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Gait and tremor investigation using machine learning techniques for the diagnosis of Parkinson disease

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HIGHLIGHTS

- A novel approach has been proposed to diagnose PD using the gait analysis.
- Various gait features were extracted using the peak detection and pulse duration.
- An average accuracy of 92.7% is achieved for the diagnosis of Parkinson's disease from gait analysis.

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ABSTRACT

Parkinson's disease (PD) is a chronic and progressive movement disorder affecting patients in large numbers throughout the world. As PD progresses, the affected person is unable to control movement normally. Individuals affected by Parkinson's disease exhibit notable symptoms like gait impairments and tremor occurrences during different stages of the disease. In this paper a novel approach has been proposed to diagnose PD using the gait analysis, that consists of the gait cycle, which can be broken down into various phases and periods to determine normative and abnormal gait. Initially, the raw force data obtained from physionet database was filtered using a Chebyshev type II high pass filter with a cut-off frequency 0.8 Hz to remove noises arising from the changes in orientation of the subject's body and other factors during measurement. The filtered data was used for extracting various gait features using the peak detection and pulse duration measuring techniques. The threshold values of the gait detection algorithm were tuned to individual subjects. From the peak detection algorithm, various kinetic features including the heel and toe forces, and their normalized values were obtained. The pulse duration algorithm was developed to extract different temporal features including the stance and swing phases, and stride time. Tremor is a common symptom in PD. Tremor is an involuntary movement of body parts. At first the tremor may appear in a specific body part like an arm, leg or one side of the body and later it may spread to both sides . This rest tremor is a cardinal sign of PD. An average accuracy of 92.7% is achieved for the diagnosis of PD from gait analysis and tremor analysis is used for knowing the severity of PD.

1. Introduction

It can be inferred from [1] that, the VGRF analysis were done based on statistical and frequency parameters and conveyed that the use of summation force values may hide the details the VGRF signals want to convey. So the analysis of separate force values show a difference between the healthy and PD subjects. Also, they have mentioned that the power distribution over the foot varies for the PD and healthy subjects.

Heida, T. et al. [2], shows that there is a continual balance between rest tremor and its repression. Thus, the power shifts across low frequency values and the range citied as tremor frequency in correspondence to change in the motor actions such as resting posture, movement of the body part that experiences tremor and other voluntary actions. It can be inferred from the result if the pathological tremor is present or absent. A person is said to be unhealthy if he/she does not exhibit pathological tremor.

