

Biomechanical sensor signal analysis based on machine learning for human gait classification

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The present study investigates the effect of wearable sensor placements and the use of various machine learning (ML) algorithms for human gait pattern recognition based on temporal gait speeds using wearable multichannel sensor data. Therefore, classifying human gait from features extracted from biomechanical sensor signals and evaluating the effect of using these sensors on gait biomechanics can be successfully achieved with a machine learning approach. In this study, firstly, IMU (Inertial Measurement Unit) and GON (Goniometer) sensor features were extracted for machine learning input using the sliding windows method, and these features were applied to ML classifiers to classify human gait speed. Our experimental findings show that multi- and fusion sensor models provide superior classification performance compared to single sensor models, and the highest accuracy is achieved with the 'FUS09' fusion sensor model and SVM-based classifier. The classification accuracies of the FUS10 fusion sensor model, where all sensor parameters were combined, the FUS09 model, where the GON_ANK and IMU_Ft parameters in this model were excluded, are 0.895 and 0.901, respectively. Consequently, wearable biomechanical sensor data and machine learning approach can be easily preferred in multiple human activity recognition.

Keywords: human gait classification, machine learning, biomechanical data, wearable sensor, biomedical signal processing

1 Introduction

In recent past, one of the emerging fields of research is the recognition of human gait patterns. Gait velocity, also known as self-selected walking speed, is a readily available and reliable screening technique that can be used to provide information about human functional ability and gait biomechanics [1]. In the field of biomechanics, studies on the recognition of human gait using wearable sensors such as IMU have been promising because they can be rapidly implemented in applications to provide accurate and precise outputs. Machine learning algorithms are used with the extracted features from IMU data to classify human gait velocity. ML-based human activity classifiers have been studied in rehabilitative and assisted robotics [2, 3], gait abnormalities [4-6], and elderly care [7, 8].

Generally, gait data are obtained using force plates and Human Activity Recognition (HAR) systems. Vision-based (cameras, movies, etc.) and sensor-based systems are two major categories of HAR systems (wearable, object tagged and device-free) [7, 9, 10, 11]. Vision-based systems have some drawbacks, such as the need for a substantial amount of data storage, difficulties in customizing camera systems for a given environment [12, 13]. On the other hand, wearable sensor technologies, including smartphones, smart watches, and textiles, can be integrated easily into bands, or worn on the body to assess human activity. To sense complex movement tasks, accelerometers, gyroscopes, magneto-

meters, inertial measurement units (IMU), electromyography (EMG), and IoT-based wearables have been extensively employed [4, 14]. Because of their small size, low energy consumption, and light weight, IMU sensors with three-dimensional (3D) accelerometers and gyroscopes are popular in HAR applications.

This study presents a machine learning approach to assess the influence of wearable IMU and GON sensor fusion, as well as single and multiple sensors, on gait speed classification performance. This study suggests a machine learning-based methodology, to assess the effects of wearable IMU and GON sensor fusion, as well as single and multiple sensors, on gait speed classification performances. Several machine learning methods are used to recognize gait patterns using the features that are extracted from wearable sensor signals. Our research focuses on classifying human gait using temporal patterns of gait based on wearable sensor data and evaluate the efficiency of various machine learning algorithms. Our aim is to determine the optimal biomechanical sensor placement and temporal features in human gait speed recognition utilizing machine learning and the sliding window approach:

- i) extensively evaluate the option of optimal biomechanical sensor types and their placement in human gait recognition,
- ii) offer a signal processing framework for multi-channel wearable sensors,

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- iii) analyse the gait recognition potential of IMU and GON sensor ML models with single, multiple, and fusion.

2 Related works

In a study by Bhakta et al. on continuous walking speed determination using embedded IMU sensors for knee and ankle prosthesis with a machine learning approach, they achieved an accuracy of Root Mean Square Error (RMSE): 0.070 ± 0.007 m/s in subject-independent models [2].

