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"Speech Signal Processing for Classification of Parkinson's Disease"

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Abstract - *Parkinson's disease is a disorder of central Nervous system. The main signs and symptoms of Parkinson's are tremor, slow movement, rigid muscle, impaired posture and balance, loss of automatic movement, speech changes and writing changes. But speech changes occurs in about 90% of people and they suffer from speech disorder like disorder of laryngeal, respiratory and articulatory function. Hence purpose of this paper is to analyse the voice samples from Parkinson's and healthy people and discriminate them using machine learning algorithms. Different features like Jitter, Shimmer, NHR and HNR are extracted.*

***Keywords*: Parkinson disease, Jitter, Shimmer, Pitch, Machine Learning, Classification, SVM, KNN.**

1. INTRODUCTION

Basic unit of nervous system is neurons. Neuron is basically cell that carries electrical impulses. The gradual loss of structure or function of neurons including death of neurons is called as neurodegeneration. Neurodegereration disease includes Amyotrophic lateral sclerosis, Parkinson's disease, Alzheimer's disease and Huntington's disease. The above disease occurs as a result of neurodegeration process. One of the degenerative disease is Parkinson's which affect the person above the age of 65 years [1]. It is basically affects the predominately dopamine-producing neurons in specific area of brain called substania nigra.

It is very difficult to identify Parkinson's disease as no diagnostic lab test are available. Since approximately 90% of people with PD suffer from speech disorder, voice analysis is most efficient method of diagnosis of PD.

Voice signal recording is the advance, simple and most non-invasive technique for diagnosis of PD [2]. As most of the people with PD affected by speech disorders [3], it could be considered as the most reasonable way for detection of PD [4]. Symptoms present in speech includes diminished loudness, rise of vocal tremor, and breathiness (noise). Vocal impairment relevant to PD is described as dysphonia (inability to produce normal vocal sounds) and dysarthria (difficulty in pronouncing words).

In literature, different researches on speech measurement for general voice disorders [5], [6], [7] and Parkinson's Disease in particular [8],[9], [10] [11], [12]. Some of the research use a regression approach to detect the level of PD utilizing the UPDRS (Unified Parkinson's Disease Rating Scale) measurements while other research approach to problem as a classification problem to detect whether the patient has Parkinson or not.

[11]Uses the dataset which contain vowel 'a' phonation of 31 subjects and get the accuracy of 91.4% by SVM with RBF kernel.

2. DATASET

The PD database consists of training and test files. The training data belongs to 20 PWP (6 female, 14 male) and 20 healthy individuals (10 female, 10 male) [13]. Training dataset consist of 26 voice samples which includes sustained vowels, numbers, words and shorts sentence. Whereas in test data file 28 PD patients ask to say only sustained vowels 'a 'and 'o' which makes the total of 168 recordings.

3. MATERIAL AND METHODS

3.1 Proposed methods

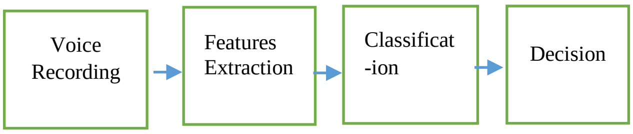

Fig 1 Proposed Method

Proposed Method involve four main blocks. It start with collection of voice sample from People with Parkinson and healthy. Voice recording includes sustained vowels, numbers, words and short sentences. From this recorded voice some important features are extracted. Features like jitter and shimmer are extracted. After feature extraction classification is an important block which discriminate PWP (People with Parkinson's) from healthy people.

3.2 Voice Recording

Voice recording includes sustained vowels, numbers, words and short sentences.

4. FEATURES EXTRACTION

Features Extraction are the most important block for analysis of voice signal. Jitter and its variants, shimmer and its variants are the two most important features as the periodicity of voice in PD is disturbed. Variation in frequency is called as Jitter whereas variation in amplitude is called as Shimmer. Other features like fundamental pitch frequency, NHR, HNR also extracted.