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During deep brain stimulation, electrical signals are passed to the regions in the brain that causes tremor. Hence, when deep brain stimulated, there is a shift in the frequency range of the power spectral density. Vrutangkumar V. Shah et al. [3] suggests that high amplitude of input signals for deep brain stimulation has a more prominent effect in reducing the tremor. This is because the tremor components in the low frequency regions will experience a considerable loss in their equivalent gain. It also indicates the non-linear relation of tremor and the amplitude of frequency stimulation. Daryl Chang et al. [4] suggested the importance of machine learning in increasing the efficiency and accuracy of diagnosing the Parkinson's Disease. The center of pressure was used a characteristic to distinguish the subjects as normal or Parkinson's Disease affected person. A detailed probe into the Support Vector Machine (SVM) algorithm and the implications of regression was carried out. Sachin Shetty et al. [5] have successfully classified the Parkinson's Disease from other neuro-degenerative disease by applying a Gaussian RBF based kernel with an SVM classifier. They have achieved a good accuracy of Parkinson's over other disease and thus, this technique of using a SVM classifier has a good potential to differentiate Parkinson's from normal and other neuro-degenerative disease. Shyam V. Perumal et al. [6] have used the wearable sensors to develop a gait monitoring system for patients with Parkinson's disease. Their aim was to distinguish between PD and healthy subjects by identifying the most significant feature. The statistical analysis of variance test using the Linear Discriminant Analysis (LDA) algorithm to differentiate the subjects based on the values of mean and pattern classification. Thus achieving a better classification accuracy rate for distinct set of gait features like stance, swing phase and step distance. Manish Dubey et al. [7] used mean coefficient of variation, mean sum of variation and mean standard deviation and mean max of GRF as features and self organizing map has been used for classification. A person is said to be unhealthy if he/she exhibit pathological tremor. P.S. Motto and J.W. Judy [8] proposed the use micro machined probes for performing the surgical procedure. Hence, when the deep brain is stimulated, there is a shift in the frequency range of the power spectral density. Vrutangkumar V. Shah et al. [3] suggest that high amplitude of input signals for deep brain stimulation has a more prominent effect in reducing the tremor. This is because the tremor components in the low frequency regions will experience a considerable loss in their equivalent gain. It also indicates the non linear relation of tremor and the amplitude of frequency stimulation. O. Bazgir et al. [9] tested the correctness of the Unified Parkinson's Disease Rating Scale(UPDRS). Daryl Chang et al. [4] suggested the importance of machine learning in increasing the efficiency and accuracy of diagnosing Parkinson disease. The center of pressure is used as an attribute to distinguish normal person from Parkinson affected person. Human gait is analyzed under three heading namely kinematics, kinetics, and electromyography (EMG) by Pei-Hao Chen et al. [10]. A. Samàa et al. [11] used the signals from triaxial accelerometer and by using machine learning algorithm to diagnose the bradykinesia severity. Tucker et al. [12] used remote data mining based methodology to differentiate between "on" and "off" medication states among PD patients using low-cost, non-wearable sensor hardware. Data miner module is prepared using association rule mining algorithm and classification is done by using partial decision tree by Exarchos T.P. et al. [13]. N. Tahir et al. [14] used gait parameters features for classifying gait input using support vector machine and artificial neural network. Frenkel Toledo et al. [15] used stride-to-stride variability of gait timing to diagnose Parkinson disease. Amende et al. [16] quantified spatial and temporal indices of gait dynamics in a mouse model of Parkinson disease and Huntington disease. Spatiotemporal variables, kinematic differences and kinetic differences are used to diagnose Parkinson disease [17]. Gait dysfunction in Parkinson affected patients is analyzed with a help of kinematics and kinetics with systematic manipulations of dopaminergic status and attention [18]. Shenkman et al. [19] used Range of Motion (ROM) extremities measured from goniometer, ROM of the spine measured from functional axial rotation test ,motion during reaching determined by 3-dimensional motion analysis, followed by multivariable analysis of variance is used to diagnose Parkinson disease. Mirek E. et al. [20] utilized Vicon 3-d system to register three dimensional motion analysis. Get up and go test method is explored by Mathias S. et al. [21] to diagnose PD. Morris M. et al. [22] investigated stride length cadence relation in gait hypokinesia and the effect of levodopa medication on footstep pattern. Post B. et al. [23] explored the prognostic factors for the progression of Parkinson disease. Gelb D.J. et al. [24] suggested three levels of diagnostic buoyancy, which are differentiated namely definite, probable and possible.

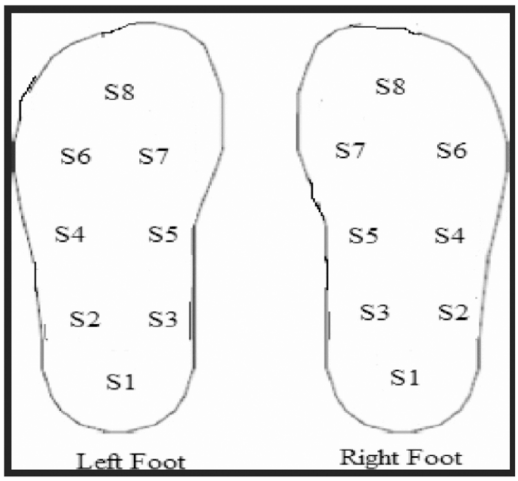

Fig. 1. Position of force sensors in the calculation of VGRF.

