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A Low-Dimensional Feature Vector Representation for Gait-based Parkinson's Disease Detection

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Abstract

Thanks to the developing technology, Parkinson's disease can be detected by using datasets which are obtained from different sources. Gait activity analysis is one of the methods used to detect Parkinson's disease. The gait activity of Parkinson's disease differs from the gait of a normal person. In this study, a support vector machine-based classification method using low-dimensional feature vector representation is proposed to detect Parkinson's disease. Pressure sensors placed under the foot are divided into 3 categories, placed on the heel of the foot, the center of the foot, and the toe. Average stance duration, average stride duration, and average distance are extracted from the heel of the foot and toe. The frequency value obtained from the center of the foot during the walking period is used. Only 4 feature values having $O(n)$ time complexity are used for the classification process. Experimental results point out that the proposed method can compete with similar studies proposed in the literature, even under these few features. According to the experimental results, high classification performance, up to 85%, is obtained under the whole dataset. Moreover, superior classification performance, up to 91%, is obtained when the datasets are evaluated individually.

1. Introduction

Diseases are defined as deteriorations or changes in the intra-corporeal or extra-corporeal [1]. In the literature, various research is carried out to understand the causes of these deteriorations or changes and to find appropriate solutions, accordingly. In this regard, high-performance approaches are proposed for the detection of different disease types.

Diseases are classified based on the systems of the body. For example, Parkinson's disease (PD), Epilepsy [2, 3], and Huntington's disease [4] originate from the body's nervous system. On the other hand, Hepatitis, Celiac, and Diabetes diseases may occur in the digestive system.

Parkinson's Disease (PD) is a nervous system disease that occurs as a result of the deterioration of the "black matter" region in the nervous system, which produces very intense amounts of dopamine [5]. In this disease, the body is not only unable to produce dopamine at the desired level but also it can produce dopamine in a defective way. As a result of dopamine deficiency or defective dopamine, symptoms such as tremors, posture disorders, muscle stiffness, tendency to write small, loss of smell, sleep problems, movement and gait problems, voice disorders, and expressionless face occur in Parkinson's patients [6].

Symptoms of PD such as tremors, muscle stiffness, inconsistent and unbalanced gait, and posture disorder are examined by doctors [6]. However, these symptoms may not be noticed in the early stages of the disease. Therefore, the disease cannot be detected at an early stage. A delay in diagnosis of the patient negatively affects the life quality of the patient and causes a delay in the treatment.

Gait pattern, which is among the symptoms of PD, naturally causes gait differences between healthy individuals and Parkinson's patients. Considering the literature studies, advanced approaches such as neural networks, deep learning, and machine learning approaches are adopted for the detection of gait-based PD. In [7], a Q-backpropagated time delay-based neural network is

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proposed to detect PD. In [8], the principal component approach (PCA) is used to reduce the number of features obtained in the gait analysis.

It is possible to extract comprehensive features by considering the additive and differential relationships between sensor data obtained from the gait patterns of Parkinson's disease and healthy individuals [9, 10].

In [11], statistical features are obtained using PD gait sensor data, then the best distinguishing features are selected among these features using Tabu and particle swarm optimization algorithms.

Parkinson's disease has different symptoms. For example, in addition to the fact that the gait pattern of the PD is different from that of healthy individuals, finger tremors appear more than in healthy individuals. In this context, in [12,13], different datasets are utilized to diagnose PD.

In [14], a support vector machine (SVM) based classification process is performed by evaluating the PD datasets separately. In the classification of Parkinson's patients, kinetic and kinematic features of gait data are used.

In [15], the pre-processing stage is applied to PD and healthy individuals. Then, the histogram is obtained by using one-dimensional local binary patterns. Statistical features are obtained by using these histograms. In the classification phase, different approaches such as Logistic Regression, Random Forest, and K-Nearest Neighbor (KNN) are utilized to detect the PD.