4.1 Jitter and its variants

It is the variation of fundamental frequency from one cycle to next. The other measurements related to jitter which also helps in measuring the perturbation are jitter local or Jitter absolute, jitter RAP(relative average perturbation), jitter PPQ (period perturbation quotient), jitter relative etc.

Jitter absolute is given as eq.(1)

$$\text{Jitter(abs)}=\frac{1}{M-1}\sum_{i=1}^{M-1}|Ti-T(i+1)| \quad (1)$$

Where Ti is Pitch Period and M is number of Pitch Periods.

Jitter rel is given as eq.(2)

$$\text{Jitter(rel)}=\frac{\frac{1}{M-1}\sum_{i=1}^{M-1}|Ti-T(i+1)|}{\frac{1}{M}\sum_{i=1}^{M}Ti} \quad (2)$$

Jitter RAP is given as eq.(3)

$$\text{Jitter (RAP)}=\frac{\frac{1}{M-1}\sum_{i=1}^{M-1}|Ti-\left(\frac{1}{3}\sum_{j=i-1}^{i+1}Tj\right)|}{\frac{1}{M}\sum_{i=1}^{M}Ti} \quad (3)$$

Jitter (PPQ5) represents the amount of periodic disturbance within five periods.
It is calculated using (4)

$$\text{Jitter (PPQ5)}=\frac{\frac{1}{M-1}\sum_{i=2}^{M-2}|Ti-\left(\frac{1}{5}\sum_{j=i-2}^{i+2}Tj\right)|}{\frac{1}{M}\sum_{i=1}^{M}Ti} \quad (4)$$

4.2 Shimmer and its variants

It is a measure of instability in amplitude. Shimmer and its variants are derived by measuring the maximum value of the amplitude of the signal within each vocal cycle.

Shimmer local(db) is given as eq.(5)

$$\text{Shimmer(db)}=\frac{1}{M-1}\sum_{i=1}^{M-1}20*\log\frac{V(i+1)}{Vi} \quad (5)$$

Shimmer relative is given as eq.(6)

$$\text{Shimmer(relative)}=\frac{\frac{1}{M-1}\sum_{i=1}^{M-1}|Vi-V(i+1)|}{\frac{1}{M}\sum_{i=1}^{M}Vi} \quad (6)$$

Where Vi is peak to peak amplitude and M is number of fundamental frequency periods.

Shimmer (APQ3) is given as eq.(7)

$$\text{Shimmer(APQ3)}=\frac{\frac{1}{M-1}\sum_{i=1}^{M-1}|Vi-\left(\frac{1}{3}\sum_{j=i-1}^{i+1}Vj\right)|}{\frac{1}{M}\sum_{i=1}^{M}Vi} \quad (7)$$

Shimmer (APQ5) is given as eq.(8)

$$\text{Shimmer(APQ5)}=\frac{\frac{1}{M-1}\sum_{i=2}^{M-2}|Vi-\left(\frac{1}{3}\sum_{j=i-2}^{i+2}Vj\right)|}{\frac{1}{M}\sum_{i=1}^{M}Vi} \quad (8)$$

Shimmer and its types are extracted using energy contours obtained by computing the frame energy of every speech frame or computing the frame average magnitude of each speech frame.

Table 1. List of features

1	Jitter (local)
2	Jitter (local, absolute)
3	Jitter (rap)
4	Jitter (ppq5)
5	Jitter (ddp)
6	Shimmer (local)
7	Shimmer (local, dB)
8	Shimmer (apq3)
9	Shimmer (apq5)
10	Shimmer (apq11)
11	Shimmer (dda)
12	AC
13	NHR(Noise Harmonic Ratio)
14	NHR(Harmonic Noise Ratio)
15	Median pitch
16	Mean pitch
17	Standard deviation
18	No. of pulses
19	Minimum pitch
20	Maximum pitch

5. CLASSIFICATION

After features extraction classification plays an important role. Proposed system classify two class which represent 0 for healthy and 1 for PWP. Different Algorithms are used for classification. Proposed System used Support Vector Machine (SVM) and K-Nearest Neighbour (KNN).

