Predictinig Parkinson's Disease Utilizing Support Vector Machines using Audio Features

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Abstract

Parkinson's disease is a prevalent chronic neurological disease that can be recognized by the severe motor system disorders that it causes. An early detection system would be beneficial to diagnose people early in order to maximize their quality of life. A system was created that utilizes exclusively audio data which allows for lightweight implementations to be created on such platforms as smartphones and personal computers.

I. Introduction

Parkinson's disease is a debilitating and neurological disorder that is manifested primarily through motor system disorders but later on in the disease progression psychiatric symptoms such as dementia and depression can occur. One million Americans and 7-10 million worldwide are affected by this disease with approximately 60,000 new diagnoses every year (in the United States). This is more than the combined number of people affected by multiple sclerosis, muscular dystrophy and Lou Gehrig's disease. Diagnosis of this disease is a growing research area as it can be difficult to distinguish Parkinson's from other neurological diseases such as Alzheimer's. There is currently no cure for Parkinson's disease, however there are many treatments that a patient can receive that will drastically improve the quality of life. Therefore early detection of this disease is crucial to help patients until a cure is found.

Previous research has been done in order to design systems for early detection but have relied exclusively on accelerometer and similar data. This is a logical choice when examining Parkinson's but is limited in the ease of implementing this system at wide scales. An audio-based system would be preferred for early detection as it can be easily implemented on a variety of platforms.

II. Data

The Michael J. Fox Foundation for Parkinson's Research has collected and opened up a large database of mobile phone data collected from healthy adults as well as those with different stages of Parkinson's. Using mobile phone data which uses a variety of sensors to collect data could lead to early detection of this disease as it primarily manifests through motor system disorders which can be registered through speech and motor patterns. The data contains data from audio, accelerometry, compass, ambient light, proximity, battery level and GPS streams. The data was recorded every minute in one hour increments during waking hours. The study lasted for 8 weeks. There were 16 participants in the study, 9 diagnosed with Parkinson's and 7 controls.

This dataset has been analyzed in the past but the focus was on the accelerometry and GPS data. This project is looking exclusively at the audio data as it has not been examined in the past. The audio data provided contains several features such as L1-norm, L2-norm, L-inf norm, power spectral density across four separate bands, 12 lowest mel-frequency cepstral coefficients. The data was provided in csv format and seperated by subject and day. Due to the vast amount of data (on the order of 200,000 data-points) the data was averaged over each day (for each subject). This reduces the data to a manageable level in order to be used for machine learning.

III. Methods

In order to classify data into Parkinson's or not Parkinson's a support vector machine was utilized. This machine learning technique is ideal for this type of problem because it is simply a binary classification. Support vector machines work by projecting the training data into a higher dimension in order to seperate it using a hyperplane. The hyperplane is defined as follows:
$f(x) = w^T \phi(x) + b$

where w is the margin or seperation between the two classes and $f(x) > 0$ implies $y = 1$ and $f(x) < 0$ implies $y = -1$ and x and y are the two classes.
To create good seperation the support vector machine attempts to maximize the margin. This is achieved by using Lagrange multipliers as shown in the following equation.
$L(w, b, a) = \frac{1}{2}||w||^2 - \sum_{n=1}^{N} \alpha_n [y_n (w \cdot x_n - b) - 1]$
Support vector machines rely on the kernel in order to seperate the data after it has been projected. There are many different types of kernels that perform differently depending on the dataset. Common kernels include linear, quadratic, other polynomials and radial basis functions. Only linear and radial basis functions were examined as kernels in this project. Support vector machines work well if there is not miss-classified data or outliers. However, outlying data points can make it extremely difficult for support vector machines to find the correct seperating hyperplane. The support vector machine may not find the hyperplane at all as it has to project to such a high dimension that computational resources are exhausted. Another, potentially more serious, problem is that a hyperplane may be found but overfits the data, it is so complicated that it is useless when classifying testing data. In order to alleviate this problem a "soft margin" term can be used which allows for outliers in the data (but penalizes them). This is implemented by using the following equation:
$C \sum_{n=1}^{N} \zeta_n + \frac{1}{2}||w||^2$

