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Cover Page Footnote

This work has been carried out in Signal Processing lab, Department of Electronics and Communication Engineering, Aditya Engineering college, Surampalem,Kakinada and Birla Institute of technology,Mesra, Ranchi,India.

Factor Analysis of Speech Signal for Parkinson's disease Prediction using Support Vector Machine

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Abstract—Speech signal can be used as marker for identification of Parkinson's disease. It is neurological disorder which is progressive in nature mainly effect the people in old age. Identification of relevant discriminate features from speech signal has been a challenge in this area. In this paper, factor analysis method is used to select distinguishing features from a set of features. These selected features are more effective for detection of the PD. From an empirical study on existing dataset and a generated dataset, it was found that the jitter, shimmer variants and noise to harmonic ratio are dominant features in detecting PD. Further, these features are employed in support vector machine for classifying PD from healthy subjects. This method provides an average accuracy of 85 % with sensitivity and specificity of about 86% and 84%. Important outcome of this study is that sustained vowels phonation captures distinguishing information for analysis and detection of PD.

Keywords: Parkinson's disease (PD), Factor analysis (FA), LOOCV (Leave One-Out Cross Validation), Support vector machine (SVM)

1. Introduction

Parkinson's disease (PD) is a type of progressive movement disorder of the central nervous system dueto gradual loss of dopamine generating neurons in the region called substantianigra of the midbrain. [1]. Millions of people worldwide is affected by PD every year [2]. The neurological progress of PD patients is evaluated by two clinical parameter unified Parkinson disease rating scale (UPDRS) and Hehn&yahr (H & Y)rating scale which include both motor and non-motor symptoms[3][4]. These symptoms include tremor, speech impairments, sleeping disorders and difficulty in muscular movement. From early research findings it has been noticed that about 90% of PD patients show speech impairments. The speech disturbance in PD is caused by muscle rigidity and limited movement range. Parkinson's disease has been shown to impact on all aspects of speech production. Common abnormal speech characteristics include hoarse, soft, or high voice, mumbling, monotonic and impairments in speech rate (talking too fast, having difficulty in initiating phonation) [5]. Phonation problems of people with PD are due to irregular vocal fold vibration and difficulty in articulation [6][7]. Another reason of speech impairment is imprecise vowel articulation leads to limited movements of the articulator. Currently, the popular diagnosis methods range from finding of Lewy bodies in the midbrain on autopsy or Single-photon emission computed tomography (SPECT) scans. In this paper speech-based technique is proposed, to build an effective PD detection system.

Literature survey: Various studies based on speech signal have been conducted for PD analysis. Little et al. [8] have used several linear and nonlinear feature of

