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Comparison of Classification Methods to Detect the parkinson disease

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Abstract— **Parkinson's disease is a chronic neurological degenerative disease affecting the central nervous system responsible for essentially progressive evolution movement disorders. The detection of this disease is made using a clinical diagnosis made by an expert.**

To save time and for more comfort in the Diagnostic and also to increase the efficiency of treatment through preventive detection, classification has found its place in the detection of this disease. For this purpose, many classification algorithms were used to achieve the best results, but the problem is which classifiers may be the most efficient for this detection, because each classification algorithms was applied to a local database, what influences the results.

In this paper we have tried to apply three types of classifiers, k-near neighbor "k-NN", the Naive Bayes "NB" and support vector machines "SVM", on the same database to compare and to know which of the three classifiers will be the most efficient.

Keywords—Voice signal; Parkinson disease; K-NN; Naïve Bayes; Support Vector Machines;

I. INTRODUCTION

Parkinson's disease is in second place behind the Alzheimer regarding the most common neurological diseases.

It is a chronic neurodegenerative disorder, slowly progressive, usually of unknown origin. It affects a structure of a few millimeters at the base of the brain and which is composed of dopaminergic neurons that are gradually disappearing. Their function is to produce and release dopamine, a neurotransmitter essential to the control of body movements, particularly the automatic movements.

Parkinson's disease begins 5-10 years before the onset of clinical symptoms, when about half of dopaminergic neurons disappeared. The diagnosis can be easy due to the presence of at least two of the following three symptoms:

- slowness of movement (bradykinesia)
- a resting tremor of the hand and / or foot-sided
- stiffness (hypertonia)

The diagnosis can be very difficult by the existence of very different non-typical signs, such as depression, pain, and fatigue. So, each patient has special signs compared to others patients.

This disease mainly affects those over 60 years, but among patients suffering from this disease there is 10% less than 50 years.

Clinical diagnosis for Parkinson's disease is subjective because it is based on signs and symptoms appeared in the patient, or we said that every patient has specific signs, so there is no definitive test for detection of this disease. For this we need new methods able to detect this disease permanently in its early stages, in order to benefit the maximum possible of medical treatment to increase its efficiency. For this purpose, the automatic classification based on learning classification algorithms is very interesting.

Because Parkinson's disease affects the patient's voice, much studies has been done on the classification of patients based on the voice and speech. This classification arises on the extraction of the voice features to detect anomalies compared to voice features from a healthy person, in order to predict Parkinson disease.

In this work, we will try to apply three different types of classifiers on the same database, in order to determine the characteristics and judge on which classifier is more effective in the detection of Parkinson's disease from voice.

Then, we selected three classifiers among the most used classifiers, k-nearest neighbor, naive Bayes and support vector machines to classify voice signals into two classes "healthy people and patients".

In the following section, we present the different methods of diagnostics for Parkinson's disease, in section III, we will give the description of our process, Section IV, presentation of the results, comparison and choice of the most efficient classifier. Then we conclude our paper in section V, and highlight the direction for future research.

II. RELATED WORK

Several researches has focused on the presentation of a method for the identification of Parkinson's disease. The study in [1] [2], reports that a PD patient has a frequency range reduced during his speech. K.Rosen and .al [3] shows acoustic signatures that have phonetic variations for a PD patient during a conversation 2 minutes. In [2] [4] [5], they reported reducing the level of the pressure of his voice (vocSPL) for a PD patient.

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Fox and Raming have found the vocSPL decreases by a margin of 2-4 decibel during a speech sets of spots for a PD patient [5].

The work presented by [6] assessing the analysis of neurons in the brain, in order to detect the PD. moreover, different acoustic studies articulatory and respiratory raised the voice disorders characterizes the PD. In other words, a PD patient is characterized by a lower voice quality, a poorly precise articulation and stress accompanying his voice and speech.

The main of study in [7] consists to evaluate the analysis of complex non-linear aperiodicity, non-Gaussian randomness and also aero acoustic of the sound, in order to evaluate the voice disorders.

In our work we use voice signals from a recognized database and published [8], we deal in MATLAB classification by learning to classification algorithms to increase the clinical utility systems diagnostic PD.