5.1 Support Vector Machine (SVM)

SVM are supervised learning model which survey data used for classification and regression problems. In SVM, all data points of different class are separated by using hyperplane. Hyperplane maximize the margin between two classes. More margin between the classes gives best hyperplane. There are basically two types of classification one is linear classification whereas other is non-linear classification.SVM performs for both linear and non-linear classification. As data is nonlinear so nonlinear classification plays very important role in this research.SVM uses different kernel to perform non-linear classification.

Different types of kernel are Linear kernel, Gaussian RBF kernel, Sigmoid kernel and Polynomial kernel. Proposed system used Gaussian kernel which provide best accuracy of 91.35%.Mathematical expression for Gaussian Kernel is given in eq.(9)

$$k(x,y) = e^{-\frac{||x-y||^2}{2\sigma^2}} \quad (9)$$

5.2 K-Nearest Neighbour (KNN)

KNN is basically algorithm which classify non-linear data. Hence KNN algorithms used in non-linear classification and regression problem.

Steps involve in KNN

1. Choose the number of K of neighbour.
2. Take the K-nearest neighbour of the new data point, according to Euclidean distance.
3. Among these K-neighbour, count the number of data points in each category.
4. Assign the new data point to the category where you counted the most neighbour.
5. Model is ready.

K value decide the accuracy of KNN algorithm. As K-value changes the accuracy may change. Proposed system gives the accuracy of 90.67% with KNN which is lesser than the SVM.

6. RESULT AND DISCUSSION

Using confusion matrix, accuracy of proposed system is calculated for different machine learning algorithm and the comparison of SVM and KNN is made. Basic measure from the confusion matrix are Sensitivity, Accuracy, Specificity, Precision and F-ratio.

ROC is the curve which plotted for True Positive Rate against False Positive Rate. True Positive Rate is also known as Sensitivity whereas False Positive Rate is known as Selectivity.

6.1 Confusion Matrix and ROC curve for SVM

Fig 2 Confusion matrix

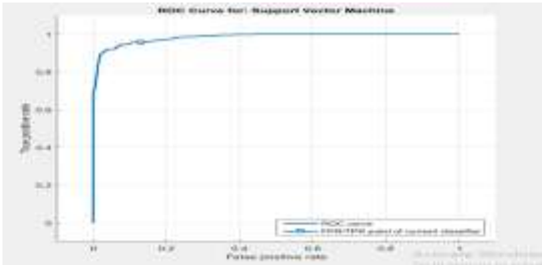

Fig 3 ROC for healthy

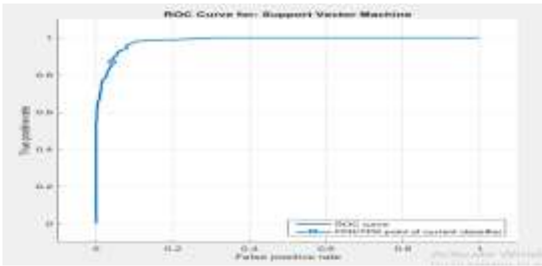

Fig4 ROC for PWP

6.2 Confusion Matrix and ROC curve for KNN

Fig.5 Confusion matrix

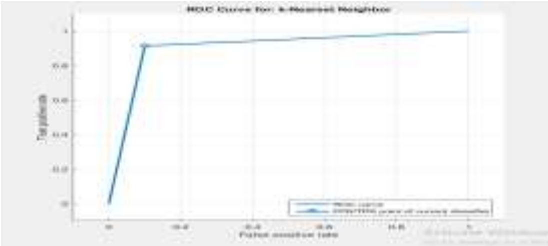

Fig.6 ROC for healthy

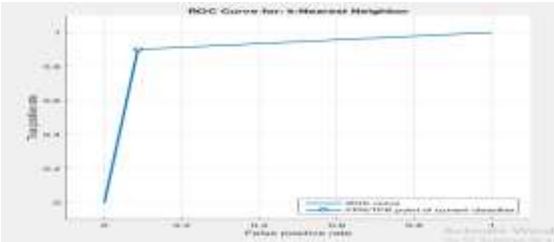

Fig.7 ROC for PWP

6.3 Comparison of SVM and KNN

	SVM	KNN
Accuracy	91.35	90.67
Sensitivity	87.99	91.23
Specificity	95.36	90.13
Precision	95.23	90.00
F-ratio	91.71	90.61

Table 2 SVM verses KNN

7. CONCLUSION

The aim of this research was diagnosis of Parkinson's disease using voice analysis. The classification process was done with various classifier algorithms and the best classification accuracy was achieved by SVM (Support Vector Machine).