speech signals to detect speech dysphonia. The 91 % accuracy is obtained with ten optimum features. Athanasios Tsanas et al. [9] proposed dysphonia measures for classification of PD and healthy people. They presented them as first-rate indicators at detecting characteristic patterns in the dysphonic PWP's voice. Sapir et al. [10] used vowel space area (VSA) and Formant centralization ratio (FCR) as first rate indicator in differentiating healthy speech and Parkinson-affected speech. Skodda et al. [11] focused in the variation of fundamental frequency (F0) and net speech rate (NSR), of the disordered voice. In another work, Skoda et al. [12] have examined first formant and second formant of the vowels /a/, /i/, and /u/ to characterize the new parameter triangular vowel space area (VSA) and Vowel Articulation Index (VAI). J Rusz et al [13] analyzed the measurement of the fundamental frequency variations in differentiating PD and healthy subject. Tobias Bockletet al. [14] have utilized acoustic, prosodic, and vocal information of disordered and healthy voice and the highest recognition rate upto90.5% recognition with 97% AUC with prosodic features. Hananel Hazanet al. [15] used two distinct data sets (from the USA and Germany) to extract the feature, formant frequency, FCR, VAI, and F2i/F2o. 85%of accuracy is obtained with proposed features. Teixeira et al. [16] developed an algorithm for the determination of jitter and shimmer parameters. Mohammad Shahbakhtiet al. [17] used genetic algorithm-based features and ANFC for classifying healthy and PD people. Sakar et al. [18] concluded that sustained vowels are more suitable in making PD prediction model**.** Bolanos et al [19] evaluated noise measure-based features for classification of PD from healthy using k-nearest neighbor (k-NN) classifier and obtained an accuracy of 66.57% using vowel /i/.Recently Karan et al.[20] proposed a PD detection system using empirical mode decomposition and Support vector machine classifier and obtained 96% accuracy. Arroyave et al.[21] presented a paper on spectral and cepstral features for Parkinson's disease identification in the Spanish language using five Spanish vowels and 24 isolated words using spectral-based features and giving an accuracy of 84% for sustained vowels.Suman Deb and S Dandapat[22] classified thespeech signal using new feature HPER (Harmonic peak to energy ratio). It out performs compared to MFCC,LPC, and related features. Biswajitet al. [23] proposed a new feature based on the Hilbert spectrum for PD analysis and detection. Recently Abhishek M.S et al. [24] performed the study based on support vector machine (SVM) and kNN and accuracy of 97.5% using optimized features. Agarwal, Aarushiet al. [25] reported accuracy of up to 90.76% using an extreme learning machine. It is observed that the PD detection is performed using raw features, which increased the training time and complexity. In this paper, factor analysis is proposed for the selection of discriminant features from the raw features. Then using a support vector machine (SVM) a model is built for the prediction of PD. The important contribution of this study is:

i) Using Factor analysis, a relevant and dominant features set is obtained which reduces the training time and complexity.
ii) The sustained vowels having discriminant characteristics for effective classification of healthy and PD affected voice signals.

The paper is organized as follows: Section 2 is about features extraction, feature selection using factor analysis (FA), and support vector machine (SVM). Section 3 provides the result of FA and classification. The conclusion of the work is described in Section4.

2. MATERIALS AND METHODS

2.1. Data Source

In this work, two datasets have been used.

i. Dataset 1: This dataset has been collected from UCI Machine Learning Repository, submitted by Sakar *et al.* This dataset consists of recording of sustained vowels, words, small sentences, and numbers of 20 healthy and 20 PD affectedpeople [18]. It co nsists the extracted features of the collected voice samples.

ii. Dataset 2: This database having voice samples of 45 people [20 healthy and 25 PD patients]. The PD patient's voice samples are collected from UCI machine learning repository [18]. The patient's age is varying from 43 to 77 year with mean 64.86 and standard deviation 8.97. The voice samples are captured using TRUST MC-1500 recorder. During recording the device is placed at distance of 10 cm from person. The ages vary from 41 to 62 years with mean age of 48.85 years and deviation of 5.373 years. The samples of healthy persons are captured in Birla Institute of Technology, Ranchi, India. Among 20 healthy people, there are 10 male and 10 females. The recording is done by a Samson Meteor microphone having a frequency range of 20Hz-20kHz, sampled at 44.1kHz with resolution of 16 bits. The distance of the subject from microphone is 10cm.

2.2. Overall Structure of PD Diagnosis System

The proposed system flow graph is shown in Figure 1. It consists of recording of voice samples, feature extraction, features reduction using factor analysis and classification using support vector machine.