In [16], a perceptron network is used for the detection of PD. In [17], 2-dimensional images were created by utilizing 1-dimensional sensor data. Then, a convolutional neural network (CNN) is applied to these images to detect Parkinson's disease. In [18], the spectrogram 2D images are generated utilizing 1D sensor data. Then, these images are fed into the neural network. In that method, the voice dataset is also used to detect Parkinson's disease. An Artificial Neural Network (ANN) based deep learning model is integrated for the voice dataset. In Table 1, a concise comparison among the related works is provided. The features, the domain information, and the contents of the methods are elaborated in Table 1.

The main contribution of the proposed method (PM) is to use a very small number of features in the detection of Parkinson's disease. By exploring only 1st order statistics of the gait sensor data, a low dimensional feature vector representation is obtained. Using these feature vectors, a simple machine learning-based classification system is proposed to classify Parkinson's patients and healthy individuals.

In Section 2, general information about the Parkinson dataset is given. The proposed method is introduced in Section 3. The experimental results are given and discussed in Section 4. Finally, the conclusion of the paper is given in Section 5.

Table 1. A concise comparison of the related works in terms of domains, features, and methods.

References	Domains	Features	Methods
[7]	Time	Raw Sensor Data	Q-backpropagated Time-Delay Neural Network
[8]	Time	Stance Phase and Swing Phase	PCA
[9]	Frequency	Statistical Features	Neural Network with Resilient Backpropagation Algorithm
[10]	Frequency	Statistical Features	Neural Network with Weighted Fuzzy Membership Functions
[11]	Time	Statistical Features	Best First Tree, Backpropagation Artificial Neural Network, SVM and KNN
[12]	Time-Frequency	Phases of Gait Cycle	Linear Discriminant Analysis
[13]	Time-Frequency	Phases of Gait Cycle	SVM
[14]	Time	Phases of Gait Cycle	SVM
[15]	Time	Statistical Features	KNN, Random Forest.
[16]	Time	Statistical Features	MLP
[17]	Time	Raw Sensor Data	CNN
[18]	Time	Raw Sensor Data	CNN and ANN

Table 2. PhysioNet Dataset.

Dataset	Status	Number of Participants	Average Age	Gender (Male)	Average Height (m)	Average Weight (kg)
GA	**Healthy Individuals**	18	72	%56	1,67	72
	PD Patients	29	71	%69	1,70	74
JU	**Healthy Individuals**	25	65	%48	1,69	71
	PD Patients	29	67	%55	1,66	70
SI	**Healthy Individuals**	29	58	%65	1,68	74
	PD Patients	35	62	%63	1,67	73
ALL	**Healthy Individuals**	72	66	%56	1,68	72
	PD Patients	93	64	%63	1,68	73

2. Parkinson Dataset

In this study, the PhysioNet dataset [19], which depends on pressure sensor data placed under the foot, is used. The dataset consists of three different sub-datasets, namely GA, JU, and SI [20-23]. Detailed information about the dataset is given in Table 2.

During the walking activity, 8 sensors, $S_i \in R^{n\times 1}$, are placed on the right and left soles, respectively, as shown in Figure 1. n corresponds to the length of the sensor data. Vertical ground reaction force (VGRF) data is gathered from these sensors. 100 samples are taken per second as a result of the sampling process. Necessary data is obtained from a 2-minute walking period. Walking activities are applied to Parkinson's patients and healthy individuals under the same conditions.