III. Methodology

A. Subjects

In this work, we use a database containing voice recordings of many PD patients and healthy people. This database is available from the University California Irvine (UCI) machine learning repository website [8]. UC Irvine machine learning repository maintains a collection of biomedical databases from healthy people and patients as a service to the machine learning community.

The PD database consists of training and test files. The training data belongs to 20 patients with Parkinson "PWP" (6 female, 14 male) and 20 healthy individuals (10 female, 10 male) who appealed at the Department of Neurology in Cerrahpasa Faculty of Medicine, Istanbul University [9]. From all subjects, multiple types of sound recordings (26 voice samples including sustained vowels, numbers, words and short sentences) are taken.

B. Features Extraction

After collecting the voice dataset, a group of 26 linear and time-frequency based features are extracted from each voice sample.

These features are described as follows, respectively [8], [9]:

- 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 (apq11), and Shimmer (dda).
- Harmonicity features 12-14: Autocorrelation, Noise-to-Harmonic, and 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 from the voice recordings have been used for three different types of classifiers. The methodology is based on the k-nearest neighbor classifier (KNN), Naive Bayes (NB) and support vector machines (SVM) algorithm with different cross-validation methods and accuracy, specificity and sensitivity evaluation metrics are reported.

C. K-Nearest Neighbor Classifier (KNN)

In this research, we apply K-NN as a classifier to identify the detection performance of PD using voice signal features.

The K-Nearest Neighbor (KNN) classification rule is conceptually quite simple: a sample is classified according to the classes of the K closest samples, i.e. it is classified according to the majority of its k-nearest neighbors in the data space. In a computational point of view, all that is necessary is to calculate and analysis a distance matrix. The distance of each sample from all the other samples is computed, and the samples are then sorted according to this distance. KNN is a non-linear classification method. Because of these characteristics, KNN has been suggested as a standard comparative method for more sophisticated classification techniques. When applying KNN, the optimal value of K must be searched for. One option for selecting K is by means of cross validation procedures, i.e. by testing a set of K values (e.g. from 1 to 10); then, the K giving the lowest classification error in cross-validation can be selected as the optimal one.

D. Support Vector Machines Classifier (SVM)

In this work, in order to identify the detection performance of PD, we use also the Support Vector Machines (SVM) as a classification method.

Conceptually, the Support Vector Machines (SVM) define a decision boundary that optimally separates two classes by maximizing the distance between them. The decision boundary can be described as a hyper-plane that is expressed in terms of a linear combination of functions parameterized by support vectors, which consist in a subset of training molecules. SVM algorithms search for the support vectors that give the best separating hyper-plane using a kernel function. Kernels included in the toolbox are: linear, radial basis functions (RBF) and polynomial. During optimization, SVM search the decision boundary with maximal margin (cost, upper bound for the coefficients alpha) among all possible hyper-planes, where the margin can be intended as the distance between the hyper-plane and the closest point for both classes.

When applying SVM, the optimal value of cost must be searched for. One option for selecting the optimal cost value is by means of cross validation procedures, i.e. by testing a set of cost values (e.g. from 0.1 to 1000); then, the cost value giving the lowest classification error in cross-validation can be selected as the optimal one. When dealing with RBF and polynomial kernels, the kernel parameter must be selected too. In this case, a set of values of kernel parameters is tested in cross validation and the value giving the lowest error in classification can be selected as the optimal one.

E. *Naïve Bayes Classifier (NB)*

For this study, we also applied the Naive Bayes classifier, for the same reason to identify the performance of the detection of PD, always based on the extracted features of the voice signals.

The classifier Naive Bayes is used in supervised learning methods, it is based on calculating the posterior probabilities to classify the new entities.

F. *The Classification Process*

The classification process is essentially based on two stages, which we present as follows:

- Training step: In this stage, we use the training samples, and the classification method computes a classification model based on these samples.
- Prediction step: In this stage, we use test data, for which the classification method predicts the class of each test sample based on the already computed model.

IV. RESULTS

The database we have, is divided into two part containing the training data, with 40 people (20 healthy and 20 PD patients), and for each training sample we have 26 feature values. The second part contains the test subjects who are also 40 people (20 healthy and 20 PD patients) and 26 feature values for each test sample.

Our three classifier KNN, Support vector machine and Naive Bayes, return in the output the class of test samples that are identified using the training samples, each classifier is based on its own classification methodology.