2. Materials and methods

2.1. Material

The Database of vertical ground reaction force (VGRF) was utilized from a public dataset maintained by Physionet. The data consists of 279 gait recordings from 93 patients with idiopathic Parkinson's Disease (PD) and 73 healthy controls, sampled at a rate of 100 Hz. To reduce the influence of subject's body weight on the force, the force values were normalized to the percentage of their body weight. During data collection, 8 sensors were placed underneath each of the subject's feet, as lying approximately at the following (X, Y) coordinates measured as a person is comfortably standing with both legs parallel to each other. For each subject, measurements of the vertical ground reaction force (VGRF) in Newton's were recorded as they walked at their usual, self-selected pace for approximately 2 min on level ground. Thus, each datum consists of 16 VGRF time series, as well as an additional 2 time series representing the aggregate force under each foot. For the tremor analysis, data from the Physionet database was utilized, resulting from the experiments conducted on 16 patients with PD. The patients were under minimum medications at the time of study to induce tremor and the data were recorded for a time period of 60 s (depending on the duration of tremor occurrence in subjects) and sampled at 100 Hz (see Fig. 1).

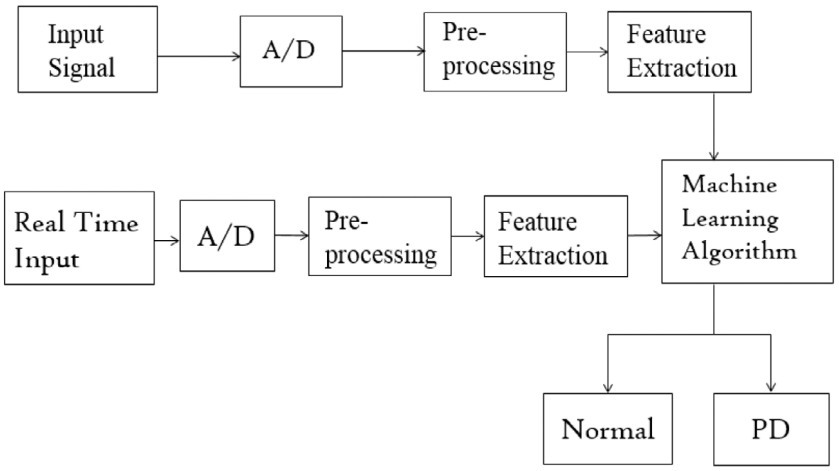

Fig. 2. Block diagram of the proposed method.

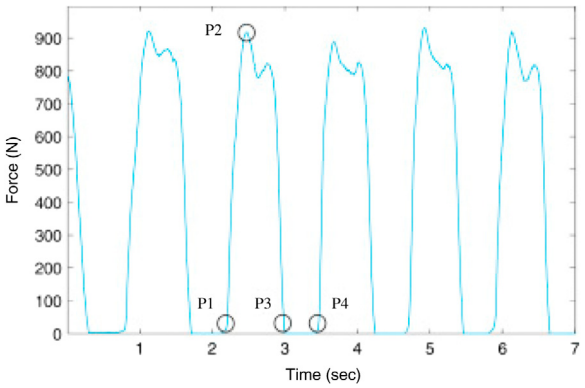

Fig. 3. Time domain representation of gait cycle using VGRF.

2.2. Methodology

2.2.1. Gait analysis in time domain

The physical signal (VGRF) was plotted with respect to time. This form of representation allows us to calculate various significant time domain features. The gait pattern is unique for every human being, but there is a considerable difference in the gait pattern of normal persons to that of the PD affected patients. The force exerted by the foot can be an important parameter in determining the gait pattern of a subject. Low or zero force values indicate that the foot is not in contact with the ground. The time domain parameters obtained for attempting to classify the subjects as PD and normal are stance time, swing time, stride time and foot strike profile (see Fig. 2).

The force readings are plotted against time for the left and right foot of the subject. From the plot, points P1–P4 are marked to denote one gait cycle. The time period between P1 and P4 defines the stride time. Additionally, time taken to reach from position P1 to P3 is the stance period. In the same way, the time taken from point P3 to P4 is defined as the swing period. Hence, the swing/stance ratio can be calculated (see Fig. 3).

2.3. Pre-processing

The Vertical ground reaction force values obtained using the force sensors contain low frequency components due to changes in the orientation of the body during measurement. These factors may influence the result of time domain gait analysis. Hence, to remove them we use type 2 Chebyshev high pass filter which results in frequency domain graph with a steeper roll off factor and an increased ripples in the pass band.

