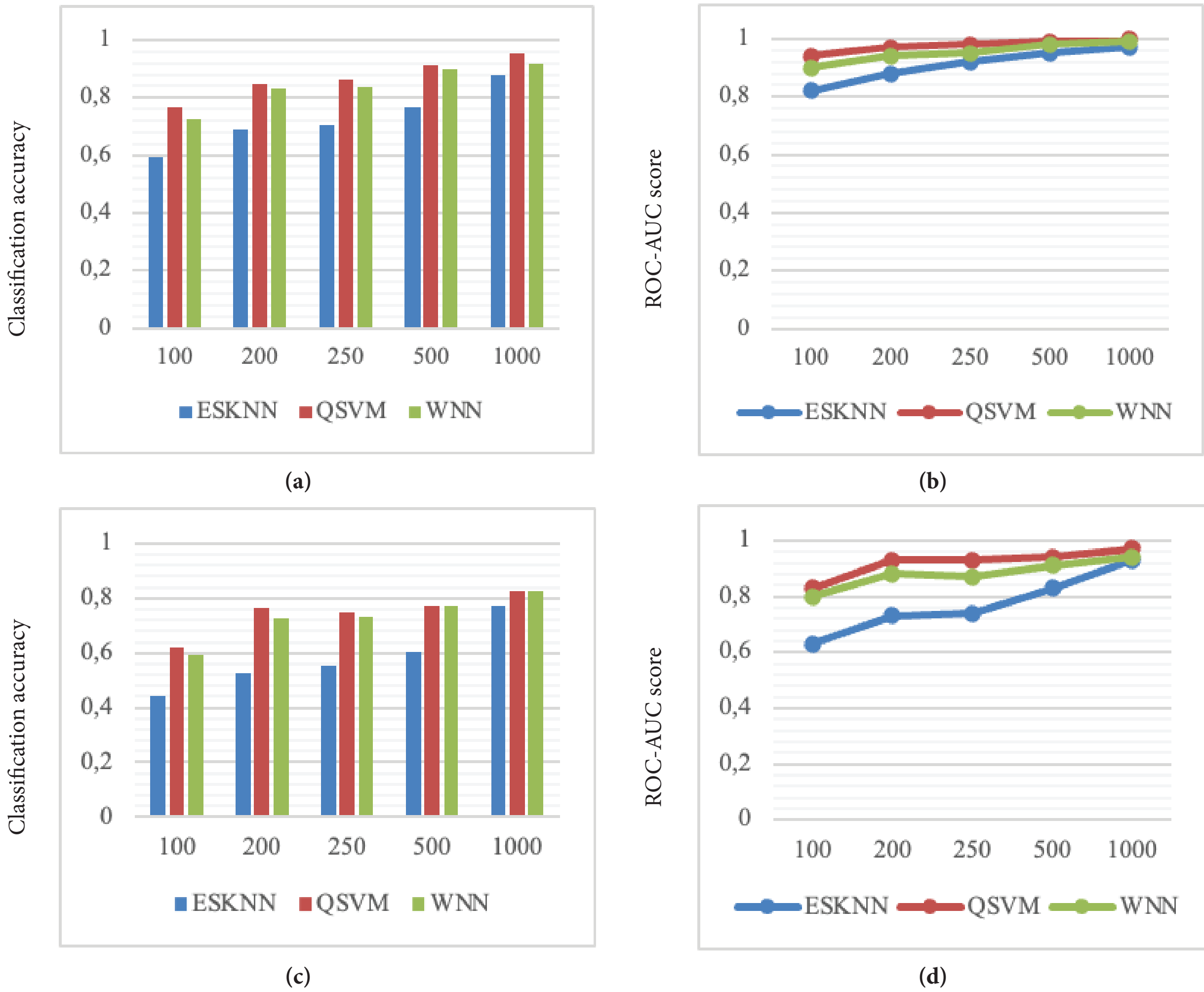


Figure 3. Comparison of IMU-based and goniometer-based sensors ML classification performance. **(a)** Classification accuracy of IMU sensor, **(b)** ROC-AUC score of IMU sensor, **(c)** Classification accuracy of GON sensor, **(d)** ROC-AUC score of GON sensor.