Camargo et al. provided detailed information about the best sensor types and placements for human gait recognition in their machine learning-based gait classification study with wearable sensor fusions. They achieved 96% accuracy with the IMU sensors at 0.04 meters per second in ground level walking speed estimation with their proposed system using IMU, GON and EMG sensors [3].

Nasrabadi et al. presented an approach for human activity recognition with IMU sensors for tele-rehabilitation of Parkinson's patients and, achieved sensitivity of over 87%. They also found that only the IMU sensors placed on the thigh achieved high performance in gait recognition with 93% recall [4]. Ferreira et al. investigated stage classification and detection in Parkinson's disease (PD) with machine learning models based on spatiotemporal gait parameters and achieved an accuracy of 0.846 in the detection of the disease [5]. In another study using the machine learning approach in the detection of PD, Trabassi et al. achieved accuracy above 0.80 with Support Vector Machine (SVM) and Decision Tree (DT) models using IMU sensor gait data [6].

De Vos et al. used a machine learning approach to classify neurodegenerative diseases using six wearable IMU sensors. Their study showed that the best classification performance was achieved when all sensors were used, while similar accuracy could be achieved with a single lumbar IMU sensor [7].

In their study to investigate the effect of sensor position on gait identification performance, Dehzangi et al., classified gait with deep learning by placing five IMU sensors on each participant's chest, waist, wrist, and knee [14]. In their study, they aimed to investigate the impact of sensor location on the gait recognition performance and, they achieved 91% gait recognition accuracy. In another study, they extracted instantaneous frequencies in the power spectrum of the multi-component signal by applying two-dimensional (2D)

time-frequency transformation to the gait data obtained with five different wearable inertial sensors. These instantaneous frequencies were used as descriptors of changes in the gait cycle and the findings of the study showed a recognition accuracy of 0.934 [11].

In a study, Zhong et al., investigated walking patterns among young and older adults using an accelerometer-based motion detection system with a smart bracelet. The result of this study showed that the root mean square (RMS) acceleration according to the right ankle accelerometer sensor increased as walking speed increased [15].

In a study by Kecici et al., they classified movements with a machine learning approach using an open-source database obtained from a wearable IMU sensor placed on the thigh, shank, and foot, which combines different human activities such as running and walking [16].

Genc et al used images from a dataset consisting of videos in their human activity recognition studies with the deep Convolutional Neural Networks- Long Short-Term Memory (CNN-LSTM) approach and achieved a classification accuracy of 0.941 [13]. In another study, Kapoor et al proposed a new descriptor evaluated by Finite Element Analysis (FEA) for human activity recognition from video data. The features obtained from this descriptor were classified with SVM and Radial Basis Function (RBF) models using machine learning approach, and 0.902 accuracy was achieved [12].

Ahad et al used wearable sensor based automatic gender and age estimation using gait data. With their proposed angle embedded gait dynamic image and deep learning approach, they achieved a successful estimation result with 0.242 estimation error in gender estimation and 5.39 mean absolute error (MAE) in age estimation [17].

3 Methods

Decision tree-based models classify data by organizing them into a tree structure and making predictions. In these models, a set of separation rules actively separates the features into multiple smaller, non-overlapping regions with similar response values [6, 16].

Support Vector Machine is a supervised learning method that is effective in high-dimensional spaces and when the number of dimensions is greater than the number of samples. A subset of training points called support vectors is used in the decision function. Different kernel functions such as Quadratic, Gaussian, and etc. can be used for the decision function to determine nonlinear decision boundaries with SVM [5, 6, 12].

One of the most common and useful classifiers, the K-nearest neighbors (KNN) algorithm, is a nonparametric classifier that uses supervised learning to classify an individual data point based on the proximity of the data points [4-6].

Ensemble classifiers combine the predictions of several base classifiers developed with a specific learning approach to optimize the generality and reliability of the model on a single classifier [12].

