Classification of Parkinson's Disease Using EMG Signals from Different Upper Limb Movements Based on Multiclass Support Vector Machine

Hamdia Murad Adem[1], Abel Worku Tessema[2], Gizeaddis Lamesgin Simegn[1,*]

[1]*Biomedical Imaging Unit, School of Biomedical Engineering*
Jimma Institute of Technology, Jimma University
Jimma, Ethiopia
E-mails: hamdisha2558@gmail.com, gizeaddis.lamesgin@ju.edu.et

[2]*Ulsan National Institute of Science and Technology*
Ulsan, Republic of Korea
E-mail: abelworku1221@gmail.com

[*]*Corresponding author*

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Abstract: *Parkinson's disease (PD) is the second most common neurodegenerative disease that affects a wide range of productive individuals worldwide. The common approach to diagnose PD is through clinical assessment of the patient, which is highly subjective and time consuming. Electromyography (EMG) can be taken as a cheap way of PD diagnosis. However, highly experienced experts are required to interpret the signals. The manual procedures are complex, time-consuming, and prone to error resulting in misdiagnosis. In this research, an automatic system for detection and classification of PD stages using EMG signals acquired from different upper limb movements is proposed. In addition, effective upper limb movement for the identification of PD has been investigated. The data required for training and testing the system was collected from flexor carpi radialis and biceps brachii muscles of 15 PD patients and 10 healthy control subjects at Jimma University Medical Center. The raw EMG signal was preprocessed and frequency and time-domain features were extracted. A multiclass support vector machine model was then trained for four-class classification (normal, early, moderate, and advanced PD levels). The performance of the system was evaluated using different performance evaluators and a promising result has been obtained. 90%, 91.7%, 95%, and 96.6% overall classification accuracies were obtained for elbow flexion by 90-degrees without load, elbow flexion by 90-degrees with load, touching the shoulder, and wrist pronation, respectively. A user-friendly interface has been also developed for ease of use of the automatic PD classification system.*

Keywords: *Classification, Detection, Electromyogram, Parkinson's disease, Support-vector machine.*

Introduction

Neurodegenerative disease is a general terminology that describes a group of neurological disorders characterized by affecting the central nervous system. These heterogeneous categories of diseases have a major impact on human health. Even though the pathophysiology of the disease's groups are distinct based on the brain part the disease affects [17] these diseases share lots of common degenerative processes that cause neuronal death leading to functional impairments and dysfunctions of brain parts [45]. Because these diseases directly affect the neurons within the brain, irreversible distraction and progressive deterioration of brain

functions can cause the death of functional neurons in the central nervous system [11]. Examples of these diseases include Parkinson's, Alzheimer's, Huntington's, Amyotrophic Lateral sclerosis and others. Patients with these kinds of disease, experience a cognitive decline over a long period. The symptoms include gait abnormalities, problems with speech, and memory loss due to progressive cognitive deterioration that affects memory, thinking, behavior, language, calculation learning and emotion capacity [45]. Physical, mental and social impact of these diseases extend far beyond the obvious characteristics of the diseases' symptoms [11]. Main risk factors for these diseases are genetic causes and increasing age. Other possible risk factors are gender, endocrine conditions, oxidative stress, inflammation, stroke, hypertension, diabetes, smoking, head trauma, depression, infection, tumors, vitamin deficiencies, immune and metabolic conditions, and environmental factors [9].

Parkinson's disease (PD) was found by James Parkinson in 1817 [38]. He medically described this disease as neurological disorder for the first time. But the disease was known in ancient Indian and ancient Chinese before 1000 BC [18]. PD is the fastest growing of neurological disorders which is the leading source of disabilities [15]. It is the second most common neurodegenerative disorder and the most common movement disorder. An estimated number of 10 million people have PD worldwide [4] and 4% of the people are under the age of 50 and most people who develop PD are 55 years of age or older [2]. According to study findings, PD is more common in men than in women [18]. Adult-onset PD is the most common, but early-onset PD (onset between 21-40 years), and juvenile-onset PD (onset before age 21) can occur in some cases [25].

Studies show that, there are low case ascertainments and high selective mortality due to PD in Africa [48]. Ethiopia is one of the countries with high prevalence of PD. A case study that was done for one year in Tikur Anbesa (Black Lion) Hospital showed that 47.7% of movement disorder cases were identified as PD [7]. Even though the prevalence of PD patients in Ethiopia is high, it remains underrecognized and undertreated disease in the country. Moreover, Ethiopian patients with PD experience highest rates PD pain related with poverty [23]. PD causes multilayered psycho-social and economic impact on patients, family members as well as their close relatives.

The most common symptoms of PD are motor symptoms such as, bradykinesia, rest tremor, rigidity, postural disturbances, falls, freezing of gait, speech and swallowing difficulties [31, 33, 36]. And the spectrum of nonmotor symptoms encompasses constipation, bladder dysfunction, hallucinations, difficulty in concentration, dribbling, dysphagia, confusion, fatigue, impulse control disorders, memory problems, mood disorders, orthostatic hypotension, paranoia, sensation of breathlessness, sleep disturbances, sweating, and sexual dysfunction [8].

PD has no definitive way of diagnosis. General diagnosis is done through assessment of motor symptoms and using medical history of patients. The neurologist looks for the presence or absence of the main symptoms of PD such as, tremor, bradykinesia and rigidity by looking facial expressions, signs of tremor while the patient is at rest, conditions of the patient while standing up from sitting and how the patient regain balance. The other method is physician prescribe a medication and based on response of the medication they decide whether the patient has PD or not. These methods need highly experienced neurologists because some symptoms are common to other diseases like, essential tremor and Amyotrophic lateral sclerosis (ALS) [40].

Additionally, neuroimaging tests using magnetic resonance imaging commonly diffusion, perfusion and functional magnetic resonance imaging (MRI) [21], positron emission tomography (PET) scan [12, 39], computed tomography scan (CT) [47] are used as supportive ways for diagnosis of PD. These neuroimaging modalities are used to assess changes in striatal dopamine and to detect subclinical nigral pathology [5]. The use of the electroencephalography (EEG) and electromyography (EMG) methods are also considered as approaches for screening of neuromuscular diseases [20].

PD affects several body muscles causing functional impairments that can be detected using EMG. Several studies have been conducted using EMG to quantify myoelectric activities and better understand the effect of PD on performance of upper and lower limb muscles while the subjects are performing different tasks [16, 30, 34, 43, 46]. Upper limb muscles provide relevant information to detect effect of PD using wrist flexion, elbow flexion and carrying objects activities [34, 43]. Biceps brachii muscle is the main muscle that is used to characterize the morphology and pattern during elbow flexion with different loading conditions. EMG signals acquired from extensor and flexor muscles like, extensor *carpi radialis brevis* and flexor *carpi-ulnaris* muscles are used to quantify the intensity of tremor in patients with PD and to differentiate the disease from essential tremor. The difference between healthy individuals and patients with PD is significant while the subjects are performing different actions such as joint movements, resting, holding, carrying weight [16, 42]. The difference between healthy individuals and patients with PD can also be analyzed using myoelectric signal recordings from tibialis anterior, gastrocnemius medialis and gastrocnemius lateralis while the subjects performing different motor tasks. Pertinent information is found from these muscles because these muscles take the major role for lower limb activities [30, 37]. Isolated lower limb tremor may indicate the onset of many neurological disease [22]. However, unilateral lower limb tremor may not bet necessarily a presenting symptom of PD and lower limb tremor as initial manifestation of PD is unusual [19, 22, 26]. Symptom onset in PD is most common in the upper limb muscles [13].

