Predicting Parkinson's Disease Progression with Smartphone Data

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Predicting Parkinson's Disease Progression with Smartphone Data

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Introduction

With the aging world population, around four to six million people suffer from Parkinson's disease (PD) worldwide[1]. The importance of early detection and management of PD is apparent from the fact that over 50,000 Americans are diagnosed with Parkinson's every year. With increased proliferation of phones as digital partners in every day life of people, these phones hold a wealth of information regarding their daily activities. The information ranges from sensor observations (e.g., captured by accelerometer, GPS, compass, and microphone) to textual observations (e.g., social media updates, and SMS).

Though we have access to heterogeneous observations of daily activities, there is a pressing need for scientific methods that can empower people with actionable information. This science of gleaning insights (actionable information) from observations is what we call *Cyber-Physical-Social Computing* [1]. In this challenge, we focus on the sensor data analytics and present a unique combination of top-down and bottom-up approaches to process observations from sensors on a phone carried by PD patients and the control group. The top-down approach includes the use of background knowledge built by our (Kno.e.sis) center, which aggregates disease-symptom-medication knowledge from multiple sources. We leverage this ontology to compile a list of symptoms for PD that can manifest in one or many of the sensor observations given in this challenge.

Approach

We would like to take a progressively expressive approach to address this challenge. Here we outline the overall approach and explain the details in the next few sections. We present only a preliminary solution due to time constraints of the challenge.

Progressively sophisticated sensor data analytics will address important questions posed by the challenge such as Can we detect PD patients? Can we characterize the progression of the disease? However, in this work, we focus only the first question while outlining ways to address the second.

1) BINARY CLASSIFICATION

Goal: Distinguish between PD patients and control group participants

Challenges:

- The data is time-stamped and hence it is not independent (violating the IID assumption), making the direct use of data for classification not feasible.

[1] http://www.parkinson.org/parkinson-s-disease.aspx

- The data is unevenly sampled leading to imbalance in the number of data samples being collected, e.g., during a time period, not all sensors may record observations.
- There may be missing data since real-world sensors may fail to collect observations, e.g., due to sensor fault.

Solution:

- Extract features that can summarize data, to build model for classification.
- Include temporal dimension in the extraction of features, e.g., through the use of resultant acceleration to compute speed and aggregate it over a day.
- Keeping the features on a per day basis, to enable avoiding gaps that are not relevant to a period of interest.

Evaluation:

- Baseline will be the PD diagnosis guidelines given by NIH/some medical agency.
- Given activity data, our system can detect PD symptoms passively.
- Classification accuracy (false positives are to be eliminated).

2) TEMPORAL ANALYSIS OF/FOR PROGRESSION

Goal: Characterize the disease progression of PD patients

Challenges:

- Recognition of diseases/risks from ambient sensors is a new area that generalizes the existing work that utilizes physiological observations [2, 3].
- There are many common behavior patterns between PD and non-PD subjects.
- Missing and unevenly sampled data.

Solution:

- We propose to use state based modeling techniques to model the health condition of a patient, e.g., using HMM.
- We will enrich the model with Dynamic Bayesian Network (DBN) or Continuous Time Bayesian Network (CTBN) to capture the richness of the domain and temporal data.
- Predict the risk of the patient based on the activity observations and prior information.

Evaluation:

- Compare the prediction of risk with the degree of severity of the patient, e.g., the model should indicate higher risk for those PD patients who are degenerating faster (as indicated by questionnaire).

3) ACTIONABLE CUES DETECTION AND REMEDY PRESCRIPTION

Goal: Translate the risk assessment into actionable information

Challenges:

- The identification of action to be taken is not part of the physical/physiological observations.

- The actionable information depends heavily on the domain knowledge, e.g., Parkinson's disease and its management, Asthma and its management.
- Recommending action based on observations from sensors and textual observations requires involvement of domain knowledge and its validation by a domain expert.

Solution:

- We propose to use knowledge of the disease (Parkinson's) such as "increased stress influences tremors" in recommending actions, e.g., in suggesting reducing stress.

Evaluation:

- The recommended action should match with the severity level of the PD patient.

Symptom Identification

Parkinson's disease can be categorized into three levels of severity[2]:

- Mild
  - Tremors occur on one side of the body
  - Change in posture and walking ability
- Moderate
  - Tremors occur on both sides of the body
  - Trouble balancing
  - Freezing episodes
- Advanced
  - Great difficulty walking (may result in fall)
  - Hallucinations and delusions

In the first phase, there may be tremors resulting in discomfort. The symptom may extend to changes in walking style. One side of the body may be affected resulting in a drag (unbalanced motion) when walking. The second phase may have tremors and problems on both sides of the body resulting in balancing problems. Due to loss of balance, patients may undergo freezing episodes resulting in intermittent motion. The advanced phase may completely disrupt normal movement and can also result in falls.

Sensor Selection and Justification

Sensors capable of detecting symptoms at various stages of PD are outlined here.

- Mild
  - **Tremors**
    - Rapid change in x, y, and z using accelerometer.
  - **Poor balance**
    - zig-zag movement using compass.
- Moderate
  - **Move slowly**
    - Average speed of movement using accelerometer.

[2] http://www.pdf.org/en/progression_parkinsons

    - **Move intermittently**
        - x, y, and z of the accelerometer do not change over time.
    - **Disturbed sleep**
        - Sounds in the night using the microphone.
    - **Slower monotone speech**
        - Energy level of the sound using the microphone.
- Advanced
    - **Fall prone**
        - Rapid change in acceleration readings.

We have mapped each symptom and its possible manifestation in the form of sensor observations. This mapping of symptoms to sensor capabilities can be formalized using SSN XG ontology [4, 5] in an extensible manner to accommodate additional symptoms of PD or any other disease. In summary, accelerometer and compass are the two important sensors that we can exploit in detecting the symptoms of PD. Audio sensor will also be valuable as a complement to other sensors.