Artificial Neural Networks (ANN) in machine learning allow the classification of unknown data at the output by learning the relationship between the inputs of the data set containing non-linear and complex interactions with the created model [3, 5, 12].

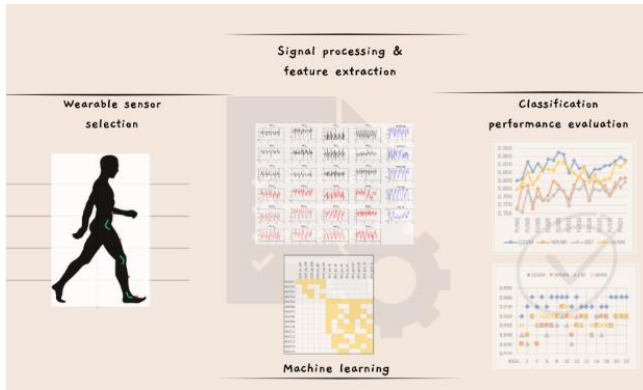


Fig. 1. The overall procedure for the recognition of walking speed

3.1 Biomechanical and wearable sensor (BWS) dataset

In this study, IMU and GON wearable sensor human walking data in level-ground locomotion mode from the open access BWS dataset by Camargo et al. were used. The dataset included walking data of 22 healthy adults (age 21 ± 3.4 years, height 1.70 ± 0.07 m, mass 68.3 ± 10.83 kg), 3 females and 19 males. A total of thirty recordings were available, with each subject having three different preferred walking speeds according to their own walking speed, and the three different walking speeds were labelled according to speed classes in the dataset. Walking speeds - fast (F), normal (N), and slow (S) - were indicated as 1.45 ± 0.27 m/s, 1.17 ± 0.21 m/s, and 0.88 ± 0.19 m/s, respectively, according to the average pelvic velocity of all subjects.

Wearable biomechanical sensors in the dataset were placed only on the right side of the subjects. The IMU data with six degrees of freedom including a three-axis accelerometer (acc) and a three-axis gyroscope (gyro) were placed on the foot (Ft), shank (Sh), thigh (Th) and trunk (Tr) with a sampling frequency of 200 Hz. The goniometer data recorded with a sampling frequency of

1000 Hz consisted of the ankle (ANK) in the sagittal (sgt) and frontal (frt) planes, the knee (KNE) in the sagittal planes and the hip (HIP) angles in the sagittal and frontal planes. In the signal pre-processing step of our study, the sampling frequency of all sensors was used as 200 Hz with the down-sampling method to balance the sampling frequency of the GON and IMU.

3.2 Biomechanical signal processing

Each wearable sensor data varied in duration and included redundant parts that were at the beginning and at the end of the signal without carrying any information. For this purpose, wearable signal preprocessing steps were applied to the signals using MATLAB (The MathWorks, 2021b). SGolay filter was initially applied to raw sensor signal to eliminate signal noise, then subsequently clipped with a 5 second (sn) duration to standardize signal lengths collected from movement repetitions among different subjects.