Even though EMG provides significant information about myoelectric activities which are important for diagnosis of PD, the interpretation of these signals require highly experienced neurologists and the procedures are expensive especially for low resource settings. Hence, diagnosis of PD remains challenging because most methods are dependent on knowledge and experience of physicians.

Numerous approaches have been proposed to classify EMG data for PD detection including Artificial neural network [3], neuro fuzzy system [1], multilayer perceptron (MLP) [12], support vector machines (SVM) [35], linear discriminant analysis (LDA) [6], and K-nearest neighbor (KNN) [10]. In [1] is proposed a fusion of fuzzy and neural networks to classify healthy and Parkinson disease patients. In [6] is also proposed classification and clustering of Parkinson's and healthy control gait dynamics using LDA and K-means clustering technique. However, these and most of the recent works [16, 28, 30] focused only on binary classification (healthy and PD). Staging of PD is important for stage-adapted treatment recommendations. Moreover, investigation of effective muscle group combined with specific movement remains still a challenge and development of an accurate system that can be easily adopted to a clinical practice is essential for diagnosis PD.

In this research, an automatic system has been proposed to identify and classify stages of PD from EMG signals acquired from upper limb muscles with different upper limb movements. In addition, the effective limb movement for PD detection has been identified.

Materials and methods

Fig. 1 demonstrates the steps followed in this study starting with data acquisition to classification of EMG signal to normal, early, moderate and advanced levels of PD. First the signal was recorded from patients with PD from each level, and age-matched healthy control subjects, then the recorded signal was processed and analyzed in steps of preprocessing, feature extraction, feature selection and feature classification using MATLAB.

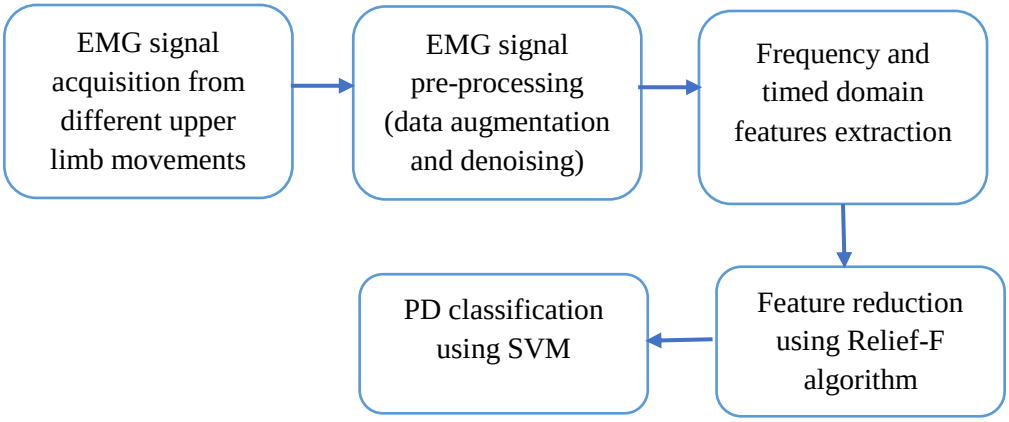


Fig. 1 Functional block diagram of the proposed PD classification using EMG signals

Data collection

Data were collected from 10 healthy subjects (6 males and 4 females, age between 38 and 51), and 15 PD patients (13 males and 2 females, age between 40 and 54), 5 for early-level, 5 for mid-level and 5 for advanced-level of PD. All data were collected using SCU-7 EMG system (channel frequency response high and lows pass: 13 ± 1.3 Hz to 463 ± 27.3 Hz, response range of biopotential coupler: 11 Hz - 3.78 KHz) according to protocols that had been approved by the institutional review board of Jimma University. Written informed consent was obtained from all volunteers. Before electrodes attachment, the skin of the subjects was cleaned using sandpaper to remove dead cells and hairs on skin. This procedure helps to decrease impedance mismatching between electrodes and skin. An electrode gel was then applied on the skin to remove motion artifacts. 1 second EMG signals were recorded by placing surface electrodes over flexor *carpi radialis* and *biceps brachii* muscles during selected upper arm movements: elbow flexed at 90-degrees, elbow flexed at 90-degrees with 1 kg load, wrist pronation and touching shoulder using (Fig. 2). The muscle types are selected based on their role on upper limb movements and because these muscles are situated most superficially.

The reference electrode was attached on the non-electrical active elbow/olecranon part. A total of 1000 myoelectric signals (250 signals for each class) were recorded from all subjects while the subjects perform arm movements within an average of 5 seconds duration each, in the following order: wrist pronation, elbow flexion at 90-degrees with 1 kg load, elbow flexion at 90-degrees without load and touching shoulder.

Pre-processing

Data augmentation and denoising has been performed on the raw EMG signal in the pre-processing stage. Data augmentation has been performed to increase the number of data samples so as to improve the accuracy and robustness of the classifier. Since EMG signal is highly random and non-stationary, adding random noise increase the randomness of the signal. Hence, white Gaussian noise with signal to noise ratio of 100 and 90 was added to augment the raw EMG signal. After data augmentation, the data has been increased to 600 signals per class

(normal, early, moderate and advanced) making the total data 2400 signals. All the EMG signals were filtered using IIR notch filter to reject 50 Hz power line interference. A 6th order Butterworth low pass and high pass filters were also applied to reject high frequency noises above 500 Hz and low-frequency noises below 20 Hz, respectively.

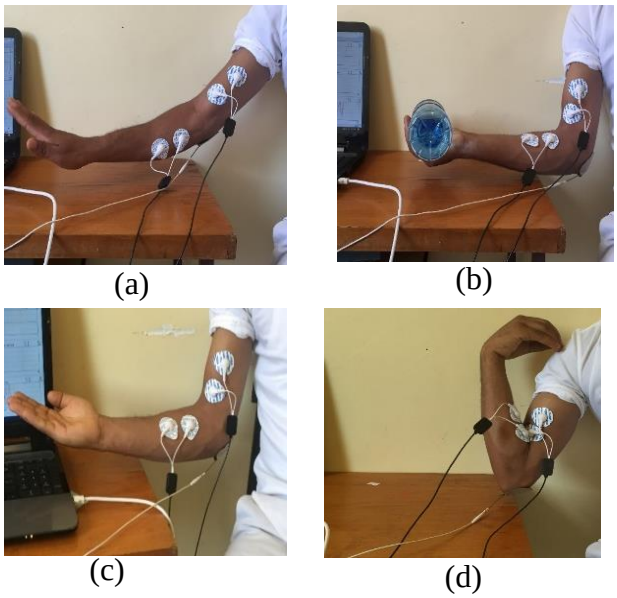


Fig. 2 Upper arm movements: (a) wrist pronation, (b) elbow flexion at 90-degrees with 1 kg load, (c) elbow flexion at 90-degrees without load, and (d) touching shoulder.

Feature extraction

In this study, initially 14 different features (12-time domain and 2 frequency domain) were extracted from the preprocessed EMG signals. The time domain features include average amplitude change (*AAC*), entropy, integrated EMG (*IEMG*), kurtosis, maximum fractal length (*MFL*), mean absolute value (*MAV*), simple square integral (*SSI*), waveform length (*WL*), root mean square (*RMS*), skewness, variance (*VAR*) and zero-crossing (*ZC*). The frequency domain features are the mean frequency (*MF*) and median frequency (*MDF*).

