Daphnet Freezing Recognition with Gait Data by Using Machine Learning Algorithms

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Abstract*—The aim of this study was to test the success of the data set obtained by a wearable health assistant developed for the symptom of freezing (FOG) in gait of Parkinson's patients and to increase the success of the system. The system was tested with different machine learning methods to measure the success of the wearable health assistant system. For all patients (ten patients), the highest success value was obtained and the mean sensitivity and specificity values of the system were calculated and compared with the results obtained in the literature review. In the literature, mean sensitivity and specificity were 73.1% and 81.6%, respectively; In this study, mean sensitivity and specificity were 91.9% and 71.14%, respectively. In order to better analyze the success of the system, two patients with successful and unsuccessful results were selected for the data set in line with the results obtained in the literature review. The success of the system was tested by using different machine learning methods on the data sets of two patients. Finally, the successes obtained by feature extraction methods were tried to be increased. Among the different machine learning methods on the data sets used for patient 8 and patient 3, the most successful method was obtained by combining the models (ensemble). The highest achievement value obtained by attribute extraction methods was obtained when PCA was applied. However, the success value obtained with raw data could not be increased. All results are tabulated and presented.

Keywords: Parkinson's disease, daphnet freezing, wearable health assistant, machine learning, feature extraction

I. Introduction

Certain parts of the human brain contain brain cells that produce chemicals called dopamine. Cells that produce dopamine in the brain are responsible for control, fluidity and harmony of movement. Due to any problems with brain receptors, dopamine-producing cells may decrease in the amount of dopamine generation. When the dopamine deficiency reaches about 70%, it becomes difficult for brain cells to communicate with each other, and symptoms of Parkinson's disease, a neurological disease, occur [1]. According to Parkinson's Disease Foundation, Parkinson's disease is the second most common neurological disease in the world and there are about ten million Parkinson's patients in the world [2]. Symptoms of Parkinson's disease are examined in two groups; movement-related ones and those that are not movement -related. The main symptoms associated with movement can be tremors in the hands, rigidity-rigidity, slowing down in movements (bradykinesia), gibbosity, dull facial expression, stiffness in the muscles and standing posture disorder [3]. Parkinson's disease decreases the quality of life considerably due to all these symptoms. Symptoms such as step length decrease and decrease in walking speed, bending in the hip and knee joints and tremors in the legs constitute a walking disorder, which causes the patient to fall very frequently. This walking freeze is called FOG (freezing of gait) and is the most common symptom of Parkinson's. FOG is that although the patient wants to walk, they can't put their feet forward or take a very small step [4]. Symptoms of walking disorder in Parkinson's patients are resistant to pharmacological treatment [5]. Rhythmic auditory stimulation (RAS) plays an important role in improving walking for Parkinson's patients [6]. Various methods have been developed by doctors and patients to overcome FOG. For example, pressing the cane, taking advantage of the cracks on the floor, listening to music or changing body weight. External stimuli such as those are considered to alleviate FOG symptoms for Parkinson's patients [7].

II. Data Set and Methods

A wearable health assistant has been developed in the non-pharmacological treatment of FOG. This wearable health assistant will be able to detect FOG online and provide RAS to ensure that the patient continues to be able to move when the FOG incident happens. The wearable health assistant will only work when the FOG incident occurs and, in other cases, will retain its transparency. The wearable health assistant performs these operations with the help of a small computer capable of data recording and online signal processing. The wearable health assistant consists of three sensors, a small computer and a headset in total [8] (Figure 1). Details of the data set are given in the study conducted by Moore and his colleagues [9].

A set of data consisting of nine attributes has been prepared based on the online FOG data obtained. Three values are taken from each sensor. Nine attributes:

- Ankle (shaft) acceleration - horizontal forward acceleration [m/s^2]
- Ankle (shaft) acceleration - vertical [m/s^2]
- Ankle (shaft) acceleration - horizontal lateral [m/s^2]
- Upper leg (thigh) acceleration- horizontal forward acceleration [m/s^2]
- Upper leg (thigh) acceleration- vertical [m/s^2]
- Upper leg (thigh) acceleration- horizontal lateral [m/s^2]
- Body acceleration- horizontal forward acceleration [m/s^2]

- Body acceleration- vertical [m/s²]
- Body acceleration- horizontal lateral [m/s²]