Feature Extraction

After mapping the symptoms to possible manifestations as sensor observations, we analyzed the data set for verifying such trends. In this step, we verified our intuitions on the PD symptoms and its manifestations in sensor observations. Activities of people are typically periodic and we treat each day as one cycle. We summarize various features for each day for each person. We hypothesize that this level of granularity will allow us to distinguish between the PD patients and control group participants. For disease progression, we need a fine-grained analysis of this data (may be every hour). Given that there are only a few days worth of data, we will assume that the patient's condition would not deteriorate too much over this limited period of observation. Please refer to the appendix for complete description of features and justification for their use in building a classification model.

Evaluation

We will use the verified features (from previous section) to build classifiers so that we can mechanize the PD detection process. A feature is the fundamental building block for characterizing symptoms, e.g., a "moving slowly" symptom is composed of three features: low acceleration along x, y, and z dimensions of the phone.

In the evaluation of classification results, we notice that the classifiers that leverage correlations among sensor observations do better in terms of classification accuracy. We explore seven different classifier models with a ten fold cross validation on data from 8 people (5 PD + 3 Control) due to resource constraints. We rely on the Weka toolset for various classification algorithms. The result of classification in terms of accuracy and confusion matrix is presented here:

Naïve Bayes (Accuracy = 66%)

Predicted =>	Control	PD
Control	25	44
PD	6	75

Bayes Net (Acc. = 74%)

Predicted =>	Control	PD
Control	44	25
PD	13	68

J.48 Decision Tree (Acc. = 72%)

Predicted =>	Control	PD
Control	52	17
PD	24	57

Random Forest (Acc. = 77%)

Predicted =>	Control	PD
Control	57	12
PD	22	59

Random Tree (Acc. = 79%)

Predicted =>	Control	PD
Control	52	17
PD	14	67

Logistic Regression (Acc. = 80%)

Predicted =>	Control	PD
Control	51	18
PD	12	69

Conclusion

We proposed a systematic approach for taking declarative knowledge of symptoms (top-down) and mapping them to their manifestation in a cyber-physical system (bottom-up). We model symptoms as a composition of primitives called features defined over sensor observation (e.g., change in value, mean, deviation, and thresholds). We leveraged these features to build classification models and evaluated their accuracy. Classifiers leveraging the correlations between features for building the model resulted in higher accuracy.

As a future work, we will explore the temporal dynamics of the observations being collected to uncover disease progression. We will explore enrichment of the model with declarative knowledge for recommending actionable information and also for better detection of PD symptoms.

References

[1] Amit Sheth, Pramod Anantharam, Cory Henson, 'Physical-Cyber-Social Computing: An Early 21st Century Approach,' IEEE Intelligent Systems, pp. 79-82, Jan./Feb. 2013

[2] Saria, Suchi. The Digital Patient: Machine Learning Techniques for Analyzing Electronic Health Record Data. Diss. Stanford University, 2011.

[3] Quinn, John A., Christopher KI Williams, and Neil McIntosh. "Factorial switching linear dynamical systems applied to physiological condition monitoring." Pattern Analysis and Machine Intelligence, IEEE Transactions on 31.9 (2009): 1537-1551.

[4] Lefort, L. et al.: Semantic Sensor Network XG Final Report. Technical report, W3C Semantic Sensor Network Incubator Group (SSN-XG) (June 2011)

[5] Compton, M. et al.: The ssn ontology of the w3c semantic sensor network incubator group. Web Semantics: Science, Services and Agents on the World Wide Web 0(0) (2012)

Predicting Parkinson's Disease Progression with Smartphone Data (Appendix)

Feature Extraction

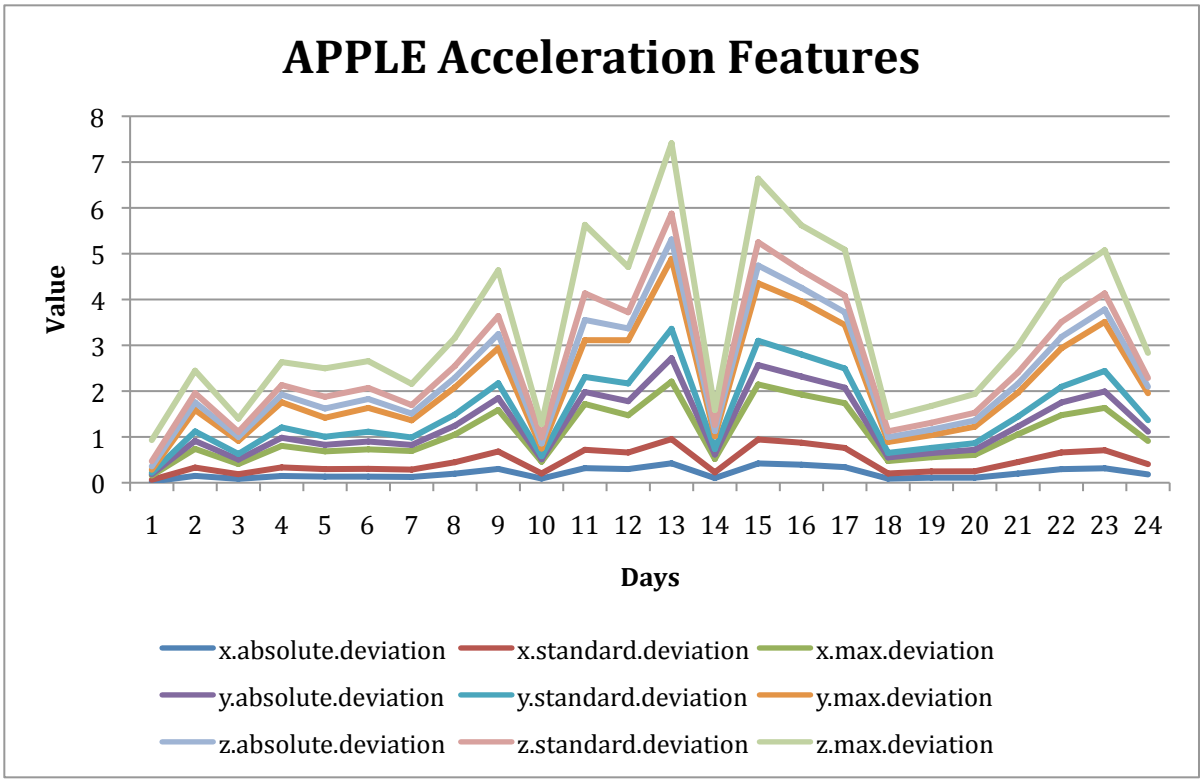
Activities of people are typically periodic and we treat each day as one cycle. We summarize various features for each day for each person. We hypothesize that this level of granularity will allow us to distinguish between the PD patients and control group. For disease progression, we need a fine-grained analysis of this data (may be every hour). Given that there are only few days worth of data, we will assume that the patient's condition would not deteriorate too much.