Equations (1)-(14) demonstrate the formulas of the fourteen features. In all equations, X indicates the input signal, N – the number of signals, P – the probability distribution of the signal, μ – the mean, and E – the expected value.

$$AAC = \frac{1}{N}\sum_{i=1}^{N-1} |X_{i+1} - X_i| \quad (1)$$

$$Entropy = \sum_{i=1}^{N} (P_i \log_2 P_i) \quad (2)$$

$$IEMG = \sum_{i=1}^{N} |X_i| \quad (3)$$

$$Kurt(x) = \frac{E\left[(X-\mu)^4\right]}{E\left([(X-\mu)^2]\right)^2} \quad (4)$$

$$MFL = \sqrt{(\sum_{i=1}^{N-1}(X_{i+1} - X_i))^2} \quad (5)$$

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |X_i| \quad (6)$$

$$SSI = \sum_{i=1}^{N} X_i^2 \quad (7)$$

$$WL = \sum_{i=1}^{N-1} |X_{i+1} - X_i| \quad (8)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2} \quad (9)$$

$$Skewness(x) = \frac{E\,[(X-\mu)^3]}{E\,([(X-\mu)^2])^{3/2}} \quad (10)$$

$$VAR = \frac{1}{N-1}\sum_{i=0}^{N} X_i^2 \quad (11)$$

$$ZC = \sum_{i=1}^{N-1}[\mathrm{sgn}(-X_i * X_{i+1}) \cap |X_i - X_{i+1}| \geq \mathrm{threshold}] \quad (12)$$

$$Sgn(X) = \begin{cases} 1, & \text{if } X \geq \text{ threshold} \\ 0, & \text{otherwise} \end{cases}$$

$$MF = \frac{\sum_{i=1}^{N} X_i}{N} \quad (13)$$

$$MDF = \frac{1}{2}\sum_{i=1}^{N} X_i \quad (14)$$

A feature reduction has been performed to reduce features and retain only significant features for classification. This reduces the computational cost and makes the algorithm time efficient. Features were ranked using Relief-F algorithm [29] and only the 9 high ranked features were selected for classification. The Relief-F algorithm finds the weights of features in the case of multiclass categorical variable. The algorithm penalizes the features that give different values to neighbors of the same class, and rewards features that give different values to neighbors of different classes. Relief-F algorithm first set the value of weight of features to zero then the weight increases or decrease based on their contribution [44].

Classification

Multiclass SVM with radial basis function (RBF) was used to classify the feature sets in to target classes. One-vs-all approach that constructs by fitting one classifier for one class [14], is commonly used for multi-SVM method. Each category is split out and all of the other categories are merged together, and the class which classifies the test data with greatest margin is selected. It categorizes an *m* class targets into *m* binary problems.

The classification was done using the set of selected feature sets. The feature sets were divided into training set consisting of 480 signals (which is 80% of the total signal data for one upper limb movement) and a test set consisting of 120 signals. Signals from different upper limb movements were treated as separate datasets and separate SVM classifiers were trained. In addition, multi class KNN and LDA models were trained with the same dataset to compare the result with our proposed model.

Results

Pre-processing

After data augmentation by adding Gaussian noise with 100 and 90 SNR, a total of 2400 raw EMG signals (600 for each upper limb movement) have been obtained. Fig. 3 demonstrates a sample raw EMG signals and data augmented equivalent signal. All the EMG data were denoised for power line interference using IIR notch filter with 50 Hz cut off frequency followed by 6th order low- and high-pass Butterworth filters. Fig. 4 shows sample of original and denoised signals.

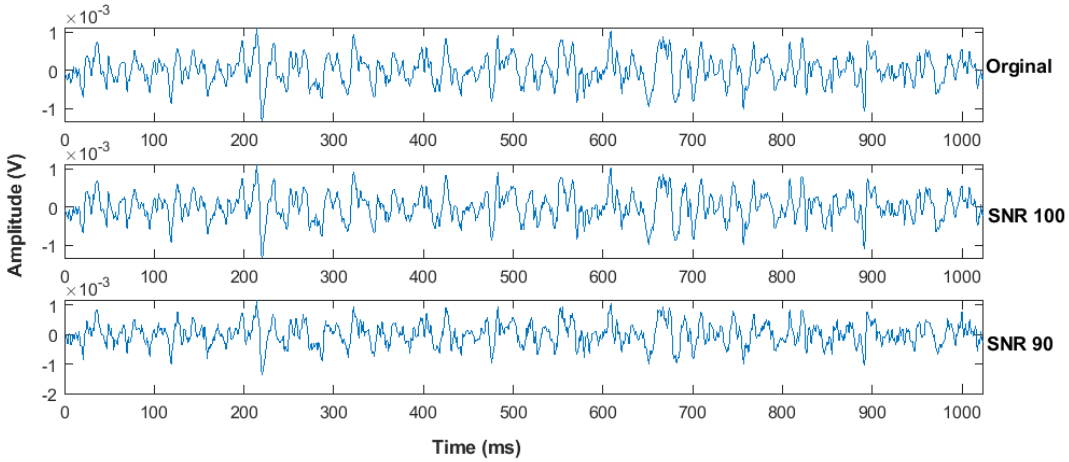


Fig. 3 Raw EMG signal and data augmented signals: (top-bottom) raw signal, signal after Gaussian noise with SNR of 100 added, signal after Gaussian noise with SNR of 90 added

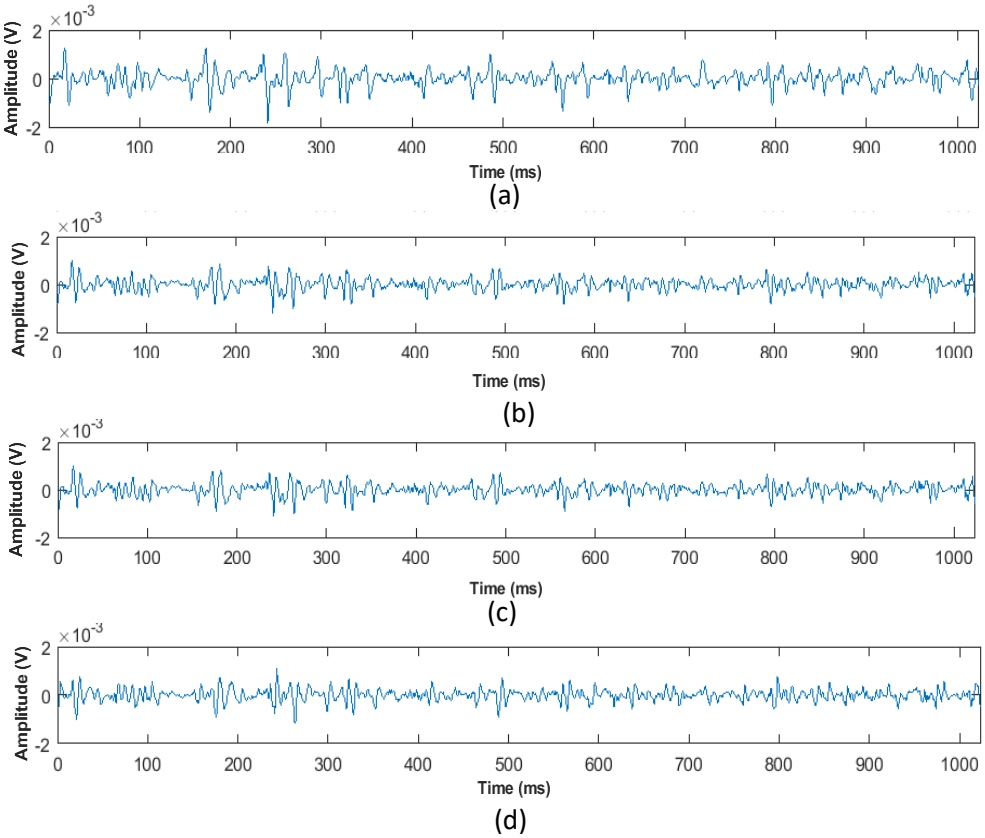


Fig. 4 Denoised EMG signal: (a) original, (b) IIR notch filtered, (c) low-pass filtered, and (d) high-pass filtered.