Table 1. The algorithm of sliding window feature extraction method

Algorithm: Sliding window feature extraction for wearable sensor data

Input: Fs, t, seglen, IMU_Data

Output: IMU_labels

```

1: Calculate nSeg = t / seglen
2: for i from 1 to nFiles
3:   Read IMU_Data
4:   Store IMU_labels{i,1} = IMU_Data.fileName for
   classification labels
5:   Compute nChn = length(IMU_Data(i,:))
6:   for j from 1 to nChn
7:     Compute Ct = {cj = IMU_Data(:,j)}
8:     for k from 1 to nSeg
9:       Set segment ranges idx = k : k + seglen -1
10:      Compute segData = Ct(idx)
11:      Extract features of segData segfts(:, j, k) =
      [timeSeriesFts(segData), timeFreqFts(segData)]
12:      Store average of all segments based on features
      IMU_labels{i,2} = mean(segfts)
13:    end
14:  end
15: end

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The sliding window algorithm calculates the number of segments (nSeg) by first dividing the signal time length (t) by the segmentation length (seglen) for IMU sensor data as listed in Table 1. 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. While mean, maximum (max), standard deviation (std), minimum (min), median absolute deviation (mad),

interquartile range (iqr), and area of under signal (AUS) were used as the signal time series features, the time-frequency domain features were max, skewness, kurtosis and AUS calculating Fast Fourier Transform (FFT) of the signal.

3.3 Machine learning

Classification with machine learning approach is considered in two parts as feature extraction and classification. Initially, feature matrices extracted from wearable sensor signals were also obtained in different combinations to evaluate the effect of sensor fusion on the classification performance. In this study, there were a total of 675 class labels consisting of 225 'F', 221 'N' and 229 'S' labels. In the ML classification section, three groups were evaluated using MATLAB Classification Learning Toolbox: single sensor (SGL) and multiple sensors (MLT) and, sensor fusion (FUS). IMU and GON sensor selection according to the sensor parameters used in the machine learning model is shown in Fig. 2.

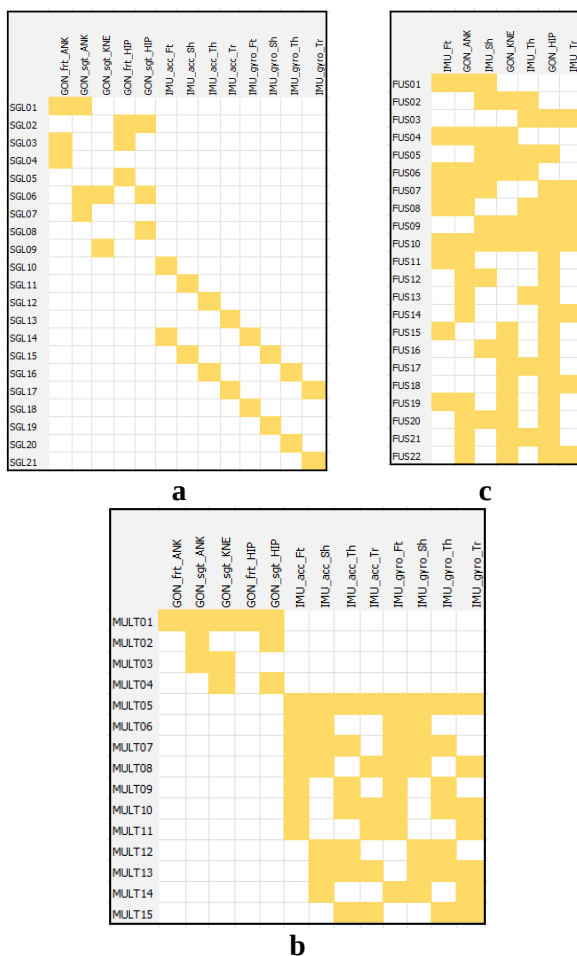


Fig. 2. Sensor selection and machine learning models: (a) single sensor, (b) multiple sensors, (c) sensor fusion

The classification step was performed using eight different ML algorithms frequently used in HAR problems: Fine Tree (FT), Quadratic Support Vector Machine (QSVM), Medium Gaussian Support Vector Machine (MGSVM), Fine Gaussian Support Vector Machine (FGSVM), Cubic K-nearest neighbors (CKNN), Wide K-nearest neighbors (WKNN), Ensemble Bagged Trees (EBT) and Wide Neural Networks (WNN). All ML algorithms were analysed with repeated 10-fold cross-validation to avoid overfitting.