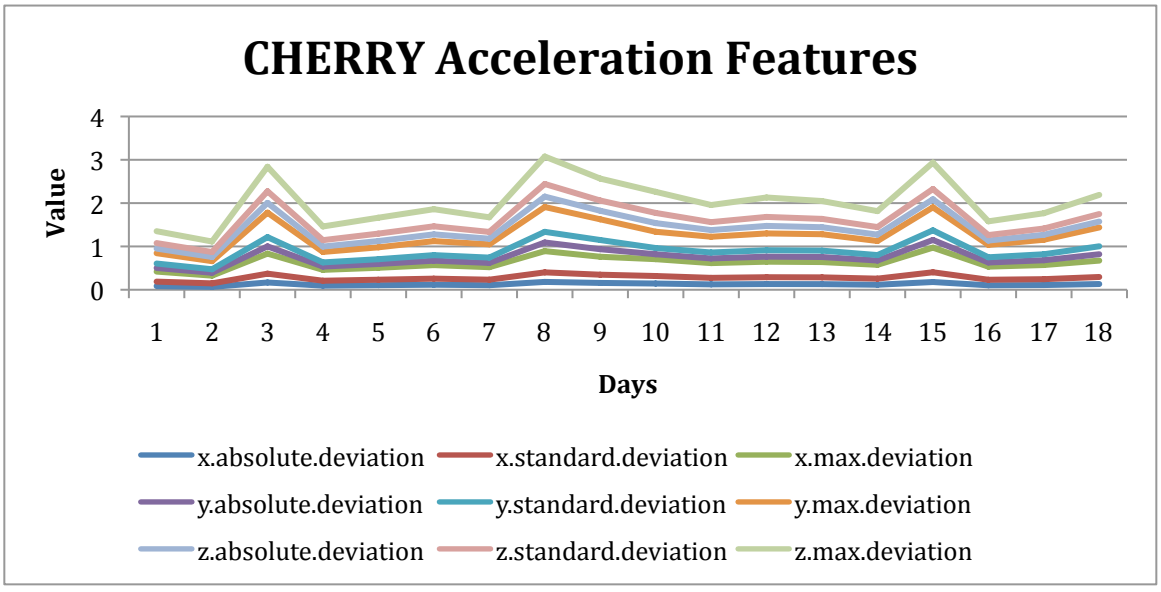
Feature extraction carried out on the following subjects:

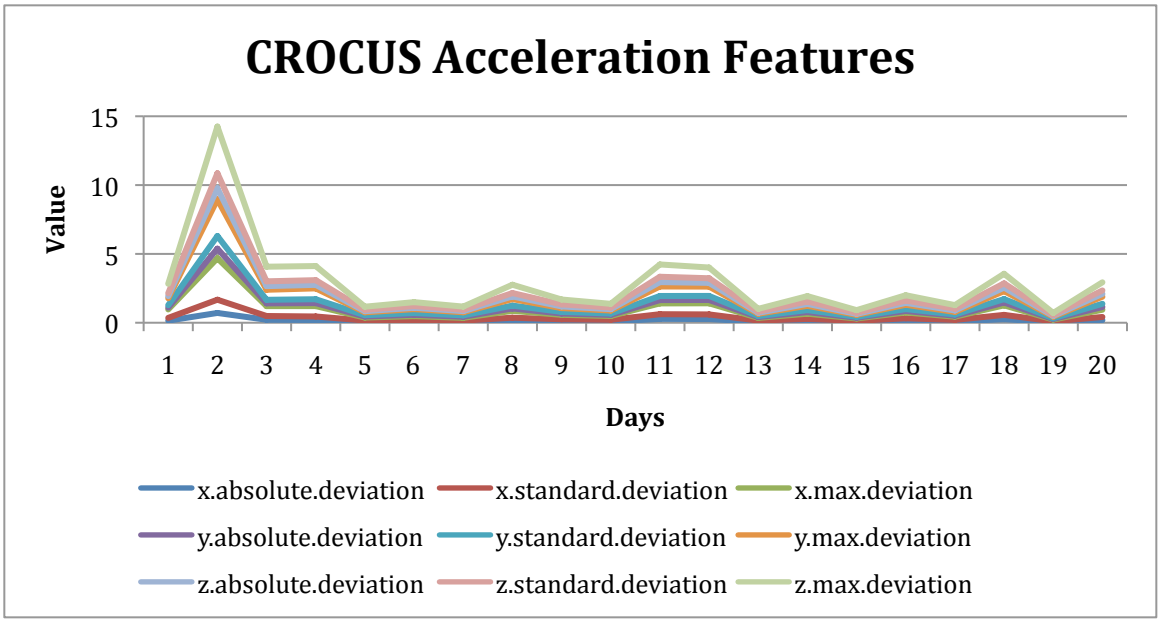
Name	PD/Control
APPLE	Control
CHERRY	PD (4 years)
CROCUS	PD (5 years)
DAFODIL	Control
DAISEY	PD (2 years)
FLOX	PD (10 years)
IRIS	PD (20 years)
LILLY	Control
MAPLE	PD (9 years)
ORANGE	Control
ORCHID	PD (4 years)
PEONY	PD (13 years)
ROSE	Control
SUNFLOWER	Control
SWEETPEA	Control
VIOLET	PD (2 years)