Table 1
Stance, swing and stride time for normal and PD patients.

Subject	Stance time	Swing time	Stride time	Normal/PD
Ga	0.647737	0.492132	1.139868	Normal
Ga	0.98722	0.272255	1.259475	PD
Si	0.672717	0.404226	1.076943	Normal
Si	0.727362	0.502319	1.229681	PD

2.4. Stance time

The time for which the foot is in contact with the ground while walking is said to be the stance time. As a person walks, he walks in a specific pattern that can be observed clearly using gait features. The postures that are a part of stance phase are heel strike, foot flat, mid stance and heel off in the same order. When a VGRF vs. time graph is plotted, the time gap between two points gives the stance time. First point is located where the vertical ground reaction force value increases from zero and the other point is where the ground reaction force drops to zero.

2.5. Swing time

The time for which there is no contact between the ground and the foot is stated to be the swing time. The gait postures involved in this phase are heel off, toe off and heel strike. This phase corresponds to zero vertical ground reaction force as there is no force exerted on the ground. The summation of values from all the sensors available in the database is used for plotting the graph. Time difference between the first and last point that is zero in one cycle is calculated as the swing time.

2.6. Stride time

The time period of the gait cycle is the stride time. Stride time is also the summation of stance and swing times. The stance time and swing time together give a stride phase. It can be seen that the stance phase is more in the case of a healthy person. The stance time and swing time are ideally in the ratio of 3:2. Subjects affected by Parkinson's Disease have a larger stride time. The center of pressure of a normal person will transfer from heel of the foot to the toe region during the stride time (see Table 1).

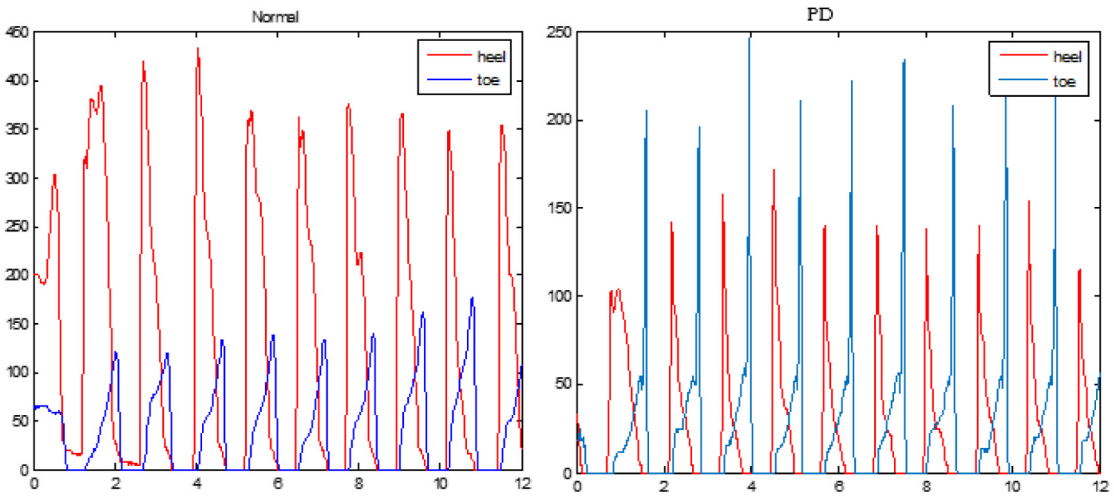

Fig. 4. Foot strike profile of normal and PD.