Decision tree-based models classify data by organizing them into a tree structure and making predictions. In these models, a set of separation rules actively separates the features into multiple smaller, non-overlapping regions with similar response values.

Support Vector Machine is a supervised learning method that is effective in high-dimensional spaces and when the number of dimensions is greater than the number of samples. A subset of training points called support vectors is used in the decision function. Different kernel functions such as Quadratic, Gaussian, and etc. can be used for the decision function to determine nonlinear decision boundaries with SVM.

One of the most common and useful classifiers, the K-nearest neighbors (KNN) algorithm, is a nonparametric classifier that uses supervised learning to classify an individual data point based on the proximity of the data points.

Ensemble classifiers combine the predictions of several base classifiers developed with a specific learning approach to optimize the generality and reliability of the model on a single classifier.

Artificial Neural Networks (ANN) in machine learning allow the classification of unknown data at the output by learning the relationship between the inputs of the data set containing non-linear and complex interactions with the created model.

The machine learning classifier models were assessed for their classification performance using area under the curve (ROC-AUC) and accuracy metrics. While accuracy represents the overall percentage of correctly classified ML models, a visual illustration of the performance of a model over all thresholds is the ROC-AUC score.

4 Results

In this study, machine learning models are utilized to automatically recognize walking speed-based human walking activity features that have been extracted from wearable IMU and GON sensor time series signals. A comprehensive and comparative analysis of the effects of single, multiple, and fusion wearable sensors selection on the performance of human gait recognition is presented.

The classification accuracies of eight different ML classifiers using only IMU and GON sensors for gait classification are shown in Fig. 3. The highest accuracies were 0.818 for WKNN classifier and SGL06 model and 0.781 for EBT classifier and SGL02 model. It is also seen that SVM based classifiers show superior performance in human gait recognition with single sensor models, while the decision tree-based FT classifier has relatively lower classification accuracy.

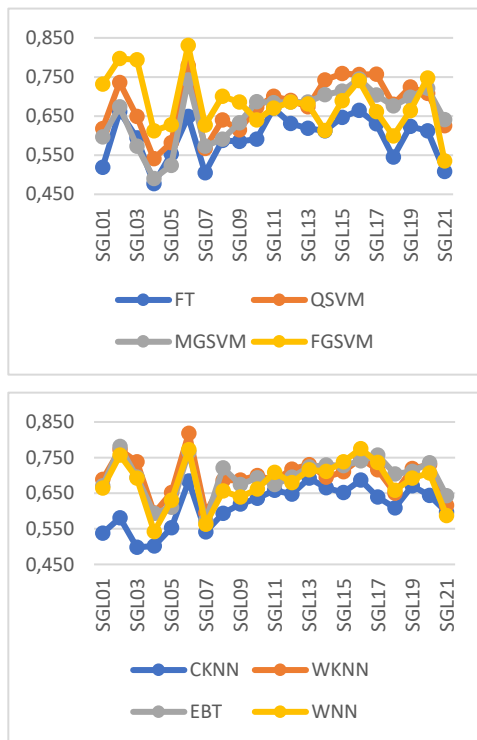


Fig. 3. Classification accuracies of single sensor ML models

The ROC-AUC scores of the ML classifiers in which these single sensor models were analysed are shown in Fig. 4. Similarly, the ROC-AUC scores of these single sensor models are higher than the other models. In addition, when comparing the ROC-AUC scores, it is seen that QSVM and KNN classifiers perform better in recognizing human walking with single-sensor models, while the decision tree-based FT classifier has relatively lower classification performance.