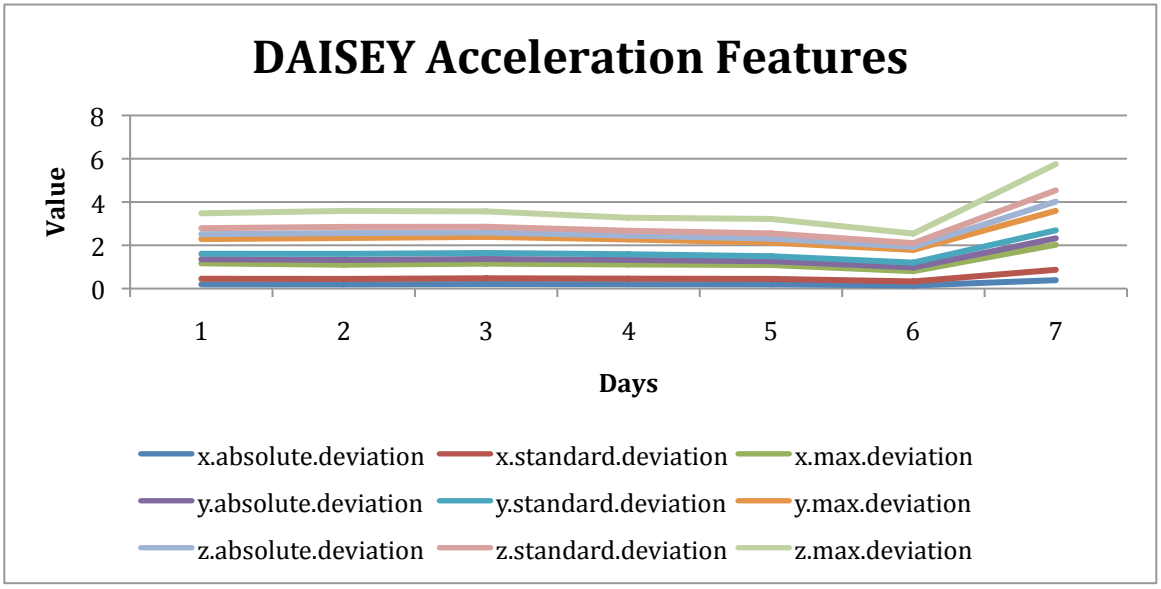
Acceleration

One of the symptoms of PD is slow movement and this is apparent from the plot of acceleration readings. APPLE has good variation in acceleration components x, y, and z. CHERRY, CROCUS, and DAISEY have very low variations in their acceleration readings indicating overall slow movements compared to APPLE. Further, CROCUS has sudden fluctuations in the z component of acceleration compared to the typical variation over twenty days, which may be indicative of a fall.


APPLE Acceleration Features
Value
Days
x.absolute.deviation
x.standard.deviation
x.max.deviation
y.absolute.deviation
y.standard.deviation
y.max.deviation
z.absolute.deviation
z.standard.deviation
z.max.deviation