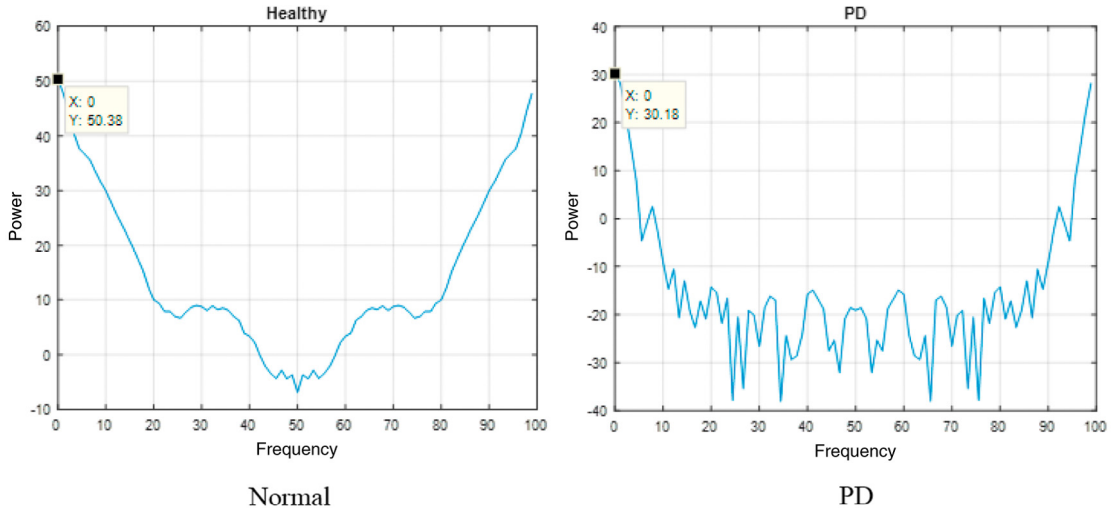

Fig. 5. Power spectral density of VGRF signal for normal and PD.

2.7. Foot strike profile

Healthy people tend to walk by lifting their heel and stepping off their toes, then landing on their heel. Whereas for Parkinson's patients the heel and toe touch the ground at relatively similar time points, which implies that they tend to have a flat foot. Motivated by this, we built a feature set that captures foot strike profile variability. For each datum, we use the 2 VGRF time series of heel (sensor 1) and toe (sensor 8) to produce time series that shows a difference between the PD and healthy subjects (see Fig. 4).

2.8. Frequency domain analysis

The frequency domain transformation of the signal, which was initially represented as time series, is important as it gives a detailed description of the signal distribution with respect to frequency. The amplitude of the signal in frequency domain is higher for the healthy subject and relatively lower for Parkinson's Disease affected subject. This representation is essential in extracting some significant features since the frequency domain characteristics offer a clearer approach in diagnosing the disease. Fast Fourier Transform (FFT) is used since it offers a faster computation in powers of two and a better performance ratio. Butterworth filter of order two was used as a preprocessing filter to obtain a maximum pass bandflatness. Hanning window was used to enhance the frequency resolution and reduce the spectral leakage.

The Butterworth function in Matlab returns the parameters required to calculate the response of the filter. These parameters are applied in the filter for the time domain signal using filter function. This filtered signal is used for further transformations to frequency domain.

2.9. Power spectral density

The power spectral density of vertical ground reaction force signals is an important parameter in determining the gait pattern of subjects. Power spectral density is the plot of strength or the magnitude of power of the signal along frequency axis. The amplitude of power that is distributed over the frequency acts as an indicator in diagnosing and confirming the presence of Parkinson's Disease (see Fig. 5).

2.10. Tremor analysis

Severity of Parkinson's Disease can be determined using tremor analysis. It involves the analyzing of the signals that reciprocate the