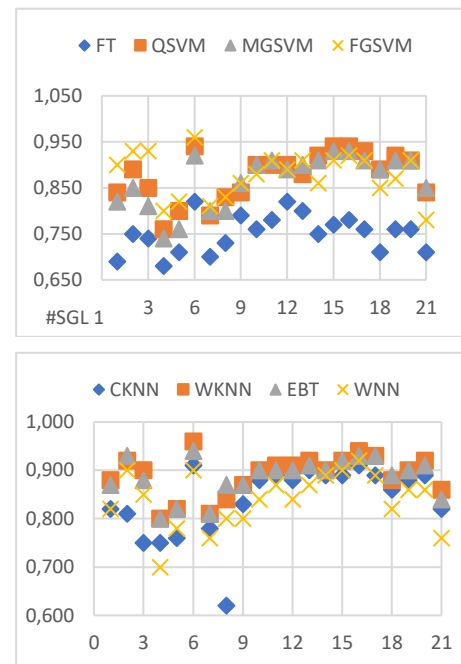
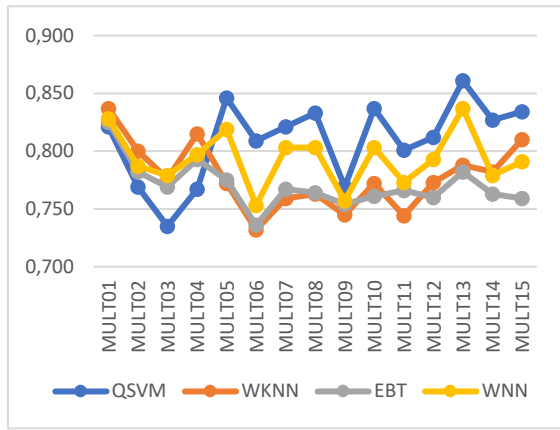
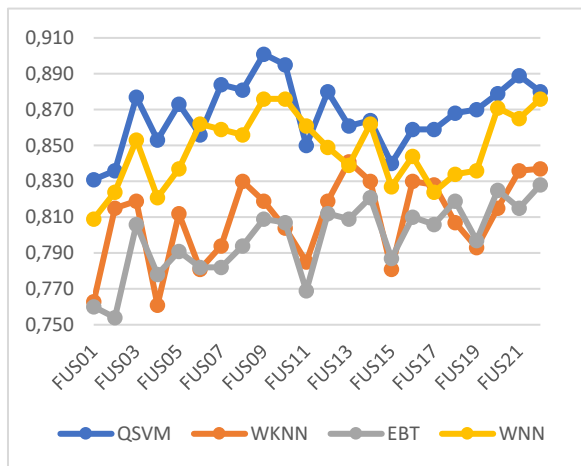


Fig. 4. ROC-AUC scores of single sensor ML models

The classification accuracies of multiple sensor models where GON and IMU sensor parameters are combined with four classifiers for human gait recognition are shown in Fig. 5(a) and ROC-AUC scores are shown in Fig. 6(a). The model accuracies where IMU sensor parameters are combined are higher than those with GON sensors. In gait recognition with QSVM classifier, MULT13 (0.861), MULT05 (0.846) and MULT10 (0.837) models are the multi-sensor models with the highest accuracy. Similarly, the ROC-AUC scores of these models were found to be the highest compared to the others with 0.97.



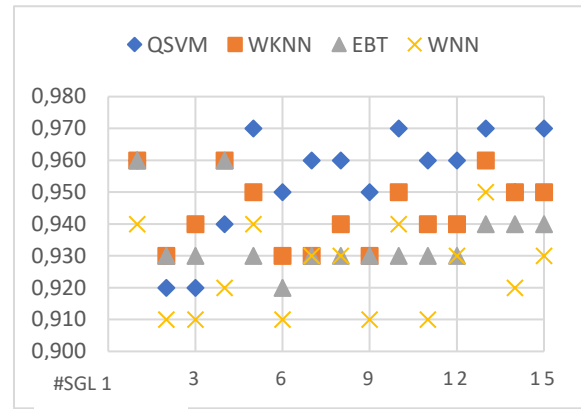
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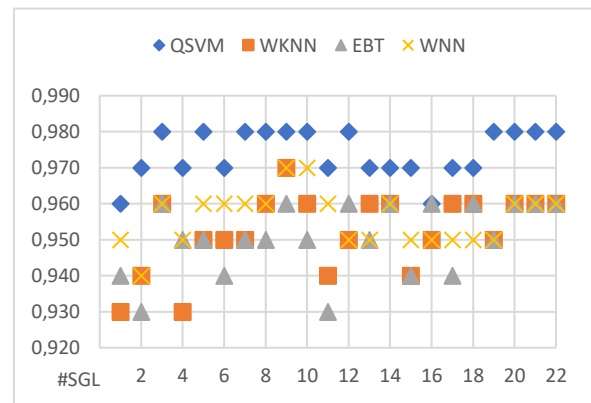
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Fig. 5. Classification accuracies of, (a) multiple sensor models, (b) sensor fusion

The classification accuracies of fusion models where wearable GON and IMU sensor parameters located biomechanically close to each other are shown in Fig. 5(b) and ROC-AUC scores are shown in Fig. 6(b) according to different classifiers in human gait recognition. The FUS09, FUS10 and FUS21 models analysed with the QSVM classifier have the highest recognition performance with classification accuracies of 0.901, 0.895 and 0.889, respectively, while the FUS01 and FUS02 models analysed with the EBT classifier have the lowest classification performance with accuracies of 0.760 and 0.754, respectively. It was found that QSVM and WNN classifiers have higher accuracy and ROC-AUC scores in human gait recognition with multiple and fusion sensor models.



a



b

Fig. 6. ROC-AUC scores of (a) multiple sensor models, (b) sensor fusion

5 Discussion

The present study aims to develop machine learning models based on wearable biomechanical sensors data to identify human ground-level walking motion. Comparing the suggested method to earlier studies, it showed similar classification performance in the problem of human walking speed recognition. The proposed approach presents valuable information to help potential investigators comprehend the significance and variations in sensor placement in human gait biomechanics.

The classification accuracies and ROC-AUC scores of wearable sensor models are compared with different machine learning classifiers to evaluate the effects of single, multiple and fusion biomechanical sensor models on human gait recognition performance. Firstly, experiments were conducted with single IMU and GON sensor models to evaluate the classification performance of models in which sensor parameters are directly used. The classification accuracies and ROC-AUC scores of these experimental results, where the models in which IMU sensor parameters are used with the SVM based classifier exhibit better performance in human gait