The confusion matrix of the three classifiers using wearable IMU and GON sensor models with various sliding window lengths for gait recognition is shown respectively, in Table 5 and Table 6. In these tables, it can be seen that the three classifiers have different recognition accuracy for the three walking speeds. QSVM has higher TP for walking speed recognition compared to other classifiers. In particular, the TP value and percentage in the experiment using QSVM classifier based on IMU sensor with sliding window length of 1000 is the highest. Unlike, the GON sensor has a lower TP value and percentage, similar to the comparison in classification accuracies. In the experiments, the lowest TP value and percentage of the three classifiers is in the N speed class. Further, using the IMU model and QSVM classifier, the highest TP values for each class of walking speed were S (218), N (215), and F (211), respectively. While using the GON model and QSVM classifier, the highest TP values for each class of walking speed were S (186), N (176), and F (196), respectively.

The classification accuracies of the three classifiers using a sliding window length of 1000 based on EMG and other wearable sensor combinations for human gait recognition are shown in Figure 4(a) and ROC-AUC scores in Figure 4(b). It can be seen from these graphs that the classifiers have different classification accuracy and ROC-AUC score for the five sensor models. QSVM has higher accuracy in gait recognition compared to other classifiers. In particular, the accuracy in the experiment using the IMU sensor and QSVM classifier is the highest among other sensor combinations and classifiers. In combinations with the IMU sensor, the accuracy was found to be higher than those with the EMG sensor. In gait recognition with QSVM classification, IMU-GON (0.961), IMU-GON-EMG (0.919) and IMU-EMG (0.895) models are seen as the models showing

Table 5. Confusion matrices of ML classifiers using IMU-based sensor

winlen	Predicted class	ESKNN			QSVM			WNN		
		Actual class								
		S	N	F	S	N	F	S	N	F
100 (0.5s)	S	**162 (0.707)**	49 (0.214)	18 (0.079)	**193 (0.843)**	34 (0.148)	2 (0.009)	**182 (0.795)**	42 (0.183)	5 (0.022)
	N	64 (0.29)	**103 (0.466)**	54 (0.244)	41 (0.186)	**154 (0.697)**	26 (0.118)	41 (0.186)	**139 (0.629)**	41 (0.186)
	F	26 (0.116)	63 (0.28)	**136 (0.604)**	3 (0.013)	52 (0.231)	**170 (0.756)**	2 (0.009)	54 (0.24)	**169 (0.751)**
200 (1s)	S	**170 (0.747)**	55 (0.24)	4 (0.017)	**195 (0.852)**	33 (0.144)	1 (0.04)	**198 (0.865)**	29 (0.127)	2 (0.09)
	N	53 (0.24)	**121 (0.548)**	47 (0.213)	21 (0.095)	**181 (0.819)**	19 (0.086)	29 (0.131)	**169 (0.765)**	23 (0.104)
	F	4 (0.018)	46 (0.204)	**175 (0.778)**	1 (0.04)	27 (0.12)	**197 (0.876)**	1 (0.04)	31 (0.138)	**193 (0.858)**
250 (1.25s)	S	**185 (0.808)**	38 (0.166)	6 (0.026)	**207 (0.904)**	21 (0.092)	1 (0.04)	**201 (0.878)**	28 (0.122)	0 (0)
	N	46 (0.208)	**132 (0.597)**	43 (0.195)	18 (0.081)	**184 (0.833)**	19 (0.086)	22 (0.1)	**168 (0.76)**	31 (0.14)
	F	13 (0.058)	52 (0.231)	**160 (0.711)**	2 (0.09)	33 (0.147)	**190 (0.844)**	2 (0.09)	28 (0.124)	**195 (0.867)**
500 (2.5s)	S	**198 (0.865)**	26 (0.114)	5 (0.022)	**212 (0.926)**	17 (0.074)	0 (0)	**214 (0.934)**	15 (0.066)	0 (0)
	N	35 (0.158)	**152 (0.688)**	34 (0.154)	12 (0.054)	**197 (0.891)**	12 (0.054)	17 (0.077)	**186 (0.842)**	18 (0.081)
	F	8 (0.036)	49 (0.218)	**168 (0.747)**	1 (0.004)	17 (0.076)	**207 (0.92)**	0 (0)	18 (0.08)	**207 (0.92)**
1000 (5s)	S	**201 (0.878)**	25 (0.109)	3 (0.013)	**218 (0.952)**	11 (0.048)	0 (0)	**220 (0.961)**	9 (0.039)	0 (0)
	N	24 (0.109)	**184 (0.833)**	13 (0.059)	3 (0.014)	**215 (0.973)**	3 (0.014)	20 (0.009)	**185 (0.837)**	16 (0.072)
	F	4 (0.018)	15 (0.067)	**206 (0.916)**	1 (0.004)	13 (0.058)	**211 (0.938)**	1 (0.004)	10 (0.044)	**214 (0.951)**