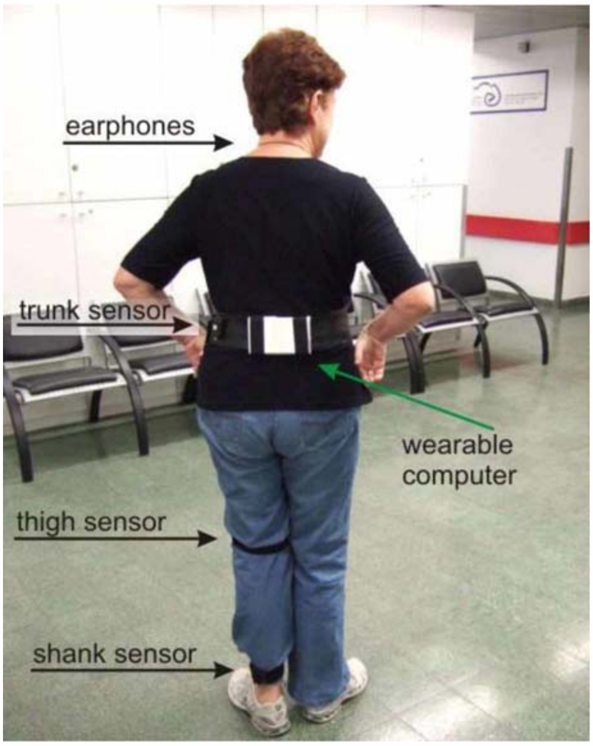

Figure 1. Wearable Health Assistant [8]

There are two classes in the data set. No freezing (FOG) is represented by 0. If there is freezing (FOG), it is represented by 1.

A total of 8 hours and 20 minutes of data was recorded. The study, which was developed with ten Parkinson's patients, observed FOG in eight patients, and two patients had no freezing. Fog events range from 0.5 seconds to 40.5 seconds [8]. 50% of FOG attacks lasted less than 5.4 seconds. Detection performances were evaluated using 0.5 seconds of time zones. As a result of the study carried out in Figure 2, [8], we see the success result achieved for each patient with sensitivity and specificity references. The system has failed to achieve equal success for each patient. Average 73.1% success was achieved for sensitivity. For specificity, an average of 81.6% success was achieved. The most successful results were achieved for the patient 4 and the patient 10. The patient 8 had the worst result with 28.7% in terms of sensitivity. The patient 8 was the patient most affected by Parkinson's [8]. They had the slowest and most limited mobility. The algorithm achieved a failed result because it had difficulty differentiating between voluntary standing and FOG. The most unsuccessful result was achieved with 38.7% in terms of specificity for patient 1. For Patient 1, the algorithm was unable to distinguish between walking times and very short freezing events. For other patients other than these two patients, the algorithm was close to 80% and more than 80% success for some patients. Figure 2 demonstrates the success of the system with a reference to specificity and sensitivity for each patient.

The shared data set consists of measurement results every 15 seconds. Applications were performed for Patient 8 and Patient 3. The closest neighbourhood (k-Nearest Neighbour, K-NN), decision trees (decision tree), support vector machines (Support Vector Machines, SVM), ensemble and bayes methods, which are frequently used in the literature, were compared to classification results.

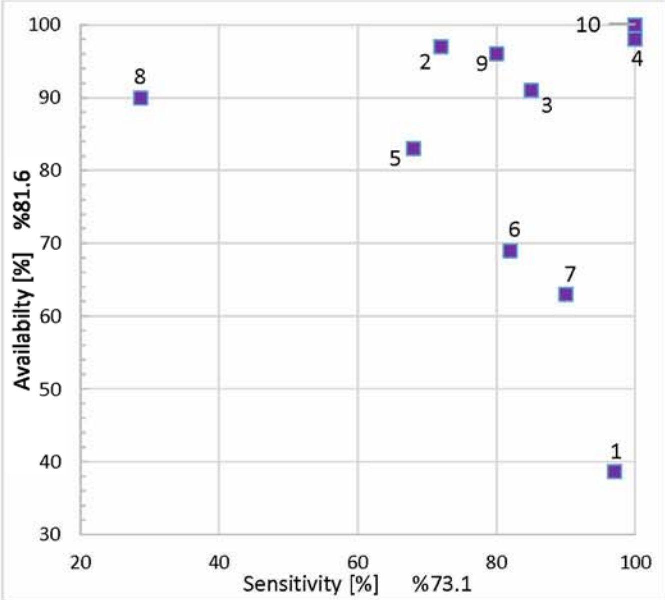

Figure 2. Sensitivity and Availability Distribution for Online Detection Accuracy [8]

III. EXPERIMENTAL STUDIES AND DISCUSSION

The application was performed with 3-minute measurements to increase success for patient 8. Accuracy results were achieved by the nearest neighborhood (K-NN), decision trees (decision tree), support vector machines (SVM), and ensemble methods. By changing the parameters in these methods, the algorithms with the highest success and the parameters they have were tried to be obtained. First, results were obtained with the K-NN algorithm. Cosine was used as a distance criterion. The number of closest neighbors (k) was tried from 1 to 9 and selected 4 'k'. When the nearest number of neighbors was 4 (k=4), there was a classification success of 86.7%. This success result is the highest success achieved for k-NN. In Table 1, we see the success results obtained in other methods. When all the results were examined, the ensemble method within the subspace K-NN parameter had the highest success rate of them all, consisting of exactly 86.8%.