REFERENCES

[1] G. Hornykiewicz O. "Biochemical aspects of Parkinson's disease". Neurology,51:S2-9. Review. PubMed PMID: 9711973.1998, Aug1998.

[2] Duffy, & Motor, R. J. (2005). Speech Disorders: Substrates, Differential Diagnosis and Management. (2nd ed.). St. Louis: Elsevier Mosby.

[3] Ho, A., Iansek, R., Marigliani, C., Bradshaw, J., & Gates, S. (1998). Speech impairment in a large sample of patients with Parkinson's disease. Behavioral Neurology, 11, 131–137.

[4] Sapir, S., Spielman, J. L., Ramig, L. O., Story, B. H., & Fox, C. (2007). Effects of intensive voice treatment (the Lee Silverman Voice Treatment [LSVT]) on vowel articulation in dysarthric individuals with idiopathic Parkinson Disease: acoustic and perceptual findings. Journal of Speech Lang Hearing Research, 50, 899–912. doi:10.1044/1092-4388. (2007/064).

[5] J. B. Alonso, J. De Leon, I. Alonso, and M. A. Ferrer, "Automatic detection of pathologies in the voice by hos based parameters," EURASIP Journal on Applied Signal Processing, vol. 4, pp. 275–284, 2001.

[6] M. Little, P. McSharry, I. Moroz, and S. Roberts, "Nonlinear, biophysically-informed speech pathology detection," in Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference on, vol. 2. IEEE, 2006, pp. II–II.

[7] B. Boyanov and S. Hadjitodorov, "Acoustic analysis of pathological voices. a voice analysis system for the screening of laryngeal diseases," Engineering in Medicine and Biology Magazine, IEEE, vol. 16, no. 4, pp. 74–82, 1997.

[8] L. Cnockaert, J. Schoentgen, P. Auzou, C. Ozsancak, L. Defebvre, and F. Grenez, "Low-frequency vocal modulations in vowels produced by parkinsonian subjects," Speech communication, vol. 50, no. 4, pp. 288–300, 2008.

[9] D. A. Rahn, M. Chou, J. J. Jiang, and Y. Zhang, "Phonatory impairment in parkinson's disease: evidence from nonlinear dynamic analysis and perturbation analysis," Journal of Voice, vol. 21, no. 1, pp. 64–71, 2007.

[10] A. Tsanas, M. Little, P. E. McSharry, J. Spielman, L. O. Ramig et al., "Novel speech signal processing algorithms for high-accuracy classification of parkinson's disease," Biomedical Engineering, IEEE Transactions on, vol. 59, no. 5, pp. 1264–1271, 2012.

[11] M. A. Little, P. E. McSharry, E. J. Hunter, J. Spielman, and L. O. Ramig, "Suitability of dysphonia measurements for telemonitoring of parkinson's disease," Biomedical Engineering, IEEE Transactions on, vol. 56, no. 4, pp. 1015–1022, 2009.

[12] A. Tsanas, M. Little, P. E. McSharry, L. O. Ramig et al., "Accurate telemonitoring of parkinson's disease progression by noninvasive speech tests," Biomedical Engineering, IEEE Transactions on, vol. 57, no. 4, pp. 884–893, 2010.

[13] Erdogdu Sakar, B., Isenkul, M., Sakar, C.O., Sertbas, A., Gurgen, F., Delil, S., Apaydin, H., Kursun, O., 'Collection and Analysis of a Parkinson Speech Dataset with Multiple Types of Sound Recordings', IEEE Journal of Biomedical and Health Informatics, vol. 17(4), pp. 828-834, 2013.