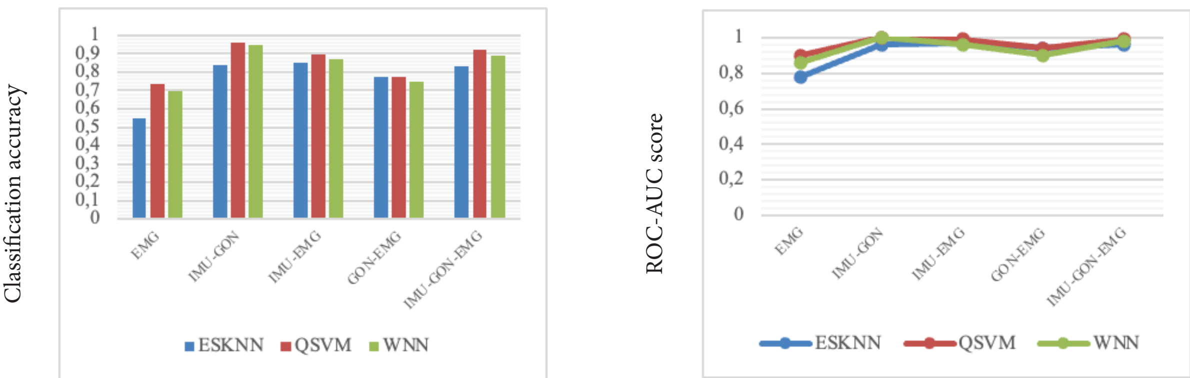
the highest accuracy. Similarly, ROC-AUC scores were also ranked by the accuracy of the models.

The confusion matrix of the three machine learning classifiers using sliding window length of 1000 based on a combination of EMG and other wearable sensors for walking speed pattern recognition is shown in Table 7. In the last rows of Table 5 and Table 6 are shown confusion matrices of three classifiers using sliding window length of 1000 based on IMU and GON sensor, respectively. In these tables, it can be seen that the three classifiers have different TP values for the three walking speeds. QSVM has higher TP for walking speed recognition compared to other algorithms. In particular, the TP value in the experiment using IMU sensor and QSVM classifier is the highest among other sensor combinations and recognition classifiers. In the experiments, the lowest TP value of the three classifiers is in the N speed class. Since it is a gait signal of healthy individuals, S speed class is confused with N speed class and F speed class is confused with N speed class, which is the main reason for the low TP value of N speed class. Further, combining the IMU-GON model and QSVM classifier, the highest TP values for each class of walking speed were S (218), N (213), and F (218), respectively.

The confusion matrices and ROC-AUC scores of the models were compared with three different classifiers to evaluate the human motion classification performance of multiple wearable biomechanical sensor combination models compared to single sensor models with the machine learning approach. Initially, the experiments of IMU and

Table 6. Confusion matrices of ML classifiers using GON-based sensor.

