Detection of Parkinson Disease through Voice Signal Features

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Abstract: Parkinson disease (PD) is a common neurodegenerative disorder, which affects a central nervous system and it is characterized by progressive loss of muscle control. The diagnosis decision of PD is obtained by clinical observation which relies on expert human observer. Therefore, an additional classification method is desirable for most comfortable and timely detection of PD as well as faster treatment is needed. Many acoustic studies have been documented that the analysis of laryngeal, respiratory and articulatory function may be useful in the diagnosis of PD patient. Therefore, in this study, we develop and validate automated classification algorithms, which are based on Naïve Bayes and K- Nearest Neighbors (KNN) using voice signal measurements to predict PD. The results show that our automated classification algorithm using Naïve Bayes is outperformed KNN and it is useful as a predictive tool for PD screening with a high degree of accuracy, approximately 93.3%.

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1. Introduction

Parkinson's disease (PD) is one of the most common neurodegenerative disorders, which affecting older people, with most cases occurring after the age of 50 [1]. This kind of disease affects a central nervous system which causes progressive loss of muscle control with the distinctive signs include shiver or shake in the hand, arm, leg, jaw, face, bradykinesia and Difficulty in swallowing, chewing, breathing ,speech [2].

Many people with PD might experience additional problems like cognitive problems, emotional changes, thinking difficulties and sleep disorders [3].

The genetic factors considers as the main factors which is might be the cause of PD. However, other factors could be associated with the relationship of developing PD [4].

A patient with PD has a higher risk of tribulation dementia compared to the healthy person. However, the patient could be benefit from the scheduled treatment. It has been reported that the problems with the PD patient could be improved with planned treatment based on regular physical exercise, especially problems related to difficulty in speech, mobility and strength [4].

A diagnosis of Parkinson's disease is subjective based on signs and symptoms review of the patient. Because there is no definitive test for the PD detection [5], therefore, new reliable methods based on clinical criteria for diagnosis and screening of PD are needed, in order to have a major benefit of the treatment on PD to be more effective. In this work, we develop an efficient algorithm for automatic classification of voice signal features to detect abnormalities in speech in order to predict PD. We use Naïve Bayes and KNN to classify voice signal into normal and PD. In the following section, we glance at a variety of PD diagnosis methods. In section III, the methodology of our proposed system is described. Section IV, demonstrates the results of our system. Then, we conclude our paper in section V, and highlight some directions for future research.

2. Related Work

Several methods have been focused on presenting automatic methods for the identification of PD disease. The work in [6] assesses the analysis of neurons in brain in order to detect PD. In addition, different acoustic, articulatory and respiratory studies have underlying the pattern of voice & speech disorder characteristics in PD. Perceptually, Person with PD is characterized by hoarse voice quality, imprecise articulation and stress in his / her voice and speech [7].

The study in [8- 10] have reported a reduced frequency range in the speech of patient with PD.

K. Rosen et. al [11] showed acoustic signatures that have phonetic variation with PD patients, where the patients and healthy people had conversational speech for two minutes. Also, the reductions in vocal sound pressure level (vocSPL) with PD patients were investigated in [7] [8] [12]. In most recent, Fox and Raming founded that vocSPL was 2-4 decibel lower across a variety of speech tasks with PD patients [7] [13].

The study in [14] assesses the analysis of complex nonlinear aperiodicity, non-Gaussian randomness and aero acoustic of the sound in order to evaluate voice disorder.

In our work, the speech signal are saved and processed off-line by an automated system we developed using MATLAB to compute different features measurements that can be used to increase the clinical usefulness of the PD diagnosis system.

3. Methodology

A. Subjects

In this work we used Parkinson speech dataset with multiple types of sound recordings. This is available from the University of California, Irvine (UCI) machine learning repository website [15]. UC Irvine machine learning repository maintains a growing collection of biomedical datasets from healthy subjects and patients as a service to the machine learning community.

The PD dataset consists of a range of voice signal measurements from 41 patients with PD and 52 healthy individuals who were recruited at the Department of Neurology in Cerrahpasa Faculty of Medicine, Istanbul University [16]. Multiple speech recordings of each patient is gathered and stored. From all subjects, 26 a wide variety of voice samples, including number from 1 to 10, nine words, four short sentences, and sustained vowels "a", "o", and "u" are recorded [16].

B. Features Extraction

After collecting the speech dataset, a series of features are extracted from the voice samples. In this context, a group of 26 linear and time-frequency based features are parsed from the dataset considering the previous works [17], [18].