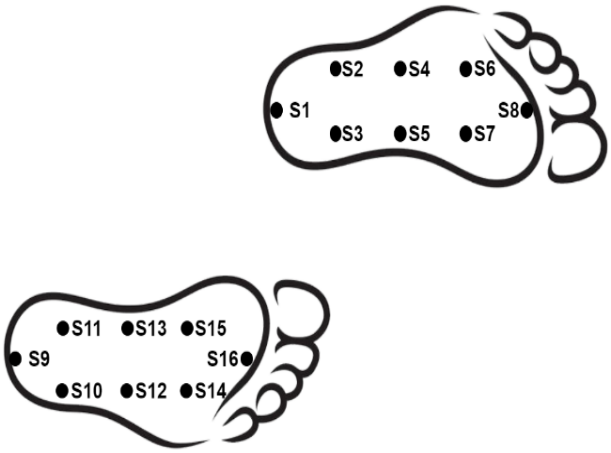


Figure 1. Locations of the sensors placed on the sole of the foot.

3. Proposed Method (PM)

In this section, some important notions about gait are provided before introducing the PM. Gait is defined as moving from one place to another as a result of the coordinated movement of muscle and bone structures [24]. The gait consists of two phases, the stance phase and the swing phase. The stance phase begins with the heel of the foot in contact with the ground. It continues until the contact of the toe with the ground is cut off. It is sufficient to evaluate the stance phase for only one foot. The time elapsed during the stance phase is called the stance duration. The swing phase starts from the moment the toes stop contacting the ground. It ends when the heel of the foot comes into contact with the ground. It is sufficient to evaluate the swing phase for only one foot. The time elapsed during the swing phase is called the swing duration. During the gait, the stance and swing phases continue in cycles. Evaluation of both together corresponds to the stride. The stride begins as soon as the heel of the foot touches the ground. It continues until the next heel contact of the same foot. The time elapsed during the stride is called stride duration. The distance traveled in one step corresponds to the stride distance.

In this study, stride durations, stride distances, and stance durations are considered feature vectors for the detection of Parkinson's disease. PM also leverages the frequency information of the sensors to show how dominant each sensor is during gait activity. Using the introduced feature vectors, a machine learning-based classification method is proposed. The flowchart of the classification stage of the PM is shown in Figure-2. Each step of the classification method is discussed in the subsections given below.

3.1. Pre-Processing

Sensor data is an inherently noisy form. In this regard, the PhysioNet dataset used in this study is also noisy. To remove noise from data, a 5-points median filtering is used. After the filtering process, the data are normalized according to the body mass index of the individual.

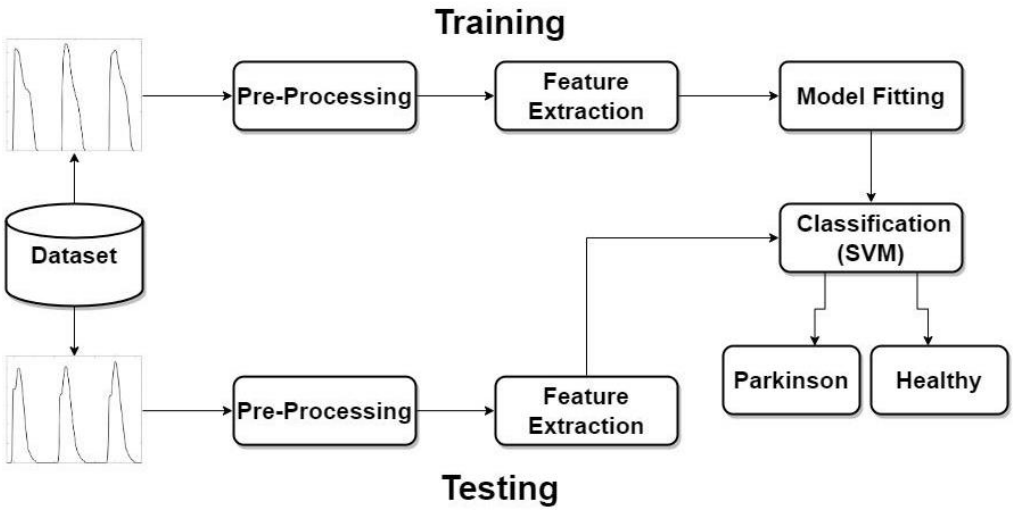


Figure 2. Classification stage of the PM

Moreover, to ignore the initial effect of the gait, the first 20 seconds of the gait are not taken into consideration.