In order to evaluate the performance of our three classifiers, and to judge which of them will be most effective, we calculated the Sensitivity, Specificity and Accuracy. We also generated confusion matrix for all classifiers candidates.

Thereafter, Figures 1, 2 and 3 show the confusion matrix related to the classification of 40 test subjects for Support Vector Machines, K-NN, and Naive Bayes respectively.

		True Condition		
		Condition Positive	Condition Negative	Total
Predicted Condition	Prediction Condition Positive	17	5	22
	Prediction Condition Negative	3	15	18
	Total	20	20	40

Fig. 1. Confusion matrix of Support Vector Machines for testing set classification

		True Condition		
		Condition Positive	Condition Negative	Total
Predicted Condition	Prediction Condition Positive	15	7	22
	Prediction Condition Negative	5	13	18
	Total	20	20	40

Fig. 2. Confusion matrix of K-NN for testing set classification

		True Condition		
		Condition Positive	Condition Negative	Total
Predicted Condition	Prediction Condition Positive	14	8	22
	Prediction Condition Negative	6	12	18
	Total	20	20	40

Fig. 3. Confusion matrix of Naïve Bayes for testing set classification

By adopting the results presented by the confusion matrix, we have compiled a comparative table between the three classifiers, containing Sensitivity, Specificity and Accuracy.

Sensitivity, Specificity and Accuracy can be calculated from the confusion matrix by the following formulas:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FP} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

TABLE I. COMPARATIVE TABLE

	Support Vector Machines Classifier	K-NN Classifier	Naïve Bayes Classifier
Sensitivity	77%	68,2%	63,6%
Specificity	83%	72%	66,6%
Accuracy	80%	70%	65%

The table shows that the K-NN have a good detection performance with 70%, and high Support Vector Machines detection performance with an accuracy of 80% correct detection rate. But we remark that the Naïve Bayes has a low quality of detection performance 65%.

Plotting ROC (Receiver operating characteristic) curves of the classifiers which present the best result (SVM classifier and KNN classifier), we can also compare the AUC (Area Under Curve), which permit to judge the performances of classifiers. The following figure shows the ROC curves of our classifiers at once:

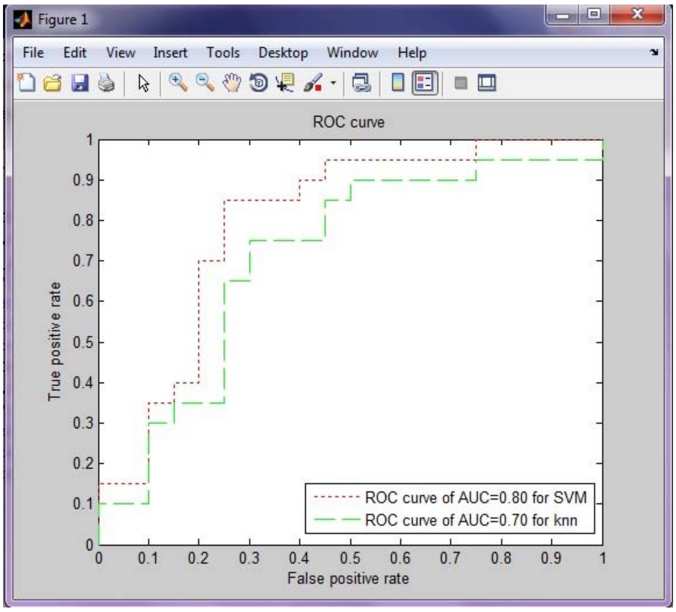

Fig. 4. ROC Curves of our three classifiers

We can clearly note that the AUC presented by SVM classifier is superior AUC of KNN classifier.

As a result, we find that the Support Vector Machines using voice signals measurements, is a practical and useful screening test to predict whether patients have Parkinson disease or not.

V. CONCLUSION

In this work, we studied the possibility of Parkinson disease detection through the voice signals. We also developed classification models using the features of recorded voice and we have evaluated their efficiency.

Based on the final results, we conclude that the model based on support vector machines classifier is more effective and present the high performance in the detection of Parkinson disease.

As a future work, we plan to increase the efficiency, and try other classification method to reach a definitive diagnosis for Parkinson disease.

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