These features are detailed as follows, respectively [15], [16]:

- Frequency features 1-5: Jitter (local), Jitter (local, absolute), Jitter (rap), Jitter (ppq5), and Jitter (ddp).
- Amplitude features 6-11: Shimmer (local), Shimmer (local, dB), Shimmer (apq3), Shimmer (apq5), Shimmer (apq11), and Shimmer (dda).
- Harmonicity features12-14: Autocorrelation, Noise-to-Harmonic, Harmonic-to-Noise.
- Pitch features 15-19: Median pitch, Mean pitch, Standard deviation, Minimum pitch, Maximum pitch.
- Pulse features 20-23: Number of pulses, Number of periods, Mean period, Standard deviation of period.
- Voicing features 24-26: Fraction of locally unvoiced frames, Number of voice breaks, Degree of voice breaks

The extracted features and downloaded data are fed into two different classifiers. The classification methodology is based on the Naïve Bayesian classifier and K-nearest neighbor algorithm (K-NN) with different cross-validation methods and accuracy, specificity and sensitivity evaluation metrics are reported.

C. Naïve Bayesian Classifier

In this research, we apply a Naïve Bayesian as a classifier to identify the diagnostic performance of PD using voice signal features.

Naïve Bayes classifier is used in supervised learning method and it is based on 'probability' concept to classify new entities. Meanwhile, it assigns a new observation to the most probable class. The process of classification based on two steps, as follows [19]:

1. Training step: Using the training samples, the method computes the probability distribution of that sample.
2. Prediction step: For test sample, the method computes the posterior probability of that unknown instance. The posterior is predicting that the sample belonging to each class according to the largest posterior probability, which is called Maximum A Posterior (MAP).

However, Naïve Bayesian classifier is one of the most practical learning methods and it has been proven to be extremely successful in assisting medical specialties in medical diagnosis applications.

D. K-Nearest Neighbor Classifier (KNN)

In this work, in order to identify the diagnostic performance of PD, we use K-NN as a classification method.

Conceptually, in KNN the concept of "nearness" is used to classify new entities. It classifies an instance by finding its nearest neighbors and picking the most popular class among the neighbors. Moreover, it is called nearest neighbor algorithm, when the class is predicted to be the class of the closest training sample (i.e. when k=1).

4. Results

Here there are 83% training samples and each sample have 26 feature values and the size of testing dataset is 17% samples and 26 features for each testing sample. Both classifiers, Naïve Bayes and KNN return the class level of testing samples identified by the help of training samples, each classifier based on its classification methodology, i.e. for Naïve Bayes based on "probability" and for KNN based on "nearness".

We evaluated the classification performance of both classifiers configurations on the test set. Sensitivity, specificity for testing and accuracy are computed. A confusion matrix is generated for both classifiers.

Figure 1 and 2 shows the confusion matrix for testing set classification of Naïve Bayes and KNN, respectively. The confusion matrix shows the total percent of correctly classified cases and the total percent of misclassified cases.

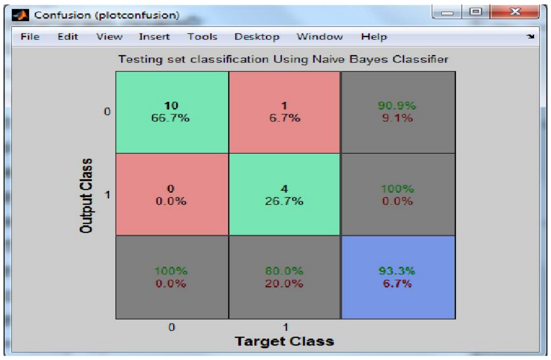

Figure 1. Confusion matrix of Naïve Bayes for testing set classification

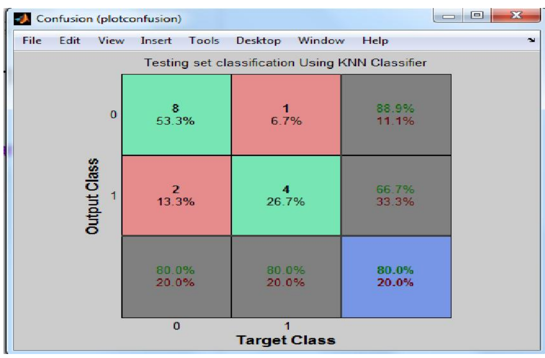

Figure 2. Confusion matrix of KNN for testing set classification

The results show very good KNN with K=1 diagnostic performance of 80% and high Naïve Bayes diagnostic performance with an accuracy of 93.3% correct detection rate (sensitivity 87.5%, and specificity 100%).

As a result, we find that Naïve Bayes using voice signal measurements is a practical and useful screening test to estimate whether patients have Parkinson disease or not.

5. Conclusion and Future Directions

In this work, we studied the possibility of the detection of Parkinson disease from the voice signal variation patterns. We further developed a model using the voice signal features and evaluated its effectiveness. From the experimental results, we conclude that the recognition rate of KNN comes out to be 80%, but, with Naïve Bayes the classification has the highest recognition rate which is 93.3%. So we can say that it is better for recognition.

As a future work, we plan to incorporate this work into a real-time monitoring system that acquires and analyze the speech signal of subjects rather than analyzing the off-line signal.

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