Feature extraction and reduction

Fig. 5 shows box plot of sample features normalized values extracted from wrist pronation upper limb movement for all levels of the disease. Features extracted from the signals of remaining three upper limb movements' show similar characteristics.

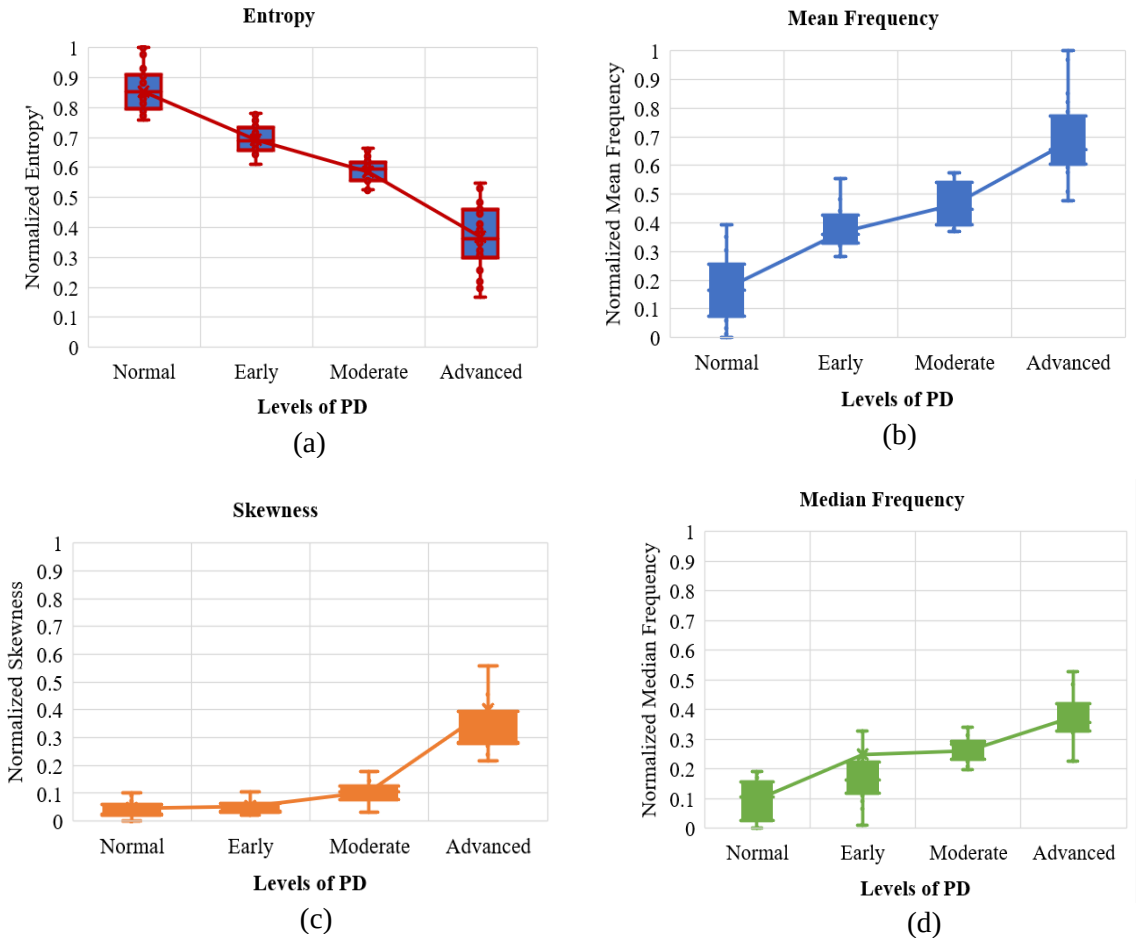


Fig. 3 Comparison of distribution of sample features normalized value versus stages of the disease for wrist pronation: (a) entropy, (b) mean frequency, (c) skewness and (d) median frequency.

After applying Relief-F algorithm for feature reduction, only 9 features have been selected as demonstrated in Table 1 along with their rank. The best ranked features are found to be entropy, mean frequency, skewness, and median frequency. Kurtosis, maximum fractal length, root mean square, integrated EMG and mean absolute value got the middle ranks. The remaining features with nearly zero or negative weight value were omitted.

Classification

After the model training, the multiclass SVM model was cross-validated to evaluate the generalization performance for all upper limb movements. In-sample classification errors and out-of-sample classification errors were computed before testing the prediction of the class for unknown or unseen data. According to the cross-validation result the in-sample loss and the out-of-sample loss did not show significant difference. This indicates that the model is neither under fitted nor over fitted and the model has good generalization performance. Table 2 shows the training losses of the model for each upper limb movements.

Table 1. List of selected features after applying Relief-F algorithm along with their weight factor

Rank	Features	Feature extraction domain	Weight factor
1	Entropy	Time	0.3408
2	Mean frequency	Frequency	0.2613
3	Skewness	Time	0.2531
4	Median frequency	Frequency	0.2350
5	Kurtosis	Time	0.2294
6	Maximum fractal length	Time	0.1223
7	Root mean square	Time	0.1131
8	Integral EMG	Time	0.1019
9	MAV	Time	0.1016

Table 2. Generalization loss of multi-class SVM for each upper limb movements (isLoss is in-sample loss, while oosLoss is out-of-sample loss)

Multi-SVM	Wrist pronation	Touching shoulder	Elbow flexion at 90° with load	Elbow flexion at 90° without load
isLoss, (%)	1.82	2.19	4.08	3.47
oosLoss, (%)	2.01	2.24	4.24	3.56

Performance evaluation methods including accuracy, sensitivity and specificity were used to analyze the efficiency of our algorithm. Confusion matrices were generated (Table 3) to demonstrate the number of true positives, true negatives, false positives and false negatives for each class and upper limb movements. The diagonal values indicate the true positive values. The other values indicate true negative and false positive counts which were wrongly classified. Performance parameters (accuracy, sensitivity and specificity) were calculated from confusion matrix values.

In addition to multi-class SVM with radial basis function, SVM with polynomial function, SVM with Gaussian function, KNN and LDA models were also trained and the performance of the models were evaluated for comparison (Table 4). The accuracy, specificity and sensitivity measured for multiclass SVM (RBF) shows better performance compared to other evaluated models. As demonstrated in Table 4, the wrist pronation showed superior accuracy compared to other upper limb movements. On the other upper limb, touching the shoulder was more sensitive than other upper limb movements for all models. Fig. 6 demonstrates the performance of multi-class SVM (RBF) for each upper limb movements graphically.