3.2. Feature Extraction

To distinguish individuals with PD from healthy individuals, distinctive features are necessary to be used as a medium. At this stage, features are obtained by using 8 sensors ($S_i, i = 1, 2, \dots 8$) data placed on the sole of the left foot. The methods used to obtain the feature matrix are given in Figure 3. Each feature extraction stage is explained in the following sections.

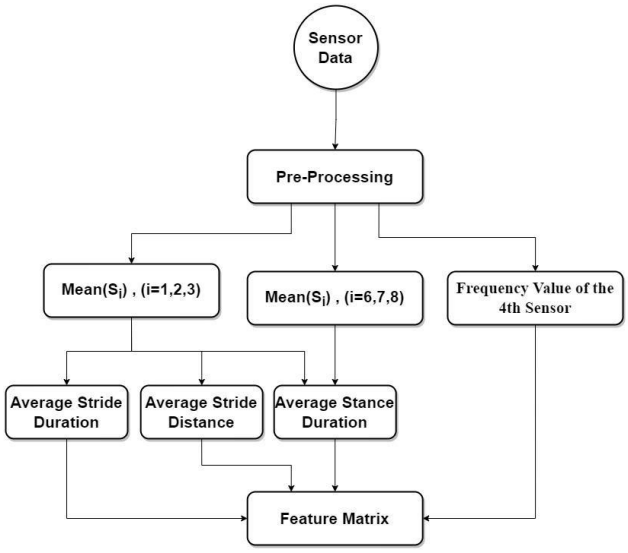


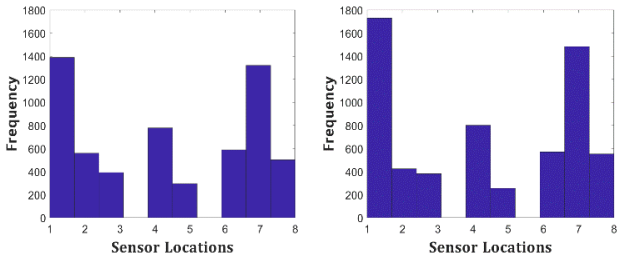
Figure 3. Feature extraction stage of the PM.

3.2.1. Frequency Value of the Sensors

At the feature extraction stage, first of all, the maximum pressure values of the sensor data of the GA, JU, and SI datasets are considered. The distribution of the maximum pressure values for each observation value of the sensors is examined. In this context, histograms are created using the frequency values of the dominant sensors. Sensor-based histogram graphs of GA, JU, and SI datasets are given in Figure 4, Figure 5, and Figure 6, respectively. Histograms are obtained separately for healthy individuals and people with Parkinson's disease. According to the histogram graphs, the differences in the frequency values of the 4th sensor between Parkinson's patients and healthy individuals can be seen. While the difference is clear in the JU and SI datasets, the difference is less so in the GA dataset. In all datasets, the frequency value of the related sensor is found to be lower for healthy individuals than for Parkinson's patients. Exploiting the frequency differences, the frequency value of the 4th sensor for Parkinson's patients and healthy individuals is determined as a feature.

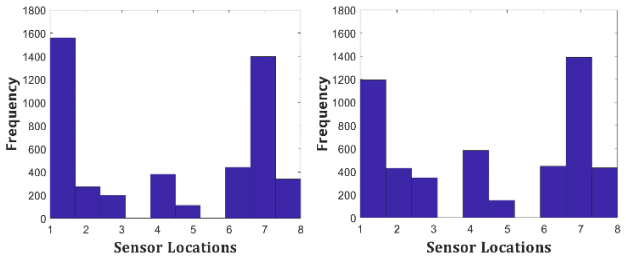
3.2.2. Average Stride Duration and Average Stride Distance

When Figure 4, Figure 5, and Figure 6 are examined, it can be seen that the frequency values of the S_1, S_2, and S_3 sensors are distinctive between healthy individuals and individuals with PD. These sensors are located at the heel of the left foot, as shown in Figure 1. To alleviate computational complexity, S_1, S_2, and S_3 sensors are combined, and the combined sensor is used for the feature extraction process. In this context, the sensor to represent the sole of the foot was calculated by the average of the S_1, S_2, and S_3 sensors. The averaging process is given in Equation (1).