In order to maximize the available data, and to prevent overfitting, k-folds cross-validation is used. This technique seperates the data in $k - 1$ training samples and k testing samples. This process is repeated k times in order for all of the available data to be used for both training and testing.
The data was first imported into MATLAB and averaged over each day in order to reduce the number of observations to allow the support vector machine to function better. The data was seperated into three different matrices, the power spectral density values, the energy values, and the Mel-frequency cepstral coefficients. These were the different features used to train and test the support vector machines. Two different groups were created, those with Parkinson's disease (positive) and the controls (negative). 10-fold cross-validation was implemented using a MATLAB function that provided indices. The support vector machine used for the classification was implemented using MATLAB and then tuned using parameter sweeping over possible soft margin values and either linear or radial basis function kernels. The rates for each pass of the cross-validation were weighted appropriately and summed to get an overall rate.

IV. Results

The classification rates when examining the Power Spectral Density feature compared to the soft margin parameter when using a linear kernel is as follows:

Soft Margin	Positive Rate	Negative Rate
0.1	0.9378	0.3216
0.2	0.9270	0.3351
0.3	0.9135	0.3405
0.4	0.9081	0.3486
0.5	0.8973	0.3649
0.6	0.9000	0.3757
0.7	0.8919	0.3676
0.8	0.8892	0.3757
0.9	0.8811	0.3865
1.0	0.8892	0.3811

The classification rates when examining the Power Spectral Density feature compared to the soft margin parameter when using a radial basis function kernel is as follows:

Soft Margin	Positive Rate	Negative Rate
0.1	0.8919	0.3514
0.2	0.8197	0.4554
0.3	0.8468	0.4635
0.4	0.8487	0.4702
0.5	0.8541	0.4720
0.6	0.8611	0.4810
0.7	0.8557	0.4953
0.8	0.8522	0.4957
0.9	0.8649	0.4918
1.0	0.8630	0.5008

The classification rates when examining the energy feature compared to the soft margin parameter when using a linear kernel is as follows:

Soft Margin	Positive Rate	Negative Rate
0.1	0.6360	0.6197
0.2	0.6719	0.6090
0.3	0.6936	0.6072
0.4	0.6936	0.6035
0.5	0.6902	0.6123
0.6	0.6920	0.6145
0.7	0.6881	0.6181
0.8	0.6885	0.6163
0.9	0.6902	0.6269
1.0	0.6881	0.6144

The classification rates when examining the energy feature compared to the soft margin parameter when using a radial basis kernel is as follows:

Soft Margin	Positive Rate	Negative Rate
0.1	0.7907	0.4761
0.2	0.7765	0.4776
0.3	0.7801	0.4921
0.4	0.7820	0.4917
0.5	0.7857	0.4953
0.6	0.7785	0.4993
0.7	0.7838	0.4972
0.8	0.7782	0.5066
0.9	0.7819	0.5007
1.0	0.7804	0.5079