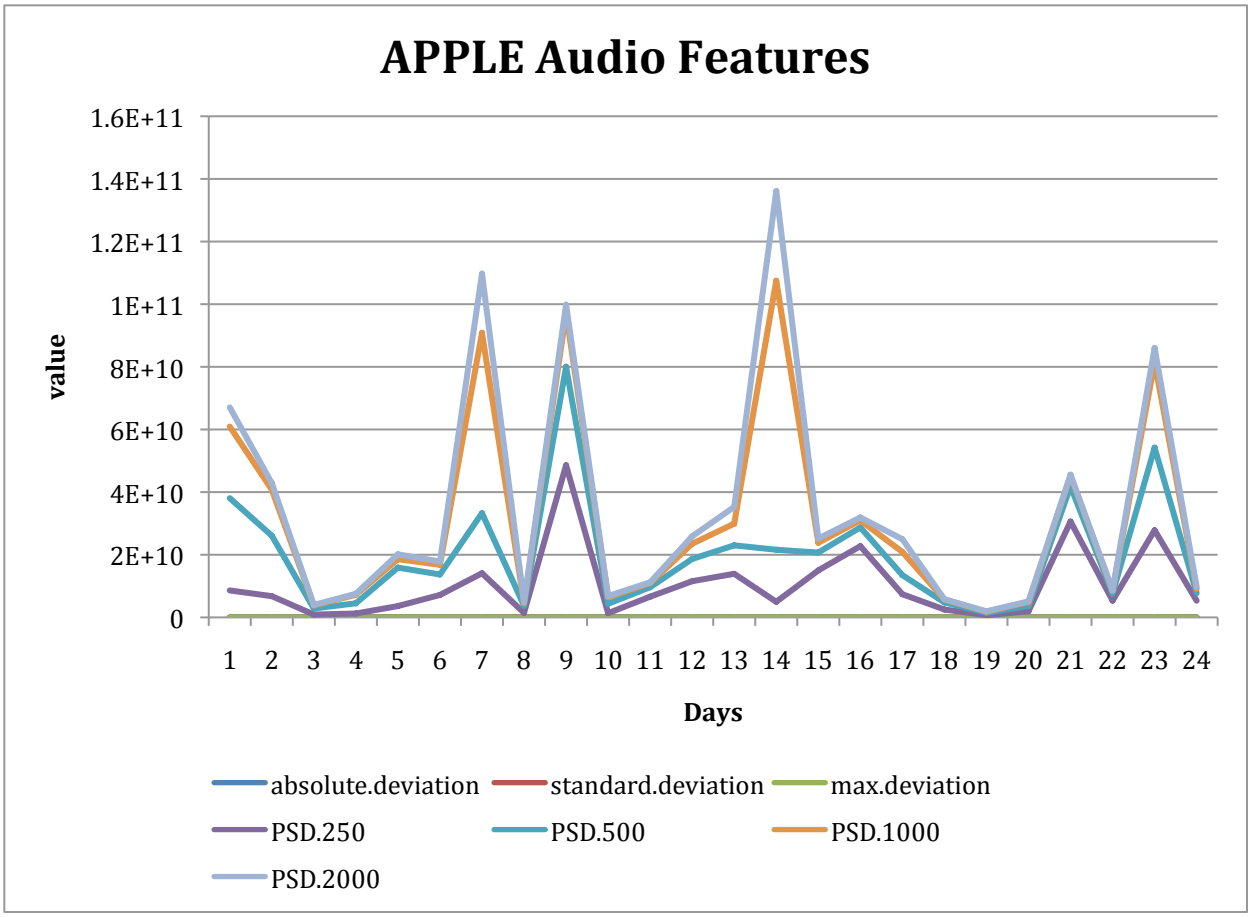

CHERRY Acceleration Features
Value
Days
x.absolute.deviation
x.standard.deviation
x.max.deviation
y.absolute.deviation
y.standard.deviation
y.max.deviation
z.absolute.deviation
z.standard.deviation
z.max.deviation