winlen		ESKNN			QSVM			WNN		
		Actual class								
	Predicted class	S	N	F	S	N	F	S	N	F
100 (0.5s)	S	**117 (0.511)**	72 (0.314)	40 (0.175)	**145 (0.633)**	68 0.297)	16 (0.007)	**152 (0.664)**	55 0.24)	22 (0.096)
	N	78 (0.353)	**81 (0.367)**	62 (0.281)	43 (0.195)	**126 (0.57)**	52 (0.235)	56 (0.253)	**98 (0.443)**	67 (0.303)
	F	51 (0.227)	75 (0.333)	**99 (0.44)**	16 (0.071)	61 (0.271)	**148 (0.658)**	18 (0.008)	59 (0.262)	**148 (0.658)**
200 (1s)	S	**113 (0.493)**	75 (0.328)	41 (0.179)	**172 (0.751)**	55 (0.24)	2 (0.009)	**179 (0.782)**	43 (0.188)	7 (0.031)
	N	54 (0.244)	**99 (0.448)**	68 (0.308)	29 (0.131)	**161 (0.729)**	31 (0.14)	41 (0.186)	**143 (0.647)**	37 (0.167)
	F	33 (0.147)	49 (0.218)	**143 (0.636)**	5 (0.022)	38 (0.169)	**182 0.809)**	6 (0.027)	49 (0.218)	**170 (0.756)**
250 (1.25s)	S	**133 (0.581)**	65 (0.284)	31 (0.135)	**177 (0.773**	44 (0.192)	8 (0.035)	**169 (0.738)**	49 (0.214)	11 (0.048)
	N	57 (0.258)	**114 (0.516)**	50 (0.226)	33 (0.149)	**155 (0.701**	33 (0.149)	41 (0.186)	**146 (0.661)**	34 (0.154)
	F	40 (0.178)	59 (0.262)	**126 (0.56)**	2 (0.009)	49 (0.218)	**174 (0.773)**	7 (0.031)	39 (0.173)	**179 (0.796)**
500 (2.5s)	S	**150 (0.655)**	54 (0.236)	25 (0.109)	**181 (0.738)**	41 (0.179)	7 (0.031)	**184 (0.803)**	42 (0.183)	3 (0.013)
	N	45 (0.204)	**130 (0.588)**	46 (0.208)	30 (0.136)	**163 (0.738)**	28 (0.127)	29 (0.131)	**153 (0.692)**	39 (0.176)
	F	27 (0.012)	70 (0.311)	**128 (0.569)**	4 (0.018)	44 (0.196)	**177 (0.787)**	6 (0.027)	34 (0.151)	**185 (0.822)**
1000 (5s)	S	**186 (0.812)**	38 (0.166)	5 (0.022)	**186 (0.812)**	43 (0.188)	0 (0)	**198 (0.865)**	29 (0.127)	2 (0.009)
	N	30 (0.136)	**151 (0.683)**	40 (0.181)	22 (0.1)	**176 (0.796)**	23 (0.104)	27 (0.122)	**167 (0.756)**	27 (0.122)
	F	6 (0.027)	34 (0.151)	**185 (0.822)**	3 (0.013)	26 (0.116)	**196 (0.871)**	2 (0.009)	29 (0.129)	**194 (0.862)**



(a) **(b)**

Figure 4. ML classification performance of multiple wearable sensor combination models. (a) Classification accuracy, (b) ROC-AUC score.

Table 7. Confusion matrices of ML classifiers of multiple wearable sensor combination models

winlen		ESKNN			QSVM			WNN		
		Actual class								
	Predicted class	S	N	F	S	N	F	S	N	F
100 (0.5s)	S	**155 (0.677)**	63 (0.275)	11 (0.048)	**172 (0.751)**	52 (0.227)	5 (0.022)	**168 (0.734)**	50 (0.218)	11 (0.048)
	N	82 (0.371)	**98 (0.443)**	41 (0.186)	46 (0.208)	**153 (0.692)**	22 (0.10)	53 (0.24)	**130 (0.588)**	38 (0.172)
	F	26 (0.116)	82 (0.364)	**117 (0.52)**	9 (0.04)	45 (0.20)	**171 (0.76)**	6 (0.027)	48 (0.213)	**171 (0.76)**
200 (1s)	S	**203 (0.886)**	24 (0.105)	2 (0.009)	**218 (0.952)**	11 (0.048)	0 (0)	**219 (0.956)**	10 (0.044)	0 (0)
	N	29 (0.131)	**160 (0.724)**	32 (0.145)	4 (0.018)	**213 (0.964)**	4 (0.018)	8 (0.036)	**202 (0.914)**	11 (0.05)
	F	6 (0.027)	18 (0.08)	**201 (0.893)**	1 (0.04)	6 (0.027)	**218 (0.969)**	0 (0)	5 (0.022)	**220 (0.978)**
250 (1.25s)	S	**197 (0.86)**	30 (0.131)	2 (0.09)	**207 (0.904)**	22 (0.096)	0 (0)	**210 (0.917)**	19 (0.083)	0 (0)
	N	27 (0.122)	**177 (0.801)**	17 (0.077)	16 (0.072)	**192 (0.869)**	13 (0.059)	24 (0.109)	**174 (0.787)**	23 (0.104)
	F	4 (0.018)	19 (0.084)	**202 (0.898)**	2 (0.09)	18 (0.08)	**205 (0.911)**	2 (0.09)	21 (0.093)	**202 (0.898)**
500 (2.5s)	S	**179 (0.782)**	43 (0.188)	7 (0.031)	**181 (0.79)**	45 (0.197)	3 (0.013)	**187 (0.817)**	38 (0.166)	4 (0.017)
	N	31 (0.14)	**158 (0.715)**	32 (0.145)	36 (0.163)	**163 (0.738)**	22 (0.10)	41 (0.186)	**137 (0.62)**	43 (0.195)
	F	8 (0.036)	30 (0.133)	**187 (0.831)**	2 (0.009)	43 (0.191)	**180 (0.80)**	4 (0.018)	40 (0.178)	**181 (0.804)**
1000 (5s)	S	**201 (0.878)**	25 (0.109)	3 (0.013)	**208 (0.908)**	21 (0.092)	0 (0)	**216 (0.943)**	13 (0.057)	0 (0)
	N	26 (0.118)	**166 (0.751)**	29 (0.131)	8 (0.036)	**205 (0.928)**	8 (0.036)	25 (0.113)	**180 (0.814)**	16 (0.072)
	F	5 (0.022)	25 (0.111)	**195 (0.867)**	1 (0.004)	17 (0.076)	**207 (0.92)**	1 (0.004)	18 (0.08)	**206 (0.916)**