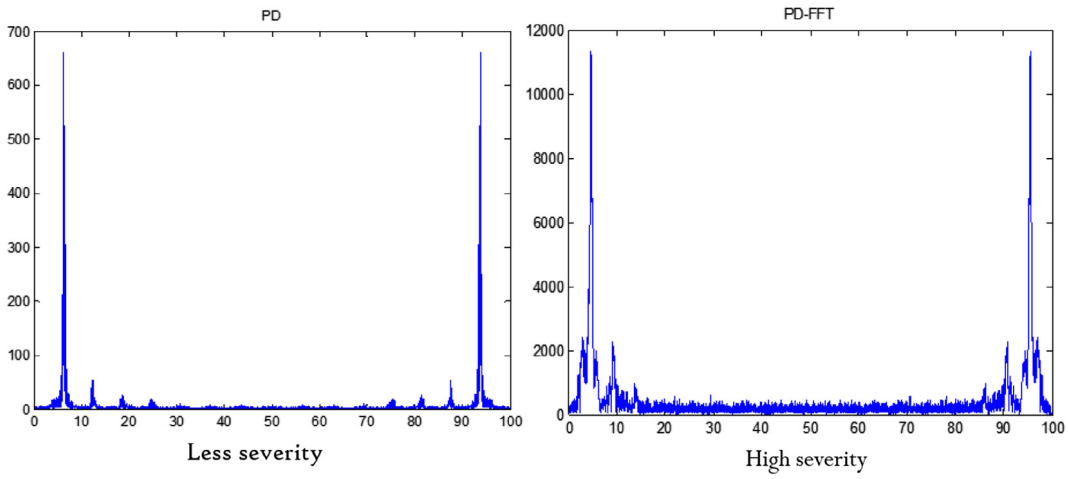

Fig. 6. FFT of the tremor signals corresponding to low and high severity level of PD.

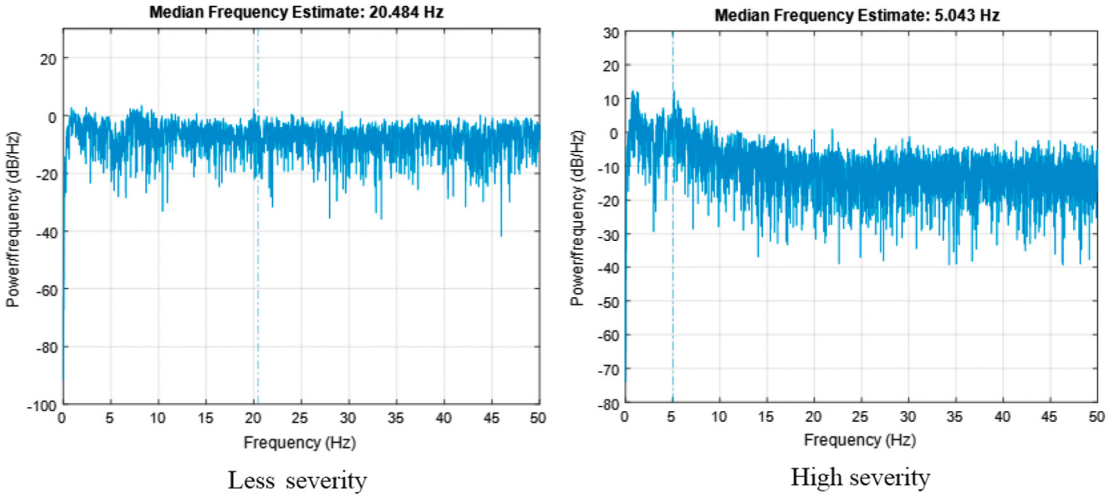

Fig. 7. Median frequency corresponding to low and high severity level PD tremor signal.

tremor response in the body. Tremor is mostly related to lack of coordination and control by the specific region in the brain. Tremor at rest that occurs in Parkinson's Disease can be distinguished from other tremors with respect to frequency characteristics. Essential tremor that is most commonly found in aged people is different from the tremor at rest in PD. The database used for experimental purpose contains the velocity readings of the tremor at fore finger obtained during deep brain stimulation. This velocity is proportional to the voltage and tremor strength. Butterworth filter of order two was used as a preprocessing filter to obtain a maximum pass bandflatness. Hanning window was used to enhance the frequency resolution and reduce the spectral leakage. Low frequency components in the signal corresponding to respiratory and cardiac oscillations are removed using high pass filter.

2.11. Fast Fourier Transform

Fast Fourier Transform (FFT) was applied to represent the signal in frequency domain. The frequency distribution gave a clear picture about the differences between the types of tremor and the severity of the Parkinson's Disease. Shift towards lower frequencies was observed with increase in severity. There is hike in the gain of the amplitude when the severity increases. The FFT function in Matlab is used for this purpose. The filtered time domain signal is given as an input to the function along with n-point value for performing FFT (see Fig. 6).