The same studies were tried for the patient 3 in order. The methods and parameters applied are given in Table 2. For patient 3, a more successful result was achieved on predominantly K-NN. Euclid as a distance criterion and reverse square as distance weight were used. The number of nearest neighbours increased from 1 to 8 respectively, with 90.8% for the nearest number of neighbors 6 (k=6). The results for the patient 3 are higher than the 8 patients. This is because, as mentioned in the second section, the patient 8 is the most affected patient from Parkinson's.

TABLO I. Success Percentages for Patient 8

Method	Parameter	Accuracy (%)
Decision Trees	Twoing Rule, Number of Panes=50	%75,6
Decision Trees	Twoing Rule, Number of Panes=100	%74,6
Support Vector Machines	Kernel function = linear	%74,1
Support Vector Machines	Kernel function = gauss	%85
Ensemble	Subspace K-NN	%86,8
Ensemble	Bag Tree	%82,7

TABLE II. Success Percentages for Patient 3

Method	Parameter	Accuracy (%)
Decision Trees	Twoing Rule, Number of Panes=50	%75,6
Decision Trees	Twoing Rule, Number of Panes =100	%74,6
Support Vector Machines	Kernel function = linear	%76,1
Support Vector Machines	Kernel fonksiyonu = gauss	%89,9
Ensemble	Subspace K-NN	%90,9
Ensemble	Bag Tree	%91

Classification achievements were calculated among all patients except patient 3 and patient 8. All results were obtained by K-NN method. The distance criterion was used as Euclidean, the distance weight was reverse square and the nearest neighbor count was 10 (k=10). The highest success is seen in patient 7 with 95.4%. Since the freezing (FOG) event for patient 4 and patient 10 could not be observed, the system success could not be calculated by any method. Then, a graph was created with specificity and sensitivity references in line with the results obtained for each patient in order to better observe the success of the system. This chart is seen in Figure 3.

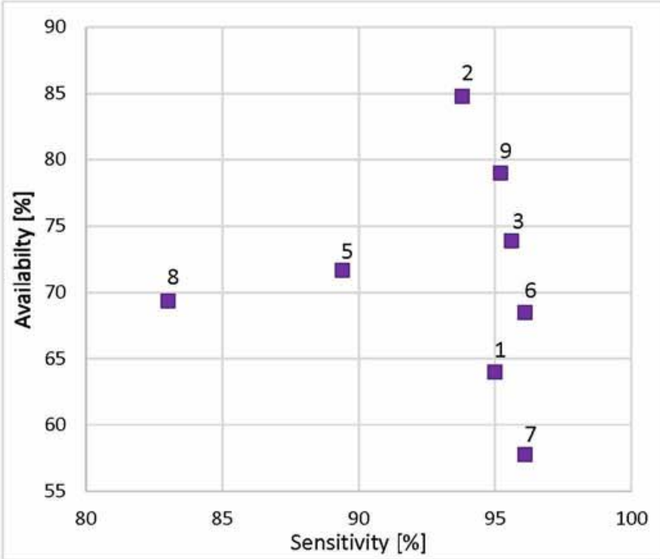

Figure 3. Sensitivity and Specific Distribution for FOG Detection Accuracy

Figure 3 shows the success results achieved with sensitivity and specificity references for patients other than patient 4 and patient 10. On average, the sensitivity and specificity of FOG detection is 91.9% and 71.14%, respectively. The worst result was achieved in terms of sensitivity for patient 8 (83% sensitivity, 69.4% specificity). The worst result was achieved in terms of specificity for patient 7 (96.1 sensitivity, 57.8% specificity). The average sensitivity value increased, and the specificity value decreased compared to the results in [8] (average sensitivity of 73.1%, 81.6%).

For two patients (patient 3 and 8), the success achieved by the methods of removing attributes was tried to be increased. The data obtained for Patient 8 is given in Table 3.

Results obtained by attribute extraction method for Patient 3 are seen in Table 4. The table created for patient 3 was created in the same format as the table created for the patient 8.
The success achieved by raw data was 91%. This success value was tried to be increased by applying attribute extraction methods. All results, methods and parameters obtained are given in Table 4.