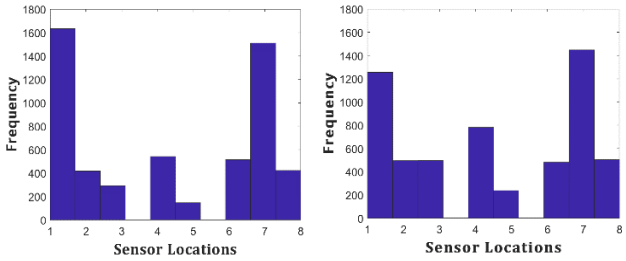
a) b)

Figure 4. Frequency values of the sensors for the GA dataset. a) Healthy individuals. b) Parkinson's patients.



a) b)

Figure 5. Frequency values of the sensors for the JU dataset. a) Healthy individuals. b) Parkinson's patients.



a) b)

Figure 6. Frequency values of the sensors for the SI dataset. a) Healthy individuals. b) Parkinson's patients.

$$\underline{S}_{(1,2,3)} = \frac{1}{3}\sum_{i=1}^{3} S_i \quad (1)$$

Stride duration and stride distance are calculated using $\underline{S}_{(1,2,3)}$. Then, the average of the stride duration and stride distance is calculated. Similarly, the average stride distance is obtained by taking the average of the stride distance.

3.2.3. Average Stance Duration

When Figure 4, Figure 5, and Figure 6 are examined, it can be seen that the frequency values of the S_6, S_7, and S_8 sensors are distinctive between healthy individuals and Parkinson's patients. As shown in Figure 1, the S_6, S_7, and S_8 sensors are located at the tip of the left foot. The same procedure applied for the heel of the foot is performed for the sensors at the tip of the foot. The sensor to represent the tip of the foot is calculated by averaging the S_6, S_7, and S_8 sensors. The averaging process is given in Equation (2).

$$\underline{S}_{(6,7,8)} = \frac{1}{3}\sum_{i=6}^{8} S_i \quad (2)$$

Stance duration is calculated using $\underline{S}_{(1,2,3)}$ and $\underline{S}_{(6,7,8)}$. The average of the stance duration is then calculated.

The features to be used in the classification stage are determined as average stride duration, average stride distance, average stance duration, and the frequency value of the 4th sensor.

3.3. Classification Stage

In this study, an SVM-based binary classification algorithm is preferred. The classification performance of the PM is evaluated under Linear, Gaussian, Polynomial, and RBF kernel functions, separately.

In the classification phase, a 5-fold cross-validation method is applied. Since the number of observations in the dataset is not high, 10-fold cross-validation, which is frequently used in the literature, is not preferred.

4. Results and Discussion

In classification performance evaluation, datasets are considered separately and as a whole. The accuracy, sensitivity, and specificity values are used as performance criteria. To calculate the accuracy, the number of correctly classified predictions is divided by all predictions, as shown in Equation (3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

The TP value represents the number of positive predictions assigned to the correct class. The TN value indicates the number of negative predictions assigned to the correct class. The FP value corresponds to the number of positive predictions assigned to the wrong class. The FN value corresponds to the number of negative predictions assigned to the wrong class. In the classification process, the TP corresponds to Parkinson's patients, while the TN corresponds to healthy individuals. In this paper, sensitivity, specificity, and Matthew's correlation coefficient (MCC) criteria are also considered for performance comparison. MCC score takes a value between -1 and 1 where +1 corresponds to the perfect prediction and -1 means the worst prediction.