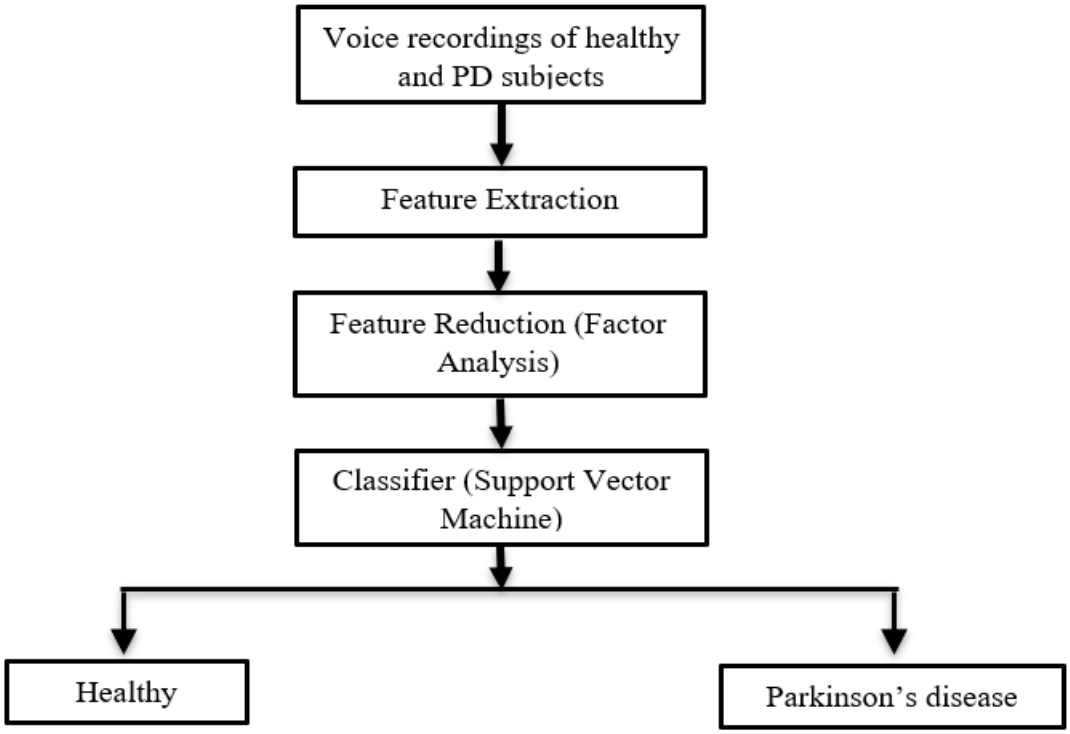

Figure1: Parkinson's disease detection process

2.3. Feature extraction

Feature extraction of voice samples plays a crucial role in detection of Parkinson's disease. For this study, six types of dysphonia parameters comprising of total twenty-six features have been extracted. The observation behind extracting these features is that vocal fold vibrations are periodic in healthy subjects and perturbed in diseased subjects [9].

Table 1 Extracted features from the speech signal. Features that share common attributes are grouped together.

GROUP	FEATURES
Frequency Parameters	Jitter (ddp), Jitter (local), Jitter (rap), Jitter (ppq5), Jitter (local, absolute)
Amplitude Parameters	Shimmer (local),Shimmer (local,dB) ,Shimmer (dda), Shimmer (apq5) ,Shimmer (apq3),Shimmer (apq11)
Voicing Parameters	Degree and number of voice breaks, Fraction of locally Unvoiced frames
Pitch Parameters	Maximum pitch Mean pitch,Standard Deviation,Minimum pitch Median pitch
Harmonicity Parameters	Autocorrelation,Harmonic-to-Noise and Noise-to-Harmonic related features
Pulse Parameters	Standard deviation of period,Mean period, Number of pulses and periods

The jitter, shimmer and harmonicity parameter can be representedmathematically as follows:

$$Jitter = \frac{1}{N-1}\sum_{i=1}^{N-1}|T_i - T_{i-1}| \quad (1)$$

$$Jitter(local) = \frac{Jitter}{\frac{1}{N}\sum_1^N T_i} \times 100 \quad (2)$$

$$Jitter(rap) = \frac{\frac{1}{N-1}\sum_1^{N-1}\left|T_i - \frac{1}{3}\sum_{n=i-1}^{i+1} T_n\right|}{\frac{1}{N}\sum_1^N T_i} \quad (3)$$

$$Jitter(ppq5) = \frac{\frac{1}{N-1}\sum_1^{N-1}\left|T_i - \frac{1}{5}\sum_{n=i-1}^{i+1} T_n\right|}{\frac{1}{N}\sum_1^N T_i} \quad (4)$$