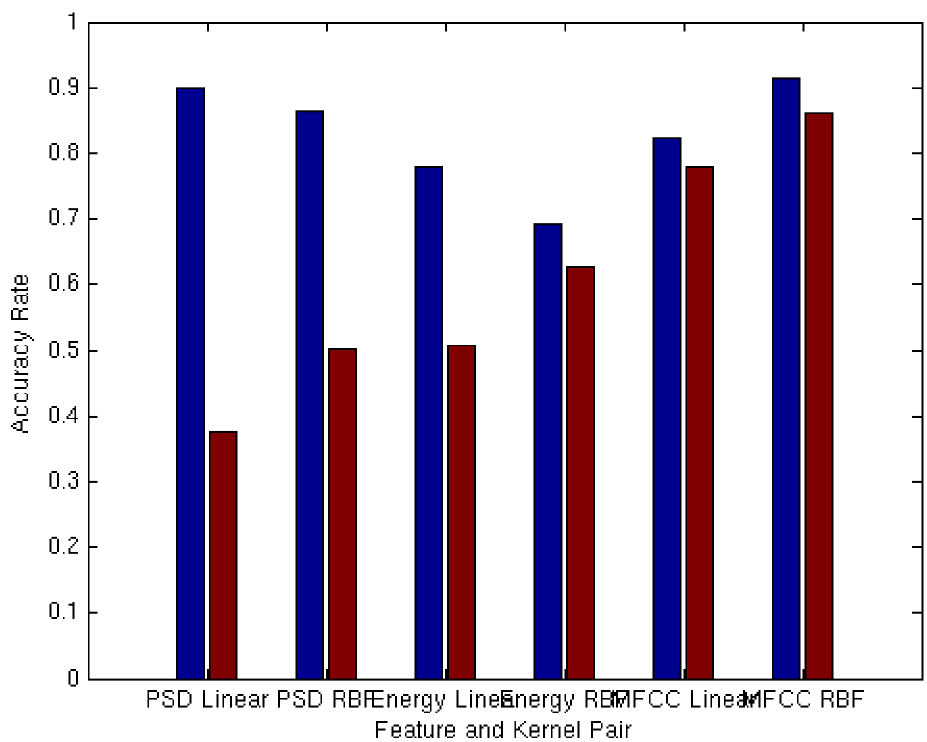
The classification rates when examining the Mel-frequency cepstrum coefficients feature compared to the soft margin parameter when using a linear kernel is as follows:

Soft Margin	Positive Rate	Negative Rate
0.1	0.8167	0.7512
0.2	0.8158	0.7623
0.3	0.8225	0.7784
0.4	0.8099	0.7678
0.5	0.0	0.0
0.6	0.0	0.0
0.7	0.0	0.0
0.8	0.0	0.0
0.9	0.0	0.0
1.0	0.0	0.0

The classification rates when examining the Mel-frequency cepstrum coefficients feature compared to the soft margin parameter when using a radial basis kernel is as follows:

Soft Margin	Positive Rate	Negative Rate
0.1	0.8774	0.7477
0.2	0.9079	0.7670
0.3	0.9295	0.7944
0.4	0.9301	0.8006
0.5	0.9076	0.8287
0.6	0.9026	0.8327
0.7	0.9196	0.8488
0.8	0.9082	0.8596
0.9	0.9129	0.8602
1.0	0.9187	0.8421

A graph of each feature after parameter optimization using both kernels is as follows:



V. Discussion and Further Study

As seen in the results the overall accuracy rates were quite varied, some features performed quite well while others did poorly. The power-spectral-density had a high positive accuracy rate but an extremely low negative accuracy rate for both the linear and the radial basis function kernels. The energy feature had better negative accuracy rates but low positive accuracy rates. The energy feature had a stark difference when using the linear kernel compared to the radial basis kernel for negative accuracy rates. The Mel-frequency cepstrum coefficients had the best classification rates, a respectable 91% positive rate and 86% negative rate. This is quite good and shows promise for further study.

Overall the data did show good positive classification rates when using the Mel-frequency cepstrum coefficients as well as the power spectal density features. However, the power-spectral density feature had quite low negative classification rates. This is not acceptable when making a real-world system as false-negatives should be minimized, people should not be told they are not at risk for Parkinson's when they are. This contrasts to false-positives where people are told they might have Parkinson's and then do not. This type of error is acceptable as it is easy to catch with further testing while false-negatives are not.

A better classification system could potentially be developed that combined the three feature types together and weighted them appropriately. The audio data classification system could also be combined with an accelerometer based system in order to increase accuracy. In addition, while outside of the available dataset other audio features could be examined. Raw audio was not available when developing this system but different audio data could be collected and analyzed in the future.