A graphical user interface (GUI) has been also developed for ease of use of our system. The GUI includes signal Load button, upper limb movement selection option and result button. Fig. 7 shows the sample GUI.

Table 3. Confusion matrix for wrist pronation, elbow flexion by 90-degrees without load, touching the shoulder and elbow flexion by 90-degrees with load

	Prediction / Actual	Normal	Early	Moderate	Advanced	Sensitivity, (%)
Wrist pronation	Normal (30)	30	0	0	0	100
	Early (30)	0	27	2	1	90
	Moderate (30)	0	1	29	0	96.7
	Advanced (30)	0	0	0	30	100
	Specificity (%)	100	98.9	96.7%	98.9	Acc = 96.6%
Elbow flexion by 90-degree without load	Normal (30)	28	2	0	0	93.3
	Early (30)	3	26	1	0	86.7
	Moderate (30)	0	0	28	2	93.3
	Advanced (30)	0	0	4	26	86.7
	Specificity (%)	96.7	97.8	94.4	97.8	Acc = 90%
Touching the shoulder	Normal (30)	30	0	0	0	100
	Early (30)	2	26	0	2	86.7
	Moderate (30)	0	2	28	0	93.3
	Advanced (30)	0	0	0	30	100
	Specificity (%)	97.8	97.8	100	97.8	Acc = 95%
Elbow flexion by 90-degree with load	Normal (30)	30	0	0	0	100
	Early (30)	2	26	0	2	86.7
	Moderate (30)	0	2	28	0	93.3
	Advanced (30)	0	0	0	30	100
	Specificity (%)	97.8	97.8	100	97.8	Acc = 95%

Table 4. Comparison of performance of multi-class SVM with radial basis function model with SVM Gaussian function, SVM with polynomial function KNN and LDA to classify PD for different upper limb movements. Ac = accuracy, Sp = specificity and Se = sensitivity.

	Wrist pronation			Touching shoulder			Elbow flexed at 90° without load			Elbow flexed at 90° with load		
	Ac (%)	Sp (%)	Se (%)	Ac (%)	Sp (%)	Se (%)	Ac (%)	Sp (%)	Se (%)	Ac (%)	Sp (%)	Se (%)
LDA	70	89	70	67	88	67.5	63.3	87.4	66.5	72.5	87	72.8
KNN	91.6	95	91.8	90	96	90.4	70	89	71	86	93	86.7
SVM (Polynomial)	92	96	92.5	81.5	92	81.7	83.3	94	83.1	85	94	85.1
SVM (Gaussian)	92.5	95.6	90.5	88.2	94	88.3	86.6	94.2	86.8	88.3	95	88.4
Multi-SVM (RBF)	**96.6**	**98.6**	**96.7**	**95**	**98.3**	**95**	**90**	**96.7**	**90**	**91.7**	**97.1**	**91.7**

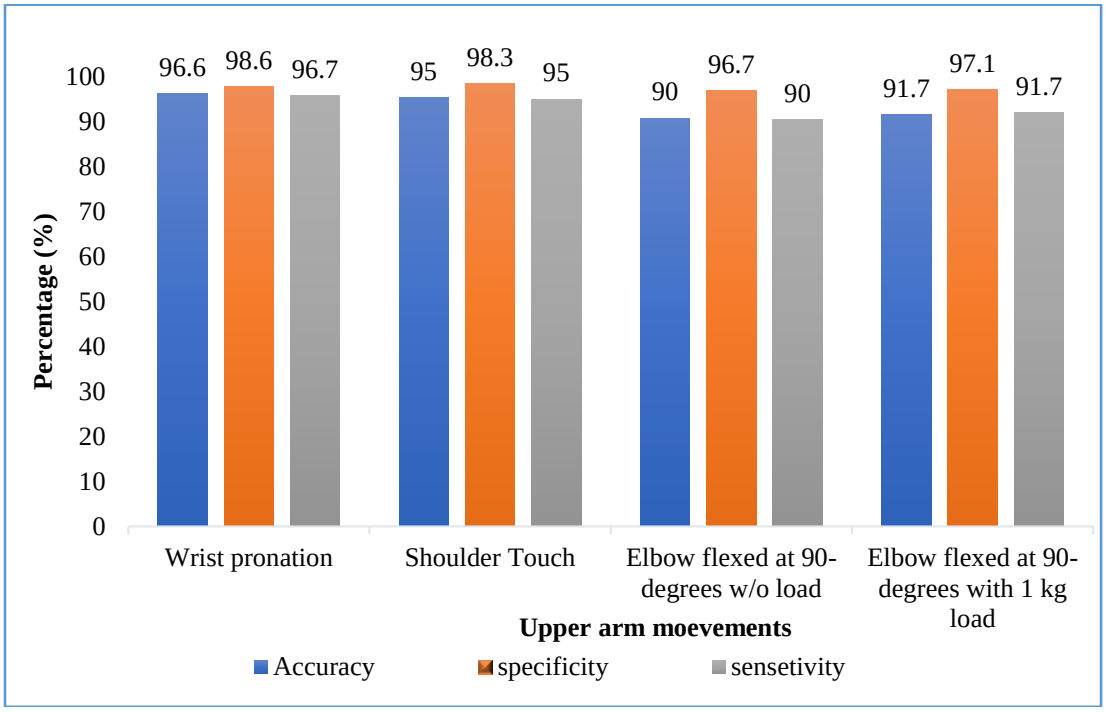
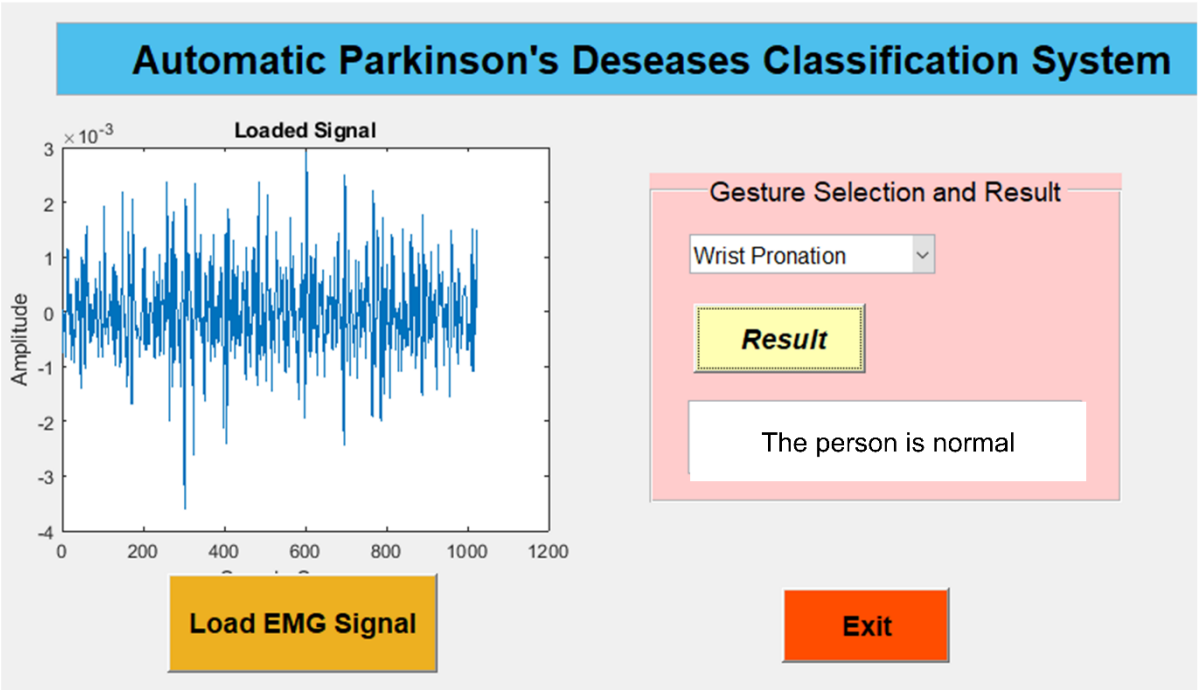
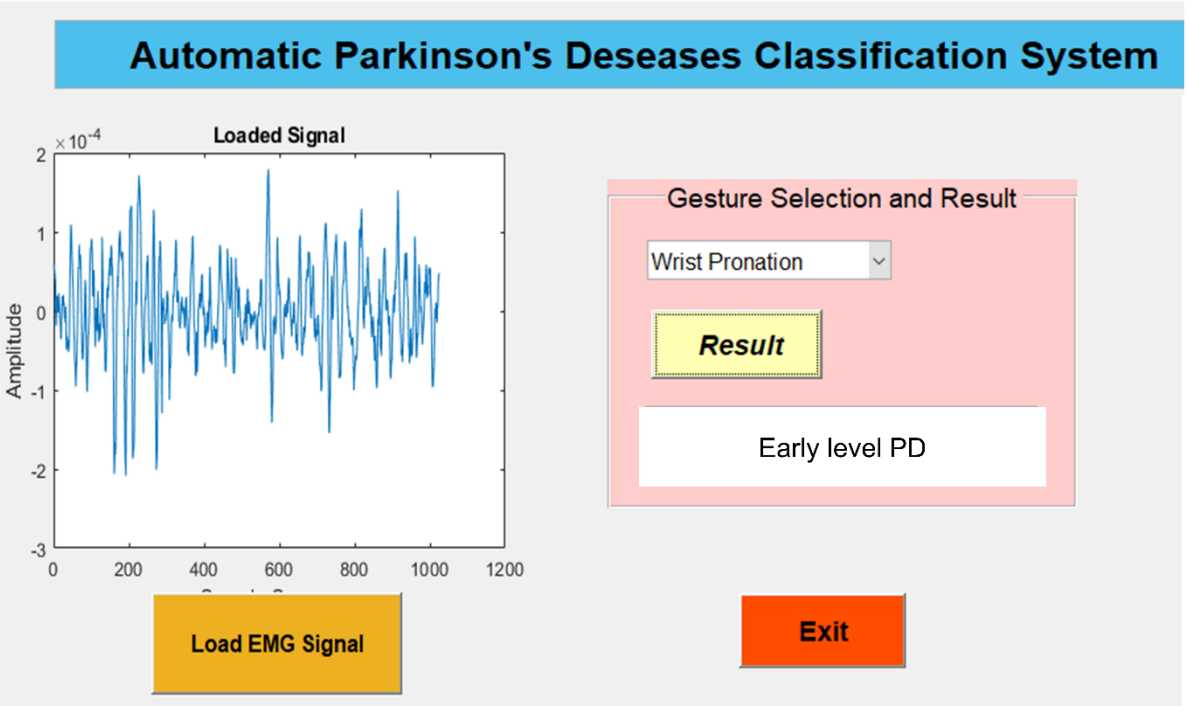