classification, are presented in Figs. 3 and 4, respectively. Then, the multi-sensor models in which the IMU and GON sensor parameters are combined within their own groups, respectively, and the fusion models in which they are fused according to biomechanical location, were evaluated and the classification performances of these models were analysed with four classifiers. The classification accuracies and ROC-AUC scores of the multi- and fusion sensor models are given on Fig. 5 and Fig. 6, respectively.

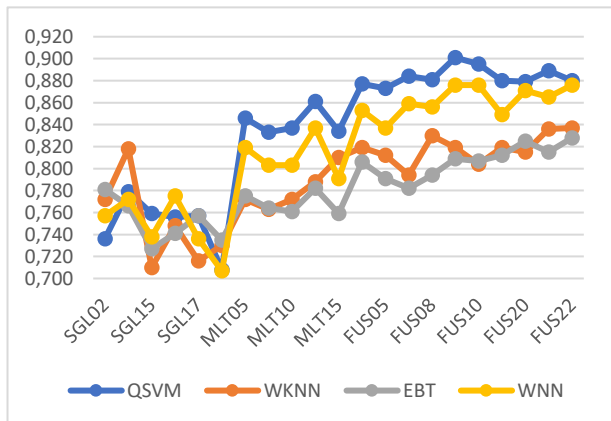


Fig. 7. Comparison classification accuracies of the sensor ML models

The wearable sensor fusion models in Fig. 7 demonstrated the highest classification accuracy of 0.901 compared to other models in gait classification according to walking speeds, in accordance with the suggested human gait identification approach. Furthermore, models with IMU sensor parameters offered better classification accuracy than GON sensor models when single and multiple models were compared, and the analysis using QSVM classifier greatly improved the classification accuracy. When compared to GON sensor models, models with several IMU sensors performed better in terms of classification accuracy. As a result, IMU sensors can be effectively applied in conjunction with machine learning techniques to recognize human gaits.

The classification accuracies of the FUS10 fusion sensor model, where all sensor parameters were combined, the FUS09 model, where the GON_ANK and IMU_Ft parameters in this model were removed, and finally the FUS21 model, where the IMU_Th parameters were added to all GON sensors, are 0.895, 0.901, and 0.889, respectively. In the multi-sensor models, the accuracies of the MULT13 model, which includes all

IMU sensors except the IMU_Ft sensor parameter, the MULT05 model, which includes all IMU sensors, and the MULT10 model, which includes all IMU sensors except the IMU_Sh sensor parameter, are 0.861, 0.846, and 0.837, respectively. In the single-sensor models, the highest accuracy is 0.818 with the SGL06 model, which uses all GON sensor parameters in the sagittal plane.

The findings of our study showed that legs are the best wearable sensor placement compared to torso for human walking speed classification. It was found that IMU sensors placed on the shank, thigh and trunk and GON sensors in the sagittal plane increased the classification accuracy. Our study also showed that fusion sensor models provide superior classification performance compared to multi-sensor models. Some previous studies have shown that walking speed estimation can be performed only with IMU sensors, and the shank is the most important sensor placement [3]. In another study on gait classification based on single and multiple IMU sensor placements, it was presented that the best option for single sensor placement was thigh, while for multiple sensor placement, waist and thigh sensors were used together [4].