Sensitivity, which is known as the true positive rate,

is calculated in the following Equation (4).

$$Sensitivity = \frac{TP}{TP + FN} \quad (4)$$

Specificity, namely true negative rate, is calculated in Equation (5).

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

MCC is calculated as follows,

$$MCC = \frac{(TP \times TN - FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (6)$$

The classification results of the proposed method under different kernel functions are given in Table 3 and Table 4. The experimental results in Table 3 are obtained under maximum classification performance while the experimental results in Table 4 are achieved under average classification performance.

According to the results given in Table 3 and Table 4, it is seen that gaussian and linear kernel classification performs better classification performance, in general. It is important to note that, in the GA, SI, and JU datasets, the numbers of Parkinson's patients and healthy individuals are few. Therefore, incorrect classification of an observation value can cause serious deviations in accuracy values.

Table 3. Maximum classification results according to cross-validation.

	5- Fold Cross Validation			
Dataset / Kernel	**GA**	**SI**	**JU**	**All**
Linear	88.9	84.0	90.9	84.8
Gaussian	88.9	84.6	90.9	84.8
Polynomial	88.9	84.6	90.0	81.8
RBF	88.9	84.6	81.8	78.8

Table 4. Average classification results according to cross-validation.

	5- Fold Cross Validation			
Dataset / Kernel	**GA**	**SI**	**JU**	**All**
Linear	81.1	73.2	85.1	76.9
Gaussian	78.9	78.1	79.6	75.7
Polynomial	78.9	74.8	83.4	74.5
RBF	78.9	75.1	76.0	75.7

Figure 7 shows the receiver operating characteristic (ROC) curve of the proposed classification model. The ROC curve is obtained by calculating Sensitivity and (1-Specificity) values at different threshold values. Considering the area under the curve (AUC), the PM achieves robust classifier performance under different thresholds.

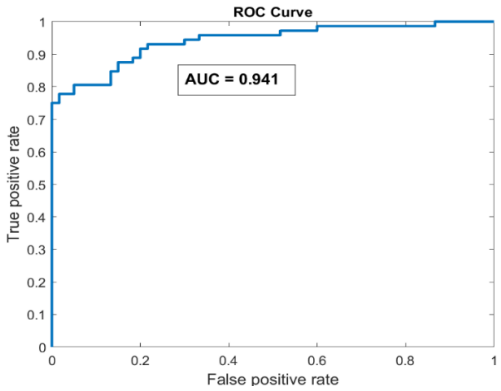


Figure 7. ROC Curve of the Classification Model

Performance comparison between PM and other methods in terms of accuracy is provided in Tablo 5. Similarly, a performance comparison between PM and other methods in terms of sensitivity, specificity, and MCC criteria is given in Tablo 6. The results of the PM in both Tables are obtained under the Gaussian kernel. Comparison is carried out according to each dataset and to the whole dataset, separately. Considering the classification accuracies denoted in Table 5, it has been seen that the classification results obtained with the PM can compete with the other methods in terms of accuracy. Considering the classification results given in Table 6, the PM has satisfactory performance with regard to the compared methods in terms of sensitivity and specificity. As seen in Table 6, the PM has balanced accordance between the predicted classes and the real classes in terms of MCC score.

Table 5. Performance comparison between PM and other methods in terms of accuracy.

	Accuracy			
Dataset / Related works	**GA**	**SI**	**JU**	**ALL**
[7]	91.49	*92.19*	90.91	-
[8]	-	-	-	81.0
[9]	-	-	-	86.7
[10]	-	-	-	77.3
[12]	*92.25*	90.0	*92.5*	86.9
[14]	88.88	**100**	**100**	-
[15]	**92.92**	90.70	76.56	**92.9**
[16]	-	-	-	*88.9*
[17]	-	-	-	88.7
[18]	-	-	-	88.1
PM	88.9	84.6	90.9	84.8

Table 6. Performance comparison between PM and other methods in terms of sensitivity, specificity, and MCC.