Fig. 4 Performance of multi-class SVM with radial basis function for different upper limb movements



(a)



(b)

Fig. 5 Graphical user interface for the automatic PD classification system demonstrating: (a) signal acquired from a normal person during wrist pronation predicted as normal, (b) signal acquired from a person with early level PD during wrist pronation predicated as early level PD.

Discussion

PD causes multilayered challenges on patients and their family members. The challenges are prolonged throughout their live because of uncurable nature of the disease. Apart from this there is no standardized way of diagnosing this disease. The common approach to diagnose this disease is through clinical assessment of the patients' sign and symptoms which is subjective and require the intervention of highly specialized experts. EMG can be used for detection of this disease but the signals are complex and irregular in nature which also require experts to interpret.

Upper limb motor impairments are common in people with PD [13, 24]. Due to this, upper limb muscles provide relevant information to detect effect of PD during wrist flexion, elbow flexion and carrying objects activities [34, 43]. In this research four different upper limb movements were selected to investigate the effect of PD on muscle activities. A total of 1000 EMG data were acquired from 10 healthy subjects (6 male and 4 female, age 38 to 51) and 15 patients (13 male and 2 female, age 40 to 54) with early stage, mid stage and severe stage PD. Butterworth high pass and low pass filters with lower and upper cut-off frequencies of 20 Hz and 500 Hz, respectively were applied to remove low frequency and high frequency artifacts out of usable range of EMG signal energy band. Additionally, notch filter with cut off frequency of 50 Hz was used to reject AC power line interference. A total of 14 features were extracted initially and by using the Relief-F algorithm, feature reduction was performed to select the 9 best features. It was found that entropy, mean frequency, skewness and median frequency differentiated the four PD classes as indicated in Fig. 5. The entropy value decreases with increasing PD severity while mean frequency, skewness and median frequency showed an increasing relationship compared to the healthy control groups. This is in agreement with a

study [30] where higher value of mean frequency and kurtosis features of EMG signals obtained from lower limb muscles of PD patients were reported compared to healthy control subjects. In addition, kurtosis, the maximal fractal length, mean absolute value, integrated EMG and root mean square values acquired from health subjects EMG signal were found to be low compared to signal features from PD patients. The remaining five features (zero crossing, waveform length, variance, simple square integral and average amplitude change) that did not show significant change for different classes were rejected using Relief-F algorithm.

The main goal of this study is detecting and classifying PD from the upper limb muscles' myoelectric signals. Our experimental results show the promising separability performance of selected features using multiclass SVM model with improved classification accuracies compared to recent studies [16, 27, 30] including those who have used a large number of features [41]. Moreover, this model classifies severity of the PD disease into three levels.

The most effective upper limb movement and muscle type to detect PD has been also identified in this study. The accuracies, sensitivities and specificities obtained for different upper limb movements using the multi class SVM model were slightly different. Less sensitivity was obtained for heathy subjects during elbow flexion with load (83.3%) and for patients with advanced level of PD during elbow flexion without load (86.7%). Relative to other classes, less average sensitivity (87.5%) was obtained for subjects with early-stage PD in all cases. Additionally, high sensitivity for advanced level of the disease was obtained in all cases (with average sensitivity of 96.5%), except elbow flexion without load. Generally, using multi class SVM overall classification accuracies of 90% for flexion by 90° without load, 91.7% for flexion by 90° with load, 95% for touching shoulder and 96.6% for wrist pronation have been obtained. The model produces high performance for EMG signal acquired from flexor *carpi radialis* and *biceps brachii* muscles during wrist pronation and touching the shoulder, respectively. This could be because of the force required for wrist pronation and touching the shoulder is higher relative to elbow flexion movements. However, this may require further investigations.

Comparison of our proposed model with other models was also part of this study. Accordingly, performance of multi class SVM classifier with radial basis kernel function was compared with multi class SVM classifier with polynomial kernel function, multi class SVM classifier with Gaussian kernel function, KNN and LDA with the similar signal datasets. As demonstrated in Table 4, multi-class SVM with radial basis function resulted higher performance in terms of accuracy, specificity and sensitivity compared to other classifiers.