Figure 7 shows that SVM-based classifier provides higher accuracy in human gait recognition. Then, ANN-based classifiers and KNN-based classifiers provided high classification accuracy. A previous study clearly classified gait data recorded with IMU sensor for PD diagnosis with 0.808 accuracy with SVM-based classifier [5]. One of the previous similar studies also revealed that KNN classifier has low RMSE and high recall performance [4]. Another study on classifying actions by extracting feature vectors from human poses showed that SVM-based and ANN-based classifiers provided high accuracy around 0.95 [12]. In our previous study using the same dataset, Short-Time Fourier Transform (STFT) was applied to the IMU signals of gait to obtain time-frequency domain representations. These images were applied to the 2D-CNN input and human gait was classified with 0.859 accuracy [19].

Table 2 presents the classification performances of the current gait recognition studies and the proposed approach comparatively. From here, the functionality of IMU and GON biomechanical sensor parameters in gait pattern recognition comes to the fore. In addition, the sliding windows method and machine learning approach for human gait recognition can be effectively applied for multi-channel wearable sensor signal analysis.

Table 2. Comparison of current human gait recognition studies and the proposed method

Sensor	Signal Processing Method	ML Classifier	Classification Accuracy	Reference
IMU GON EMG	Sliding window method	ANN	0.98	[3]
IMU	Spatial-temporal gait parameters	KNN	0.88	[4]
IMU	Spatial-temporal gait parameters	SVM	0.808	[5]
IMU	Feature extraction of video frames	RBF-SVM	0.95	[12]
IMU	STFT	2D-CNN	0.859	[19]
IMU GON	Sliding window method	SVM	0.901	Proposed method

6 Conclusion

Practical systems that can accurately identify human gait and assess various wearable sensor data sets are therefore highly needed. This work proposes a method for recognizing human gait using wearable sensors and machine learning. Using this method, the impact of several sensor locations of the IMU and GON sensor parameters – single, multiple, and fusion – on the ability to recognize human gait was assessed. Our study conclusion highlighted that the 'FUS09' fusion sensor model and QSVM classifier yielded the greatest accuracy of 0.901. Current studies on human activity recognition demonstrate that the classification performance is improved by analysing multi-dimensional wearable sensor data with a machine learning approach, including new data sets, and modelling this data as big data. Thus, the machine learning approach can be easily preferred in multiple human activity recognition.

Acknowledgment

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