2.12. Power Spectral Density

Power Spectral Density (PSD) is plotted for the tremor values as well. This would give us an idea about the distribution of the power over various frequencies. If the strength of the signal is distributed uniformly over the frequencies, there are no specific peaks observed in the PSD plot. Also the median frequency is calculated. The medfreq function in Matlab is used to calculate the median frequency about which the frequency is equally distributed. The power and frequency values obtained from the periodogram function is given as an input to the medfreq (see Figs. 7 and 8).

3. Classification

The gait cycle plot in the time domain gives us a means of differentiating the Parkinson's gait from the normal gait. A prominent dip is observed in the gait cycle of a normal person. This can be related to the fact that a person's stance and swing times are approximately in the ratio of 3:2. This is not the case in a Parkinson's disease affected subject as they offer friction to the ground for a longer time while walking. The power of a healthy subject is greater when compared to the PD subject, as they exerts

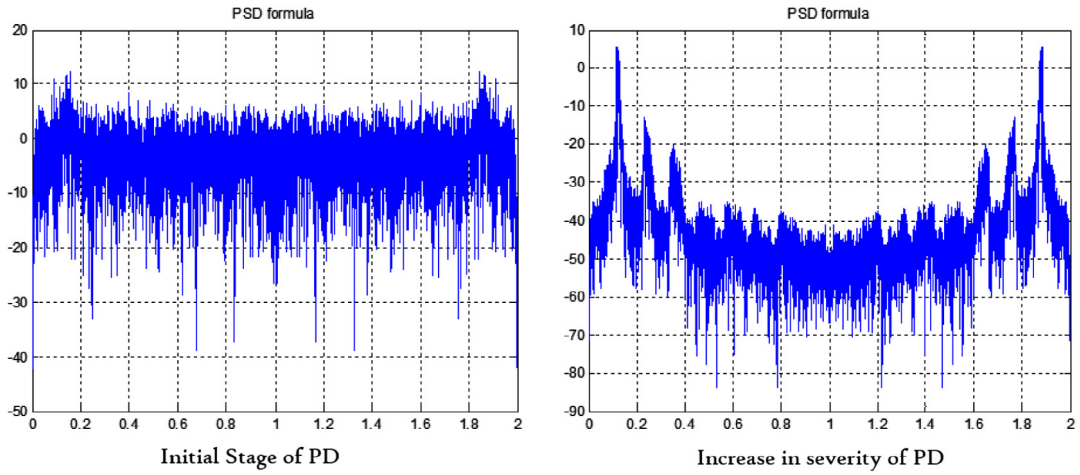

Fig. 8. PSD of Tremor signal corresponding to different stages of PD.