In summary, the proposed system enables identifications of early, moderate and severe PD patients from healthy subjects with high accuracy which can be clinically applicable with user friendly GUI. This can be used as a decision support system for physicians, especially for those in low resource setting by detecting and classifying PD at early stage. This will have a great impact in reducing the disease progression and the mortality rate due to PD.

We acknowledge that signal recording in this study was conducted using two electrodes for each channel, but assessing the muscle activities by additional number of electrodes and channels may help further improve the accuracy and reliability of the system.

Conclusion

An automated system was proposed to detect and classify different levels Parkinson's disease using surface EMG signals recorded from flexor *carpi radialis* and *biceps brachii* muscles for four different upper limb movements. The results demonstrate that the proposed multiclass SVM algorithm provides excellent classification and detection performance for Parkinson's disease. Moreover, our experimental results showed that EMG signal acquired from flexor *carpi radialis* and *biceps brachii* muscles produced more accurate results during wrist pronation which indicates the most effective upper limb movement for Parkinson's disease detection. The proposed model has a potential for adoption into clinical screening programs as a decision support system for physicians, especially for those in low resource setting where both the expertise and the means are in scarce.

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References

1. Abiyev R. H., S. Abizade (2016). Diagnosing Parkinson's Diseases Using Fuzzy Neural System, Computational and Mathematical Methods in Medicine, Vol. 2016, Article ID 1267919, https://doi.org/10.1155/2016/1267919.
2. Alves G., E. B. Forsaa, K. F. Pedersen, M. D. Gjerstad, J. P. Larsen (2008). Epidemiology of Parkinson's Disease, Journal of Neurology, 255(Suppl 5), 18-32.
3. Ariyanto M., W. Caesarendra, K. A. Mustaqim, M. Irfan, J. A. Pakpahan, J. D. Setiawan, A. R. Winoto (2015). Finger Movement Pattern Recognition Method Using Artificial Neural Network Based on Electromyography (EMG) Sensor, 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-mechanical System, and Information Technology, 12-17, doi: 10.1109/ICACOMIT.2015.7440146.
4. Ball N., W.-P. Teo, S. Chandra, J. Chapman (2019). Parkinson's Disease and the Environment, Front Neurol, 10, 218, doi: 10.3389/fneur.2019.00218.
5. Barber T. R., J. C. Klein, C. E. Mackay, M. T. M. Hu (2017). Neuroimaging in Pre-motor Parkinson's Disease, Neuroimage Clin, 15, 215-227.
6. Bhoi A. K. (2017). Classification and Clustering of Parkinson's and Healthy Control Gait Dynamics Using LDA and K-means, International Journal Bioautomation, 21(1), 19-30.
7. Bower J. H., M. Teshome, Z. Melaku, G. Zenebe (2005). Frequency of Movement Disorders in an Ethiopian University Practice, Movement Disorders, 20(9), 1209-1213.
8. Bronner G., D. B. Vodušek (2011). Management of Sexual Dysfunction in Parkinson's Disease, Ther Adv Neurol Disord, 4(6), 375-383.
9. Brown R. C., A. H. Lockwood, B. R. Sonawane (2005). Neurodegenerative Diseases: An Overview of Environmental Risk Factors, Environ Health Perspect, 113(9), 1250-1256.
10. Cai Z.-N., J. Gu, C. Wen, D. Zhao, C. Huang, H. Huang, C. Tong, J. Li, H. Chen (2018). An Intelligent Parkinson's Disease Diagnostic System Based on a Chaotic Bacterial Foraging Optimization Enhanced Fuzzy KNN Approach, Comp and Math Methods in Medicine, 2018, Article ID 2396952, https://doi.org/10.1155/2018/2396952.
11. Chekani F., V. Bali, R. R. Aparasu (2016). Quality of Life of Patients with Parkinson's Disease and Neurodegenerative Dementia: A Nationally Representative Study, Research in Social & Administrative Pharmacy, 12(4), 604-613.

12. Dey R., A. Ghoshal, B. Tudu (2018). Electromyogram (EMG) Signal Categorization in Parkinson's Disease Tremor Detection by Applying MLP (Multilayer Perceptron) Technique: A Review, Advances in Systems, Control and Automation, Springer, 693-699.
13. Dickson J. M., R. A. Grünewald (2004). Somatic Symptom Progression in Idiopathic Parkinson's Disease, Parkinsonism & Related Disorders, 10(8), 487-492.
14. Fei B., J. Liu (2006). Binary Tree of SVM: A New Fast Multiclass Training and Classification Algorithm, IEEE Transactions on Neural Networks, 17(3), 696-704.
15. GBD 2016 Parkinson's Disease Collaborators (2018). Global, Regional, and National Burden of Parkinson's Disease, 1990-2016: A Systematic Analysis for the Global Burden of Disease Study 2016, Lancet Neurol, 17(11), 939-953.
16. Ghassemi N. H., F. Marxreiter, C. F. Pasluosta, P. Kugler, J. Schlachetzki, A. Schramm, B. M. Eskofier, J. Klucken (2016). Combined Accelerometer and EMG Analysis to Differentiate Essential Tremor from Parkinson's Disease, Annu Int Conf IEEE Eng Med Biol Soc, 672-675, doi: 10.1109/EMBC.2016.7590791.
17. Gitler A. D., P. Dhillon, J. Shorter (2017). Neurodegenerative Disease: Models, Mechanisms, and a New Hope, Disease Models & Mechanisms, 10(5), 499-502.
18. Goetz C. G. (2011). The History of Parkinson's Disease: Early Clinical Descriptions and Neurological Therapies, Cold Spring Harb Perspect Med, 1(1), a008862, doi: 10.1101/cshperspect.a008862.
19. Gowers W. R. (1888). A Manual of Diseases of the Nervous System, In: Gowers W. R., J. Taylor (Eds.), Philadelphia: P. Blakiston's Son & Co., 995-1010.
20. Hallett M., J. Rothwell (2011). Milestones in Clinical Neurophysiology, Mov Disord, 26(6), 958-967.
21. Heim B., F. Krismer, R. De Marzi, K. Seppi (2017). Magnetic Resonance Imaging for the Diagnosis of Parkinson's Disease, J Neural Transm (Vienna), 124(8), 915-964.
22. Hellmann M. A., E. Melamed, A. P. Steinmetz, R. Djaldetti (2010). Unilateral Lower Limb Rest Tremor is not Necessarily a Presenting Symptom of Parkinson's Disease, Movement Disorders: Official Journal of the Movement Disorder Society, 25(7), 924-927.
23. Hirsi J. O., Y. M. Yifru, G. Z. Metaferia, J. H. Bower (2019). Prevalence of Pain in Patients with Parkinson's Disease in Addis Ababa, Ethiopia, Parkinsonism & Related Disorders, 61, 214-218.
24. Ingram L. A., V. K. Carroll, A. A. Butler, M. A. Brodie, S. C. Gandevia, S. R. Lord (2021). Quantifying Upper Limb Motor Impairment in People with Parkinson's Disease: A Physiological Profiling Approach, PeerJ, 9, e10735, https://doi.org/10.7717/peerj.10735.
25. Iwasa Y., I. Saito, C. Fujii (2019). Investigation of the Treatment and Living Assistance Needed by Patients with Young-onset Parkinson's Disease, Kobe J Med Sci, 64(5), E180-E188.
26. Jankovic J. (2008). Parkinson's Disease: Clinical Features and Diagnosis, J Neurol Neurosurg Psychiatry, 79, 368-376.
27. Jeon H., W. Lee, H. Park, H. J. Lee, S. K. Kim, H. B. Kim, B. Jeon, K. S. Park (2017). Automatic Classification of Tremor Severity in Parkinson's Disease Using a Wearable Device, Sensors, 17(9), 2067.
28. Khoury N., F. Attal, Y. Amirat, L. Oukhellou, S. Mohammed (2019). Data-driven Based Approach to Aid Parkinson's Disease Diagnosis, Sensors, 19(2), 242.
29. Kononenko I. (1994). Estimating Attributes: Analysis and extensions of RELIEF. In: Bergadano F., L. De Raedt (Eds.), Machine Learning: ECML-94. ECML 1994, Lecture Notes in Computer Science, 784, Springer, Berlin, Heidelberg, https://doi.org/10.1007/3-540-57868-4_57.
30. Kugler P., C. Jaremenko, J. Schlachetzki, J. Winkler, J. Klucken, B. Eskofier (2013). Automatic Recognition of Parkinson's Disease Using Surface Electromyography during