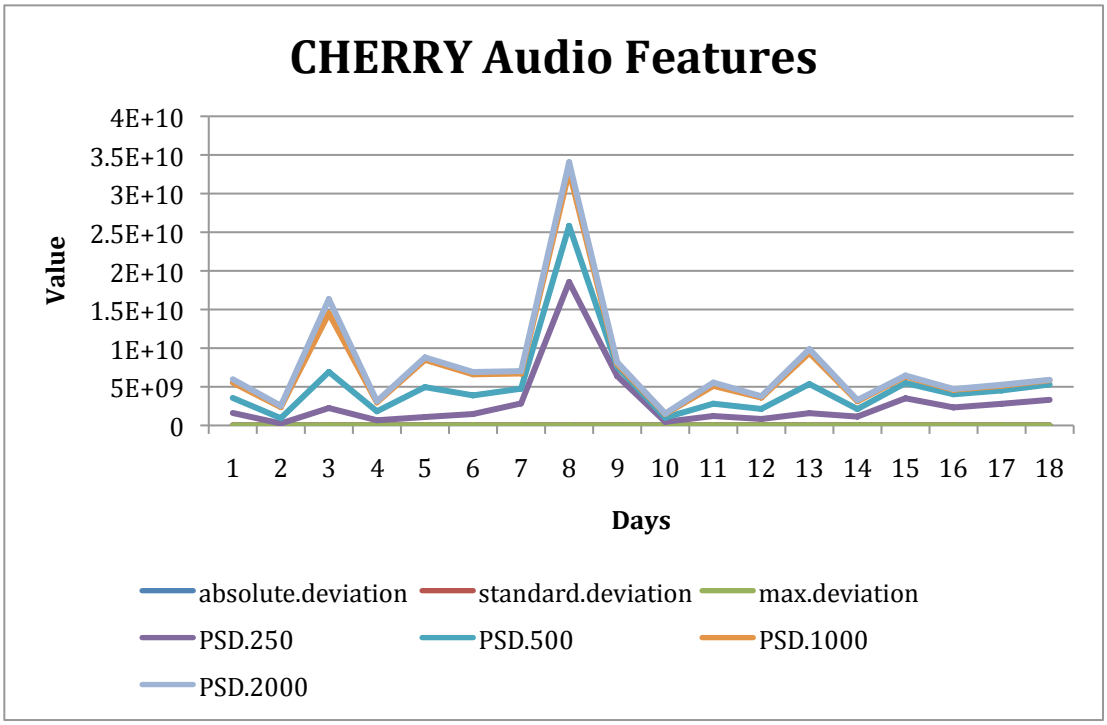


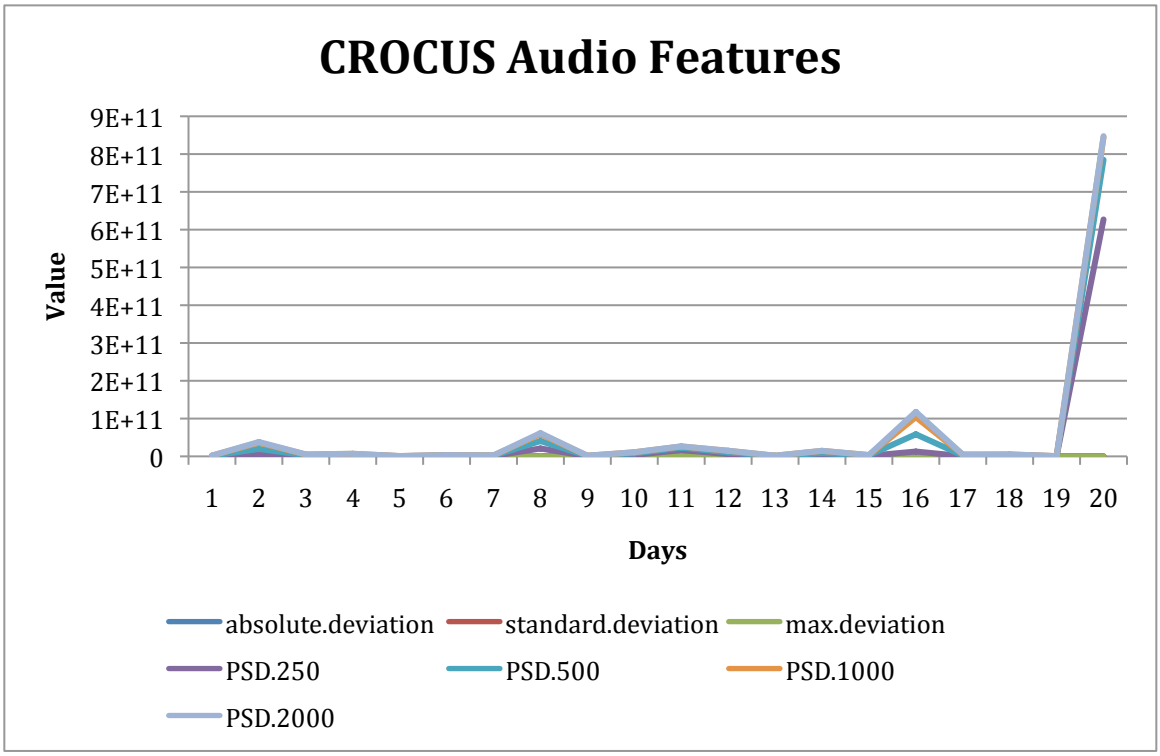


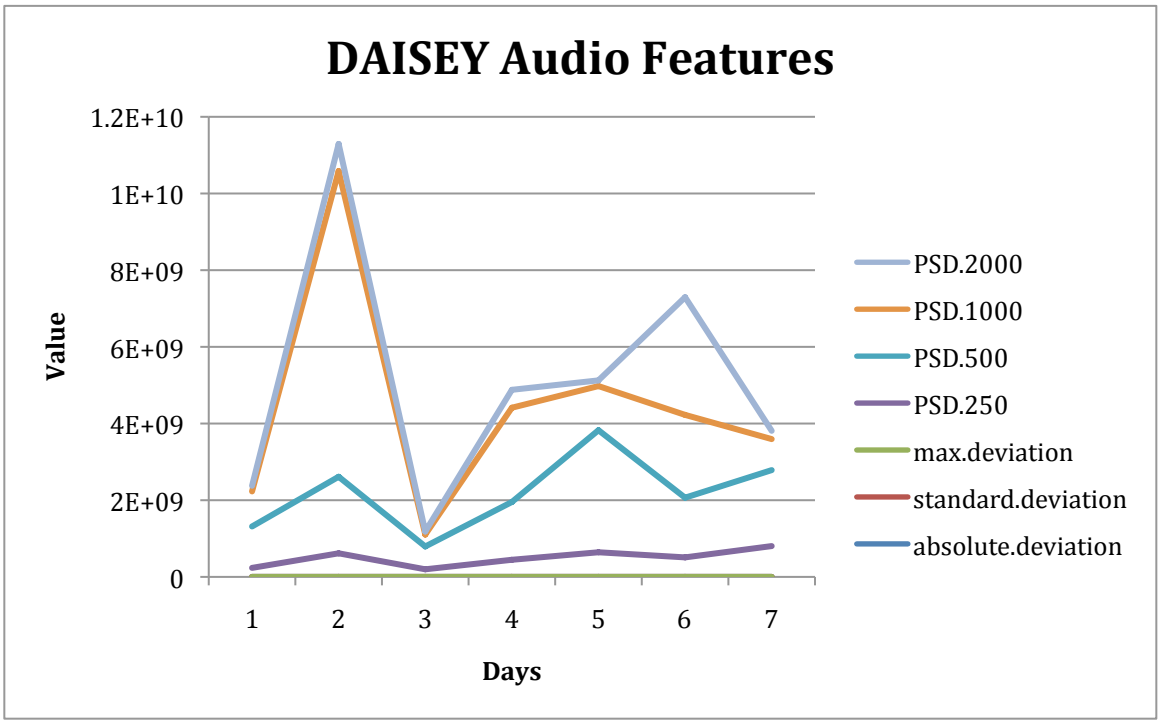
Audio Features

Slower *monotone* speech is one of the symptoms of PD. APPLE has a good variation of low, low mid, mid-high, and high frequency of energy captured, while CROCUS has very limited variation which implies that he has a monotonic voice. This is a good indication of PD.


APPLE Audio Features
value
1.6E+11
1.4E+11
1.2E+11
1E+11
8E+10
6E+10
4E+10
2E+10
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Days
absolute.deviation
standard.deviation
max.deviation
PSD.250
PSD.500
PSD.1000
PSD.2000