$$Shimmer = \frac{\frac{1}{N-1}\sum_1^{N-1}|A_i - A_{i+1}|}{\frac{1}{N}\sum_1^N A_i} \quad (5)$$

$$Shimmer(rap) = \frac{\frac{1}{N-1}\sum_{1}^{N-1}\left|A_i - \frac{1}{3}\sum_{n=i-1}^{i+1} A_n\right|}{\frac{1}{N}\sum_{1}^{N} A_i} \quad (6)$$

$$Shimmer(ppq5) = \frac{\frac{1}{N-1}\sum_{1}^{N-1}\left|A_i - \frac{1}{5}\sum_{n=i-1}^{i+1} A_n\right|}{\frac{1}{N}\sum_{1}^{N} A_i} \quad (7)$$

Where, N=number of periods, $(T_i\ ,\ T_{i-1})$= Consecutive periods,($A_{i,}A_{i+1}$)= Amplitude of consecutive periods,

2.4. Feature Selection

Extraction of relevant features is extremely important for exact detection of Parkinson's disease. The computational complexity of the model can be further reduced by selecting the dominant features. In this study, we have used a statistical method called factor analysis for feature selection. Factor analysis [28] works on the principle that measurable and observable variables can be expressed with fewer latent variables that share a common variance and are unobservable.

Each factor is represented as:

$$S_n = \lambda_n f + e_n \quad (8)$$

Where, S_n- n^{th} feature, *f*- latent variable, $\boldsymbol{\lambda}_n$-factor gives the correlation value between factors and variables e_n–a variation of the variable from the factor.

The factor loadings are a measure of how much a variable has influenced the factor. The greater the factor loading, the greater the contribution of the variable to that factor.The factor analysis can be represented by equation 2[29].

$$A = BCB' + U^2 \quad (9)$$

where A -matrix of correlation coefficients among the observed variables.
B -primary factor pattern or loading matrix.
C is the correlations among common factors.
andU^2- diagonal matrix.

2.5. *Support Vector Machine (SVM)*

SVM is a set of supervised learning methods and is based on optimization principle [26.It is a type of linear classifier that divides input data into classes by creating an idea hyperplane in the feature space with the greatest feasible margin while keeping a suitable computational efficiency.SVM translates data to a higher dimensional feature space where it becomes linearly separable when it is not linearly separable in the present space.On either side of the hyperplane, two parallel hyperplanesare built to separate the data. The separating hyperplane for input vector $(x_i)$is defined as:

$$f(x) = w^T x + b = 0 \quad (10)$$

In equation (3), wis defined as weight vector and b as bias. The hyperplane is obtained by minimized cost function given bellow:

$$J(w) = \frac{1}{2}w^T w = \frac{1}{2} \quad (11)$$

This is subjected to the constraints:

$$d_i[w^T x_i + b] \geq 1, i = 1,2,..N \quad (12)$$

Where d_i indicates the class in which datapoint x_i belongs to. In our study d_i is either 1 or -1. In this work, rbf kernel is used because, from different study it has been foundthat the radial basis function (rbf) has good generalization capability and shown good accuracy, among other kernel in support vector machine [18,27] for pathological speech classification.Secondly, the SVM with radial basis function requires only two parameters for optimization [23] which saves time.

2.6. Evaluation Parameters

Cross-validation is a technique is used to assess the prediction accuracy.The classifier is trained on a subset of the training dataset and then evaluated on the rest in this method. This approach is continued in a systematic manner until all of the training set's points have been tested. Leave-one-out The model is trained via cross-validation. The following parameters were used to assess the categorization technique's effectiveness:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (13)$$

$$Specificity = \frac{TN}{FP+TN} \quad (14)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (15)$$

where TP is True positive, the count of diseased subjects predicted accurately as diseased; false negative (FN) is the count of diseased patients predicted to be healthy; false positive (FP) is the count of healthy individuals predicted as diseased and true negative (TN) is the count of healthy patients accurately predicted healthy.

3. Results & Discussion

Support Vector Machine (SVM) is used to build the prediction model. All the experimentation is performed in the Python platform. The scikit learn package of python has been used to implement the support vector machine which implements the LibSVM method. The SVM model used the rbf kernel.