Standardized Gait Tests, Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 5781-5784.
31. Lauzé M., J.-F. Daneault, C. Duval (2016). The Effects of Physical Activity in Parkinson's Disease: A Review, J Parkinsons Dis, 6(4), 685-698.
32. Loane C., M. Politis (2011). Positron Emission Tomography Neuroimaging in Parkinson's Disease, Am J Transl Res, 3(4), 323-341.
33. Magrinelli F., A. Picelli, P. Tocco, A. Federico, L. Roncari, N. Smania, G. Zanette, S. Tamburin (2016). Pathophysiology of Motor Dysfunction in Parkinson's Disease as the Rationale for Drug Treatment and Rehabilitation, Parkinson's Disease, 2016, 9832839.
34. Meigal A. Y., S. M. Rissanen, M. P. Tarvainen, O. Airaksinen, M. Kankaanpää, P. A. Karjalainen (2013). Non-Linear EMG Parameters for Differential and Early Diagnostics of Parkinson's Disease, Front Neurol, 4, 135, doi: 10.3389/fneur.2013.00135.
35. Naghavi N., A. Miller, E. Wade (2019). Towards Real-time Prediction of Freezing of Gait in Patients with Parkinson's Disease: Addressing the Class Imbalance Problem, Sensors, 19(18), 3898.
36. Oliveira de Carvalho A., A. S. S. Filho, E. Murillo-Rodriguez, N. B. Rocha, M. G. Carta, S. Machado (2018). Physical Exercise for Parkinson's Disease: Clinical and Experimental Evidence, Clin Pract Epidemiol Ment Health, 14, 89-98.
37. Pardoel S., J. Kofman, J. Nantel, E. D. Lemaire (2019). Wearable-sensor-based Detection and Prediction of Freezing of Gait in Parkinson's Disease: A Review, Sensors, 19(23), 5141.
38. Parkinson J. (2002). An Essay on the Shaking Palsy. 1817, The Journal of Neuropsychiatry and Clinical Neurosciences, 14(2), 223-236.
39. Poston K. L., D. Eidelberg (2010). FDG PET in the Evaluation of Parkinson's Disease, PET Clin, 5(1), 55-64.
40. Puschmann A., Z. K. Wszolek (2011). Diagnosis and Treatment of Common Forms of Tremor, Semin Neurol, 31(1), 65-77.
41. Putri F., W. Caesarendra, E. D. Pamanasari, M. Ariyanto, J. D. Setiawan (2018). Parkinson Disease Detection Based on Voice and EMG Pattern Classification Method for Indonesian Case Study, Journal of Energy, Mechanical, Material, and Manufacturing Engineering, 3(2), 87-98. https://doi.org/10.22219/jemmme.v3i2.6977.
42. Rezghian Moghadam H., H. R. Kobravi, M. Homam (2018). Quantification of Parkinson Tremor Intensity Based on EMG Signal Analysis Using Fast Orthogonal Search Algorithm, Iranian Journal of Electrical and Electronic Engineering, 14(2), 106-115.
43. Rissanen S., M. Kankaanpaa, M. P. Tarvainen, J. Nuutinen, I. M. Tarkka, O. Airaksinen, P. A. Karjalainen (2007). Analysis of Surface EMG Signal Morphology in Parkinson's Disease, Physiological Measurement, 28(12), 1507-1521.
44. Robnik-Šikonja M., I. Kononenko (2003). Theoretical and Empirical Analysis of ReliefF and RReliefF, Machine Learning, 53(1), 23-69.
45. Sheikh S., Safia, E. Haque, S. S. Mir (2013). Neurodegenerative Diseases: Multifactorial Conformational Diseases and Their Therapeutic Interventions, Journal of Neurodegenerative Diseases, 2013, 563481, doi: 10.1155/2013/563481.
46. Spasojević S., T. V. Ilić, I. Stojković, V. Potkonjak, A. Rodić, J. Santos-Victor (2017). Quantitative Assessment of the Arm/Upper Limb Movements in Parkinson's Disease Using a Wireless Armband Device, Front Neurol, 8, 388, doi: 10.3389/fneur.2017.00388.
47. Steiner I., J. M. Gomori, E. Melamed (1985). Features of Brain Atrophy in Parkinson's Disease. A CT Scan Study, Neuroradiology, 27(2), 158-160.
48. Williams U., O. Bandmann, R. Walker (2018). Parkinson's Disease in Sub-Saharan Africa: A Review of Epidemiology, Genetics and Access to Care, Journal of Movement Disorders, 11(2), 53-64.

Hamdia Murad Adem, M.Sc.
E-mail: hamdisha2558@gmail.com

Hamdia Murad Adem received her B.Sc. Degree in Biomedical Engineering in 2017 and M.Sc. Degree in Biomedical Imaging in 2020 from the School of Biomedical Engineering, Jimma Institute of Technology, Jimma University, Ethiopia. She is currently working as a lecturer in the School of Biomedical Engineering at Jimma Institute of Technology, Jimma University, Ethiopia.

Abel Worku Tessema, Ph.D. Student
E-mail: abelworku1221@gmail.com

Abel Worku Tessema got his B.Sc. Degree in Biomedical Engineering in 2015 and his M.Sc. Degree in Biomedical Imaging in 2019. Currently he is studying towards his Ph.D. in Korea. Since 2015 Abel Tessema has been working as a lecturer and researcher at Jimma University, Jimma Institute of Technology, School of Biomedical Engineering. He is interested in research related to medical image analysis. Abel Tessema has been engaged in different researches and won the First Grand Challenges Ethiopia Seed Grant Competition in 2017.

Assist. Prof. Gizeaddis Lamesgin Simegn, Ph.D.
E-mail: gizeaddis.lamesgin@ju.edu.et

Gizeaddis Lamesgin Simegn is an Assistant Professor in the School of Biomedical Engineering and Chair of Biomedical Imaging program. He graduated from Jimma University with B.Sc. Degree in Electrical Engineering in 2010, from Addis Ababa University with M.Sc. degree in Biomedical Engineering in 2014 and from University of Cape Town with Ph.D. degree in Biomedical Engineering in 2019. His research interests include medical image processing and analysis, biosignal processing, MRI pulse sequence programming, MRI image reconstruction and analysis.