TABLE III. Attribute Extraction for Patient 8

ATTRIBUTE EXRACTION	PATIENT 8			
	METHOD	PARAMETER	SUCCESS	RAW DATA SUCCESS
First Measurement Value of The Sensors	Ensemble	Learner Type: K-NN Method: Subspace	81,90%	86,80%

Average Data from The Sensors	Ensemble	Learner Type: K-NN Method: Subspace	81,50%	86,80%
Standard Deviation of Data	Ensemble	Learner Type: K-NN Method: Subspace	77,30%	86,80%
RMS Value of The Sensors	K-NN	Distance Criterion: Euclid k = 15	75,80%	83%
PCA	Ensemble	Component Reduction Criterion: 90	85,60%	86,80%

TABLO IV. Attribute Extraction for Patient 3

ATTRIBUTE EXRACTION	PATIENT 3			
	METHOD	PARAMETER	SUCCESS	RAW DATA SUCCESS
First Measurement Value of The Sensors	Ensemble	Learner Type: K-NN Method: Subspace	81,90%	86,80%
Average Data from The Sensors	Ensemble	Learner Type: K-NN Method: Subspace	81,50%	86,80%
Standard Deviation of Data	Ensemble	Type: K-NN Method: Subspace	77,30%	86,80%
RMS Value of The Sensors	K-NN	Distance Criterion: Euclid k = 15	75,80%	83%
PCA	Ensemble	Component Reduction Criterion: 90	85,60%	86,80%

IV. CONCLUSION

Improvements have been made to contribute to studies in the literature by applying different attribute extraction and classification algorithms to the database prepared for the detection of the FOG event, which is most common in Parkinson's patients. Classification achievements were compared by working especially on patients with the most advanced Parkinson's disease.

When the ensemble method and PCA feature extraction were applied, the highest success value was obtained as 86.6 % for all patients. Compared to the literature, it was observed that the mean success rate increased from 77.35% to 81.52 %%. Higher success has been achieved with fewer features. In the literature, mean sensitivity and specificity were 73.1% and 81.6%, respectively; In this study, mean sensitivity and specificity were 91.9% and 71.14%, respectively. When comparing the literature and the results obtained in this study, a more efficient result was obtained in this study in terms of sensitivity. The most successful result for all patients from different classification algorithms has been the production model merge (ensemble) algorithms. In order to increase the success of the system, success was tried to be increased by selecting two patients with successful and unsuccessful results for the data set according to the results obtained in the literature review. Therefore, it was tried to increase the success with feature extraction and PCA methods. However, although many attribute extraction methods have been tried, success is not increased too much. The same success value was obtained for almost all methods for both patients and the highest success value was found to be 86.6% for both patients. In the continuation of this study, it is aimed to achieve the full data and increase different attribute extraction methods and more comprehensive classification success in less time.

REFERENCES

[1] H. Braak, E. Ghebremedhin, U. R¨ub, H. Bratzke, and K. D. Tredici, "Stages in the development of parkinson's disease-related pathology," Cell and Tissue Research, vol. 318, no. 1, pp. 121–134, October 2004.

[2] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," IEEE Transl. Journal of Magnetics in Japan, Vol. 2, No. 8, 1987, pp. 740-741.

[3] M. M. Hoehn and M. D. Yahr, "Parkinsonism: onset, progression and mortality," Neurology, vol. 17, no. 5, pp. 427–42, May 1967.M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[4] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[5] S. T. Moore, H. G. MacDougall, and W. G. Ondo, "Ambulatory monitoring of freezing of gait in parkinson's disease," Journal of Neuroscience Methods, vol. 167, no. 2, pp. 340–348, 2008.

[6] N. Giladi, M. P. McDermott and C. Tanner, "Freezing of gait in PD: Prospective assessment in the DATATOP cohort," Neurology, vol. 56, no. 12, pp. 1712–1721, 2001.

[7] A. Nieuwboer, W. de Weerdt, R. Dom, and E. Lesaffre, "A frequency and correlation analysis of motor deficits in parkinson patients," Disability and Rehabilitation, vol. 20, no. 4, pp. 142–150, 1998.

[8] Marc B¨achlin, Meir Plotnik, and Gerhard Tr¨oster, Wearable assistant for Parkinson's disease patients with the freezing of gait symptom, 2009.

[9] S. T. Moore, H. G. MacDougall, and W. G. Ondo, "Ambulatory monitoring of freezing of gait in parkinson's disease," Journal of Neuroscience Methods, vol. 167, no. 2, pp. 340–348, 2008.