GON sensor models in 0.5s, 1s, 1.25s, 2.5s and 5s time intervals were carried out in order to evaluate the effect of different sliding window lengths on classification performance. The classification accuracies and ROC-AUC scores of these experimental results, in which the sliding window length in the 5s time interval showed high performance in human motion recognition, are shown in Figure 3, and the confusion matrices are shown in Table 5 and Table 6. Then, the EMG sensor model using the sliding window length in the 5s time interval was included in the study and the single and multiple classification performance of the wearable sensor models was analyzed with three different classifiers.

The classification accuracies and ROC-AUC scores of the EMG sensor model and wearable sensor combination models are given in Figure 4, and the confusion matrices are given in Table 7.

IMU-based sensor with window length of 1000 (5s) model has the highest 0.954 classification accuracy for classifying human gait at different walking speeds based on proposed method. As shown in Figure 3(a) and Figure 3(c), among the ML models using different sliding window lengths, window length of 1000 models for all of wearable sensors have the highest classification accuracy, while GON-based sensor with window length of 100 (0.5s) has the lowest classification accuracy. When ML models of GON-based sensor with window length of 1000 was compared to ML models of IMU-based sensor with window length of 200 (1s), the classification accuracy of these models was observed to be close to each other. IMU sensors showed precise classification performance compared to GON sensors even at short window periods. Therefore, IMU sensors can be preferred in human lower extremity movement pattern recognition studies.

The sliding time-window analysis have been frequently used in human activity recognition. Ma et al. have recognized wheelchair users' daily activities using DT and KNN classifiers and 10-fold cross-validation of fixed and adaptive sliding time-window approaches. Although only fixed posture activities can produce good outcomes with a fixed time window, it has been revealed that fixed posture and transition activities are recognized more effectively when applying an adaptive sliding window. Both adaptive and fixed window approaches have been demonstrated to have a 0.90 accuracy rate in recognizing postural activities on level-ground [18]. Noor et al. developed a novel adjustable sliding window approach for human activity recognition based on utilizing a single accelerometer. In this approach, the window size is continuously evaluated based on activity signal analysis. Comparing the proposed adjustable sliding window approach to existing approaches that use fixed windows, the findings of the study revealed that the adjustable sliding window approach reached an accuracy rate of 0.954 in the tests [19].

The classification accuracies of the three classifiers using a sliding window length of 1000 based on only IMU and other wearable sensor combinations for human gait recognition are shown in Table 8, comparatively. It can be seen from this table that the classifiers have different classification accuracy for the seven sensor models. QSVM has higher accuracy in gait recognition compared to WNN and ESKNN classifiers. In particular, the accuracy (0.961) in the experiment using the IMU and GON multiple sensor and QSVM classifier is the highest among other sensor combinations and classifiers. When QSVM classification and gait recognition were compared, the accuracies were found as IMU (0.954), GON (0.827) and EMG (0.735) sensor models, respectively. Then, in dual sensor combination models, the highest accuracy was achieved in IMU-GON (0.961), IMU-EMG (0.895) and GON-EMG (0.776) sensor models, respectively. Finally, the accuracy of the IMU-GON-EMG model, in which all three sensors are included, is 0.919. The findings of this study showed that IMU sensor models improved the classification performance in level-ground gait pattern recognition, and their use together with GON sensor models contributed positively to this performance. It has been found that EMG sensor models show lower classification performance compared to IMU sensor models.