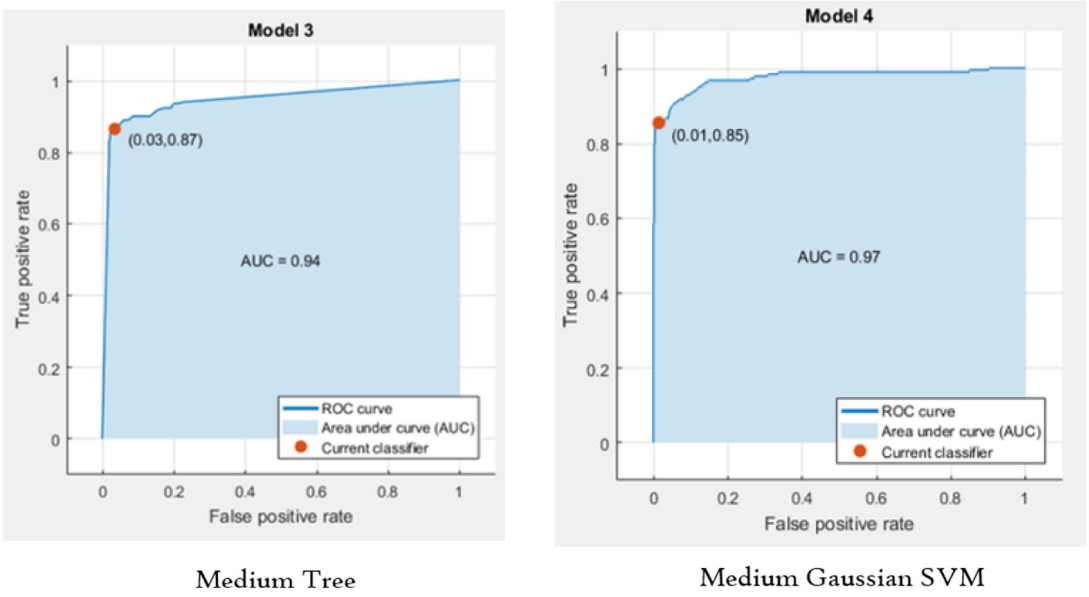

Fig. 9. ROC graph obtained for Medium Tree and Medium Gaussian SVM classifier.

more force on the ground at certain frequencies. PD subjects have a curved response along the frequency in PSD. From this, it can be inferred that the foot of the person is at similar position for more than one frequency. The foot strike profile shows a clear difference between the normal and PD subjects. For a normal person the heel force is greater than the toe force but, for a PD subject the toe force is slightly greater than the heel force. This is because the Parkinson Disease affected person exerts more pressure on his toe than his heel.

The frequency distribution of tremor values served as an indicator of severity in Parkinson's Disease. The peak amplitude was found to be around 4–6 Hz for a normal person but as the disease progressed the peak shifted towards lower frequency values. The amplitude also increased with severity. This is due to the increase in the intensity of the tremor for a longer time period which explains the shift towards the lower frequency. Power Spectral Density also reflects the same idea. In the initial stages of the PD the power is around the origin, whereas it shifts towards negative power axis for increased severity. Distinguishable peaks can be observed for more severe subjects. Also a shift in the median frequency towards lower frequency can be observed for obvious reasons.

The stride time, stance time, swing time and foot strike profile were used to classify normal and PD subjects. The results show that these features classified the subjects with an accuracy of more than 90%. The Medium Gaussian SVM shows a maximum accuracy of 94.8%. The Receiver Operator Characteristic curve (ROC) gave a true positive rate of 85% and false positive rate of 1%. Also the Area Under the Curve (AUC) was 97%. The best 2×2 confusion matrix was obtained for linear SVM where only 24 normal people were misdiagnosed from a total of 179 subjects and 11 out of 418 PD affected subjects were falsely misinterpreted as normal. The sensitivity was 97% and 87% for Parkinson's affected subject and normal subject respectively (see Figs. 9 and 10).

4. Conclusion

In the proposed method, we have analyzed the possibilities of diagnosing a Parkinson's disease affected subjects from a normal subject. Gait and tremor features that were extracted from the data available were recorded for classification. The gait features helped in the diagnosis of Parkinson's disease. The tremor characteristics indicated the severity of the disease.

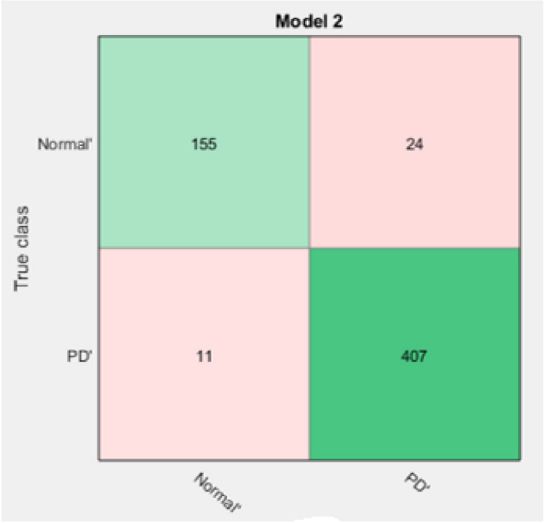

Fig. 10. Confusion matrix.

From the results we can observe that the stride time, stance time, swing time and foot strike profile provided an efficient means of distinguishing a healthy person and a Parkinson's Disease affected person. An average accuracy rate of 92.7% was observed from the results. The power spectral density of VGRF values obtained using wearable sensors provided distinct range for both the types of subjects. The tremor characteristics of frequency distribution and power spectral density offered means to identify the severity conditions of a person affected with Parkinson Disease.

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