Table 2: Factor Analysis results for dataset 1

Features	Total Samples	Healthy Samples	PD Samples
Jitter(%)	**0.68**	**0.62**	**0.94**
Jitter(abs)	**0.55**	**0.44**	**0.76**
Jitter(RAP)	**0.64**	**0.57**	**0.99**
Jitter(PPQ)	**0.61**	**0.54**	**0.94**
Jitter(DDP)	**0.64**	**0.57**	**0.99**
Shimmer	**0.78**	**0.82**	**0.66**
Shimmer(dB)	**0.78**	**0.81**	**0.65**
Shimmer(APQ3)	**0.66**	**0.69**	**0.55**
Shimmer(APQ5)	**0.65**	**0.66**	**0.57**
Shimmer(APQ)	**0.50**	**0.51**	**0.51**

Shimmer(DDA)	**0.66**	**0.69**	**0.55**
Mean autocorrelation	-0.99	-0.99	-0.76
NHR	**0.98**	**0.99**	**0.77**
HNR	-0.90	-0.91	-0.67
Median pitch	0.10	0.23	0.05
Mean pitch	0.19	0.3	0.17
Std deviation	**0.43**	**0.45**	**0.37**
Minimum pitch	0.01	0.13	0.02
Maximum pitch	**0.35**	**0.36**	**0.36**
No of pulses	-0.29	-0.27	-0.24
No of periods	-0.31	-0.31	-0.25
Mean period	-0.07	-0.18	-0.13
Standard deviation of period	**0.41**	**0.38**	**0.35**
Unvoiced frames	**0.57**	**0.53**	**0.5**
No of voice breaks	0.33	0.28	0.27
Degree of voice breaks	0.41	0.36	0.32

Table 3: Factor Analysis results for dataset 2

Features	Total Samples	Healthy Samples	PD Samples
Jitter(%)	**0.99591**	**0.51322**	**0.99618**
Jitter(abs)	**0.95072**	**0.47091**	**0.94217**
Jitter(RAP)	**0.99837**	**0.49769**	**0.99856**
Jitter(PPQ)	**0.97951**	**0.57637**	**0.97722**
Jitter(DDP)	**0.99837**	**0.49778**	**0.99856**
Shimmer	**0.66835**	**0.99588**	**0.67225**
Shimmer(dB)	**0.71246**	**0.98921**	**0.72451**
Shimmer(APQ3)	**0.65977**	**0.9981**	**0.64656**
Shimmer(APQ5)	**0.65531**	**0.97261**	**0.6912**
Shimmer(APQ)	**0.70121**	**0.96106**	**0.68693**
Shimmer(DDA)	**0.65978**	**0.9981**	**0.64657**
Mean autocorrelation	-0.90907	-0.8022	-0.90778
Mean noise-to-harmonics ratio(NHR)	**0.90918**	**0.73005**	**0.90405**
Mean harmonics-to-noise ratio(HNR)	-0.71973	-0.75827	-0.71501
Median pitch	-0.1372	-0.2088	-0.049812
Mean pitch	-0.10172	-0.23761	-0.0029172
Standard deviation	0.37544	0.072583	0.33179
Minimum pitch	-0.22657	-0.082124	-0.15496
Maximum pitch	0.15263	-0.10183	0.21218
No of pulses	-0.30855	-0.24876	-0.15361

No of periods	-0.31853	-0.24966	-0.16416
Mean period	0.10359	0.17561	0.0080422
Standard deviation of period	0.39705	0.14383	0.30683
Unvoiced frames	0.39687	0.029772	0.24598
Number of voice breaks	**0.58427**	**0.045134**	**0.52764**
Degree of voice breaks	**0.51288**	**0.099945**	**0.43099**

The factor analysis of the features for dataset 1 is shown in Table 2. Table 3 shows a similar factor analysis assessment for data set 2. In these tables, the factor loading values for all the samples, healthy samples and PD samples are presented separately.