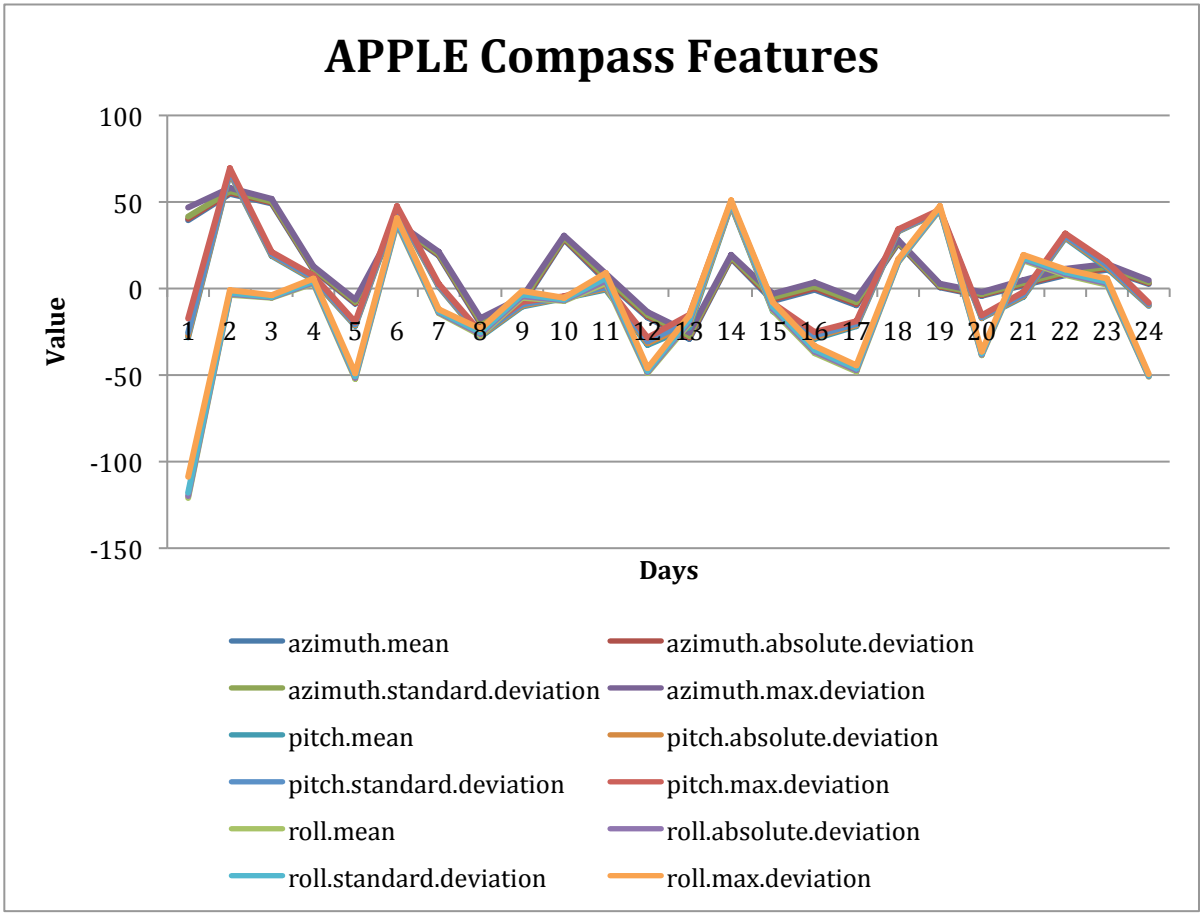

CHERRY Audio Features
Value
4E+10
3.5E+10
3E+10
2.5E+10
2E+10
1.5E+10
1E+10
5E+09
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
Days
absolute.deviation
standard.deviation
max.deviation
PSD.250
PSD.500
PSD.1000
PSD.2000