Table 8. Comparison of machine learning models using single and multiple wearable sensors.

	Machine Learning Models		
Sensor combination	**ESKNN**	**QSVM**	**WNN**
IMU	0.876	0.954	0.917
GON	0.773	0.827	0.828
EMG	0.548	0.735	0.695
IMU-GON	0.836	0.961	0.95
IMU-EMG	0.853	0.895	0.868
GON-EMG	0.776	0.776	0.746
IMU-GON-EMG	0.833	0.919	0.892

It can be seen that the proposed method gave results that were roughly comparable to those of the studies mentioned in previous studies, when the wearable sensor combination models and only the IMU sensor model are compared in human gait pattern recognition. Dong et al. evaluated the performance of four algorithms as SVM, ANN, AlexNet and LeNet5 in recognizing gait phases and patterns. Their experimental results showed that with the model using the EMG and IMU signal together, the four algorithms were able to achieve a recognition accuracy of 0.977 for gait phases and an average recognition accuracy of over 0.992 for gait patterns. In the model in which they used only the IMU sensor with the SVM algorithm, they reached 0.941 and 0.987 accuracy for gait phases and gait pattern, respectively [29]. With the same dataset we used in the study, Camargo et al. performed speed estimation in level-ground locomotion using dataset, including EMG, GON, and IMU data. Even with a single IMU, it has been demonstrated that using an IMU sensor for speed estimation rather than an EMG or GON sensor decreases model error. They revealed that ML-based SVM models for determining walking speed had the lowest classification error rate. Additionally, they demonstrated in their study which sensor type is significant for various walking area conditions, indicating that mechanical sensors like IMU and GON are more significant for classification than EMG sensors in estimating walking speed on level ground [28].

These results point out the possible utility of walking speed as biomechanical indicators, from which it can be extended using the sliding time-window method and different machine learning classifiers proposed in this study. The gait recognition approaches in this study include the single use of biomechanical sensor models as well as the multiple use of their different combination models. Table 8 demonstrates that the highest classification accuracy is 0.961 and 0.954, respectively, when the model including IMU and GON sensor and the single IMU sensor model are used to classify human gait with the QSVM classifier. In addition, in the classification of gait pattern with the ESKNN classifier, the lowest accuracy was found to be 0.548 and 0.776, respectively, when the EMG sensor model and the model including the EMG and GON sensor were used. This result can be attributed to the efficiency of the IMU sensor model in correctly addressing temporal gait parameters, and also that EMG sensor models with machine learning approach lag behind IMU and GON sensor models in gait recognition.

CONLUSION

Human movement classification studies can readily be performed using machine learning algorithms and wearable biomechanical sensors. The technique used in this study may also make it possible to track stride length and walking speed on an individual basis for wearable assistive device designs and rehabilitative gait exercise programs. Consequently, there is a clear demand for applicable systems that can accurately categorize human movement and analyze biomechanical data.

In this study, we present a wearable biomechanical sensor-based system for recognizing human walking movement. The proposed approach requires extracting the proposed features, namely time domain and frequency domain features, by segmenting using the sliding windows method from various biomechanical signals based on IMU, GON and EMG sensor data. These variables performed incredibly well in classifying human movement based on walking speeds when applied as inputs for machine learning classifiers. Furthermore, our experiment findings highlighted that the proposed approach was capable of distinguishing between healthy human subjects walking at three different speeds (Fast, Normal, and Slow) and that the IMU sensor and its sensor combination models were able to achieve an average accuracy of 0.932 for movement classification with the QSVM classifier using sliding window length of 1000.

The methodology used in this study may be used as a model for future significant strategies for the complete diagnosis and phase assessment of gait disorders, as well as for the identification of gait biomarkers for assistive and rehabilitation wearable technologies. The outcomes of this study may also help assess the progression of gait disorders by extending machine learning approaches from the research area to the realm of biomedicine. Further study, the same lower limb biomechanics dataset would be utilized to create popular deep learning models like 2D-CNN and LSTM to recognize human activities including ramp and stair movement.

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AUTHORSHIP CONTRIBUTIONS

HK, the machine learning analysis and model, biomedical signal processing, interpretation of the data, original draft preparation and revision of the manuscript. FK, supervision, the development of the machine learning model, and revising of the manuscript. All authors read and agreed to the published version of the manuscript.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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