Table 2 shows that the jitter variants, shimmer variants, NHR, maximum pitch, standard deviation of pitch & period and number of unvoiced frames are dominant features for the discrimination of PD and healthy. From Table 3, 14 relevant features are selected that include jitter, shimmer variants, NHR, number of voice breaks and degree of voice breaks. Hence, it is observed that jitter variants, shimmer variants and NHR are the most dominant features as these features are related to vocal fold information of the speaker and may be more effective in distinguishing PD affected people and healthy people. For cross validation, LOOCV (Leave One-Out Cross Validation) is used in which one sample is kept for testing and the rest are used for training. The process is repeated such that all samples are once tested upon.

Two separate experiments are conducted to show the effectiveness of the proposed approach. Experiment 1 shows the results with dataset-1 and experiment 2 shows the results of dataset-2. In both the experiments gender consideration is not performed in classification. Here both genders are considered as a whole group in both the class.

Experiment 1: In this experiment classification experiment is conducted with dataset 1. Table 4 shows the performance of dataset 1 when considering all twenty-six features, and Table 5 shows the results with dominant features.

Table 4: Performance analysis of SVM using LOOCV on alltwenty-six features of dataset 1

SVM parameter		**Overall Accuracy**	**Specificity (Healthy)**	**Sensitivity (PD)**
σ	**C**			
0.05	10	70.09	66.92	73.26
0.05	100	68.84	67.5	70.19
0.1	**10**	**72.5**	**71.92**	**73.07**
0.1	200	69.13	69.42	68.84
0.5	10	64.80	72.5	57.11

Table 5: Performance analysis of SVM using LOOCV on fourteen dominant features of dataset 1

SVM parameter		**Overall Accuracy**	**Specificity (Healthy)**	**Sensitivity (PD)**
σ	**C**			
0.05	10	65.76	58.07	73.46
0.05	**100**	**69.71**	**65.19**	**74.23**
0.1	10	67.5	61.53	73.46
0.1	200	67.21	65.76	68.65
0.5	10	64.90	67.88	61.92

As depicted in Table 4 and 5, when all the features are considered, an overall accuracy of 72.5% with σ=0.1 and C=10 as the optimal parameters of SVM. The model built by only the dominant features gives a comparable accuracy of 69.71% with σ=0.05 and C=100 as the optimal parameters of SVM. The performance comparison of classifier with original and dominant features is presented in terms of region of convergence and area under curve value shown in figure 2.

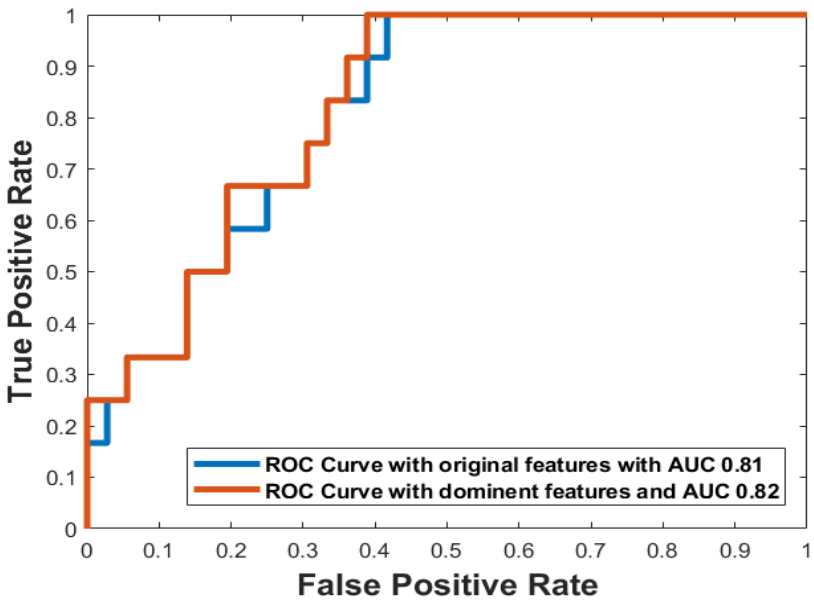

Figure 2: Performance comparison of classifier performance with original features and dominant features of dataset 1.