	Sensitivity				Specificity				MCC			
Dataset / Related works	**GA**	**SI**	**JU**	**ALL**	**GA**	**SI**	**JU**	**ALL**	**GA**	**SI**	**JU**	**ALL**
[7]	*0.77*	*0.94*	*0.74*	-	*0.55*	**0.90**	**0.83**	-	-	-	-	-
[8]	-	-	-	0.86	-	-	-	0.76	-	-	-	-
[9]	-	-	-	-	-	-	-	-	-	-	-	-
[10]	-	-	-	0.81	-	-	-	0.65	-	-	-	-
[12]	-	-	-	0.72	-	-	-	0.81	-	-	-	-
[14]	-	-	-	-	-	-	-	-	-	-	-	-
[15]	-	-	-	0.88	-	-	-	**0.88**	-	-	-	-
[16]	-	-	-	*0.89*	-	-	-	*0.82*	-	-	-	-
[17]	-	-	-	-	-	-	-	-	-	-	-	-
[18]	-	-	-	-	-	-	-	-	-	-	-	-
PM	**0.86**	**1**	**1**	**0.92**	**1**	*0.60*	*0.80*	0.80	**0.76**	**0.70**	**0.83**	**0.71**

Table 7. Comparison of feature dimension between PM and other methods.

Related works	[7]	[8]	[9]	[10]	[12]	[14]	[15]	[16]	[17]	[18]	PM
Number of Features	60	100	156	40	10	12	30	108	2328	1472	4

4.1. Time Complexity Analysis in Feature Extraction

In a typical classification task, the feature extraction stage can be crucial for the performance of classification. An increase in the number of features can lead to a curse of dimensionality as well as increase the classification performance. As the number of features increases, the feature space also grows. In this regard, the execution time generally increases with the number of features. So, a huge amount of computation can be needed for the classification task. This paper proposes a low-dimensional feature vector representation for the PD classification task.

Table 7 shows the number of features used in PM and in other methods. It can be seen that the number of features used in PM is significantly less than the compared methods. The methods in [17,18] apply to deep learning approaches to obtain features while the method in [8] uses the PCA approach to reduce the dimension of the feature space. On the other hand, the methods in [12, 14] make use of the time-frequency domain, while the methods in [11, 13] use only the frequency domain. Thanks to PM, only 4 features are considered in the time domain.

Besides the number of features, time complexity also needs to be taken into account. Table 8 shows the time complexity of the feature extraction methods used in PM. As seen in the Table, the features can be extracted with $O(n)$ complexity at the worst case.

Table 8. Time Complexity in Feature Extraction

Features	**Time Complexity**
Frequency Value of the Sensors	$O(n)$
Average Stance Duration	$O(n) + O(logn)$
Average Stride Duration	$O(n)$
Average Stride Distance	$O(n)$
Total	$4O(n) + O(logn)$

5. Conclusions

In this study, a low-dimensional feature vector representation is proposed to detect Parkinson's disease. Thanks to the proposed method, a small number of features with low time complexity can be used without compromising the classification performance.

In the literature, a large number of features are usually utilized at the classification stage. In addition, extracting the features from different domains such as time and frequency can increase the computational cost. By implementingthe proposed method, satisfactory classification results are achieved using a small number of features obtained from only the time domain.

According to the classification results obtained with the accuracy criterion, high classification performance, up to 85%, is obtained under the whole dataset. On the other hand, superior classification performance, up to 91%, is obtained when the datasets are evaluated individually. Moreover, according to the sensitivity criterion, the proposed method exhibits the best performance among the compared methods.

Declaration of Ethical Standards

The materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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