Experiment 2: A similar assessment has been carried with dataset 2 and the performance results are reported in Tables 6 and 7 for all features and dominant features, respectively.

Table 6: Performance analysis of SVM using LOOCV on all features of dataset 2

SVM parameter		Overall Accuracy	Specificity (Healthy)	Sensitivity (PD)
σ	**C**			
0.05	**10**	**96.66**	**96.66**	**96.66**
0.05	100	96.26	95	97.33
0.1	10	95.55	95	96
0.1	200	96.29	95	97.33
0.5	10	92.59	87.55	96.66

Table 7: Performance analysis of SVM using LOOCV on dominant features of dataset 2

SVM parameter		Overall Accuracy	Specificity (Healthy)	Sensitivity (PD)
σ	**C**			
0.05	10	84.81	94.16	77.33
0.05	100	85.18	86.66	84
0.1	10	85.55	92.5	80
0.1	**200**	**85.55**	**86.66**	**84.66**
0.5	10	82.59	81.66	83.33

It is observed that for all features, σ =0.05 with C=10 is the optimal parameters of SVM. It showsan overall accuracyof 96% in detection of both healthy and PD. The reduced features give an overall accuracy of 85.5% with σ=0.1 and C=200 as the optimal parameters of SVM. The performance of PD detection system is represented in more compact form using region of convergence (ROC) curve shown in figure 3.

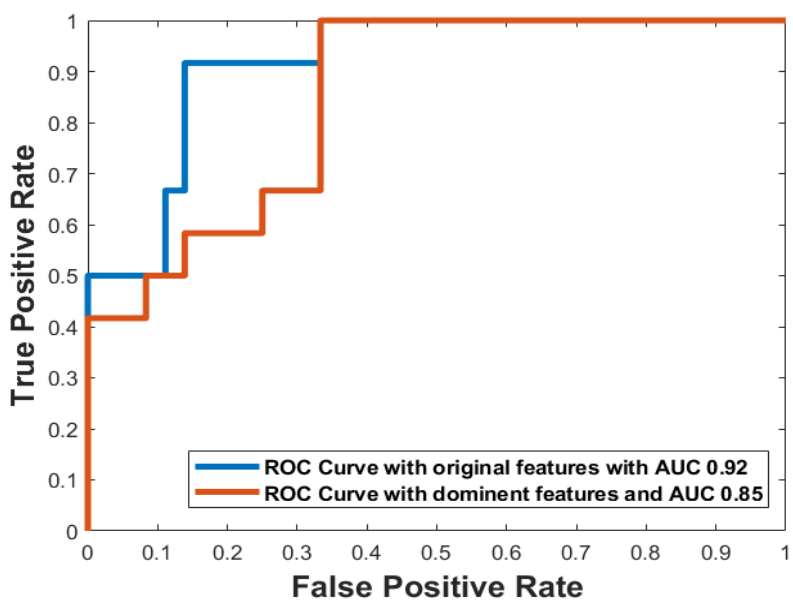

Figure 3: Performance comparison of classifier performance with original features and dominant features of dataset 2.

It shows that the reduced discriminant features are good enough to predict Parkinson's disease.

4. Conclusion

In this paper, factor analysis is proposed to select the dominant and discriminative features from the voice samples to efficiently predict Parkinson's disease. It has been found that the Jitter variants, shimmer variants, and noise to harmonic ratio are important in discriminating the PD. These reduced features provide an average accuracy of 85% with sensitivity and specificity of about 86% and 84% when tested on a generated dataset.It is seen that the reduced features provide comparable results with the accuracy obtained considering all the extracted features. The proposed methodology reduces the complexity by dimensionality reduction using factor analysis. Again, the results obtained from experiments, the maintained vowels are thought to provide enough information to discriminate between PD and normal people. The proposed work may be used for the effective modelling of the tele monitoring system.

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