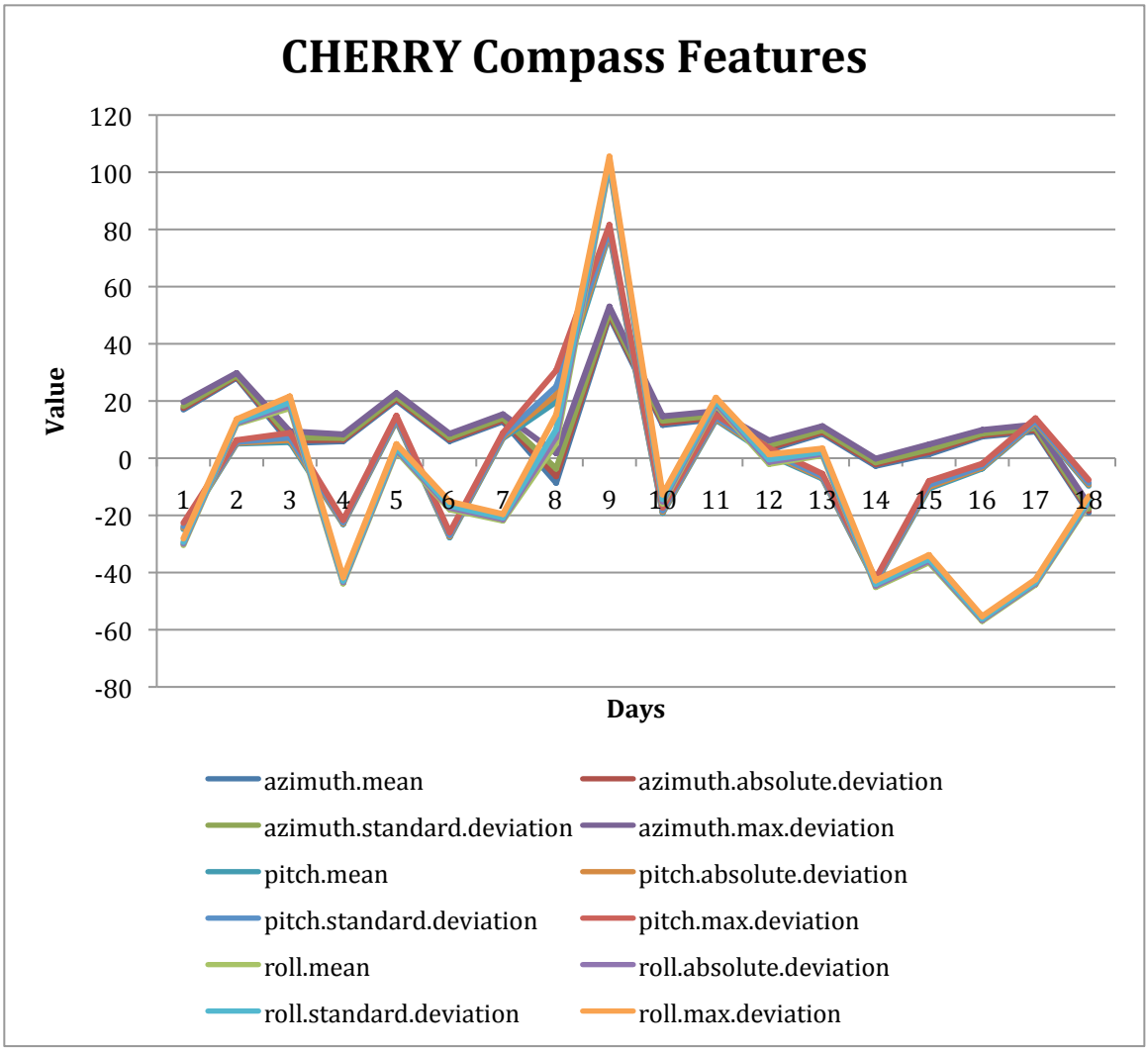

CROCUS Audio Features
9E+11
8E+11
7E+11
6E+11
5E+11
4E+11
3E+11
2E+11
1E+11
0
Value
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Days
absolute.deviation
standard.deviation
max.deviation
PSD.250
PSD.500
PSD.1000
PSD.2000

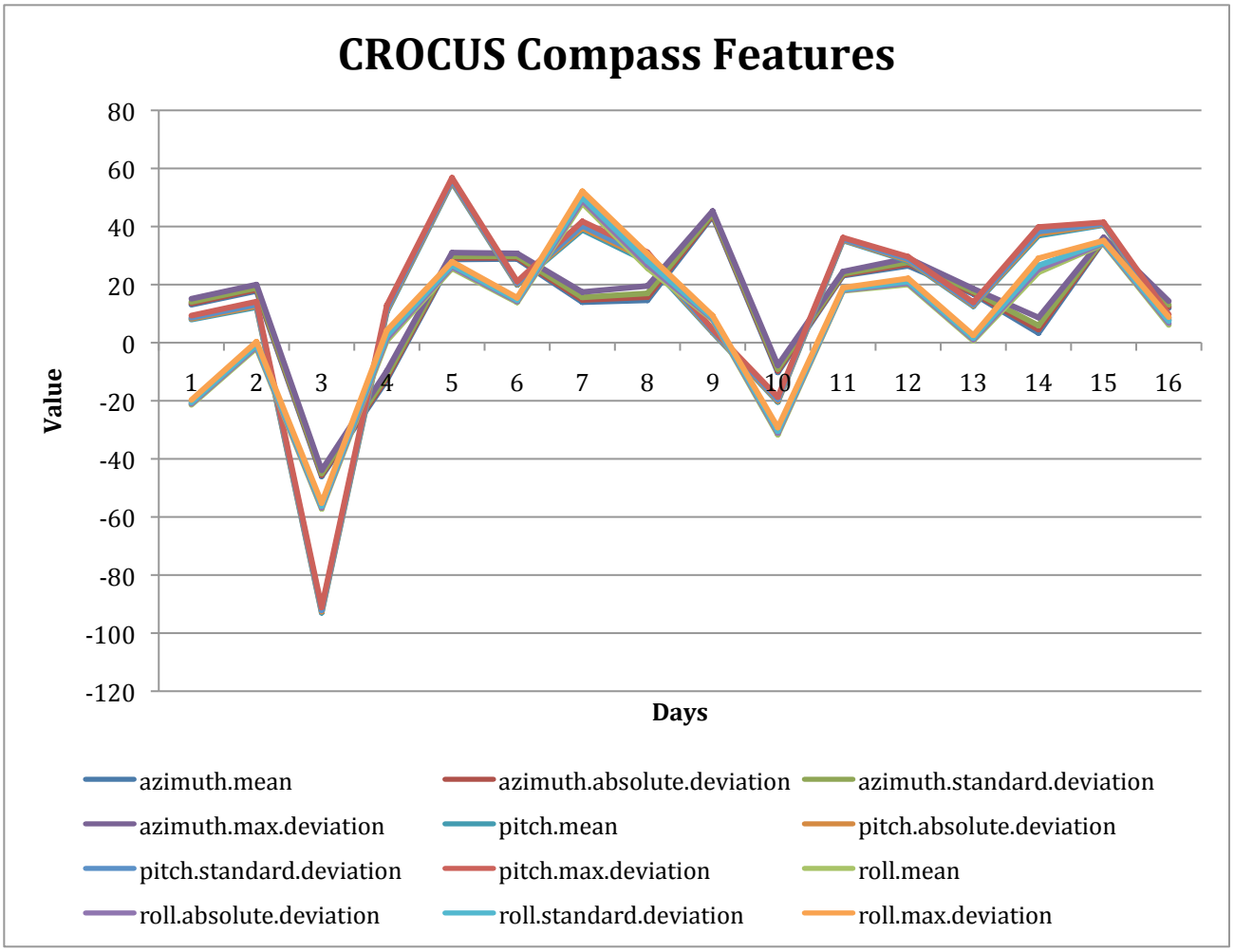

DAISEY Audio Features
1.2E+10
1E+10
8E+09
6E+09
4E+09
2E+09
0
Value
1 2 3 4 5 6 7
Days
PSD.2000
PSD.1000
PSD.500
PSD.250
max.deviation
standard.deviation
absolute.deviation

Compass

Compass features are indicative of the change in direction of the person with respect to the magnetic north of the earth. A control group member will have no bias in his movement since their body well balanced. In contrast, a PD patient will have a bias in their movements with a tendency to move toward one side over the other side. APPLE has peaks uniformly distributed and the peaks are between +50 and -50, while CHERRY and CORCUS have a tendency to move in one direction with non-uniformly distributed peaks.




CHERRY Compass Features
120
100
80
60
40
20
0
-20
-40
-60
-80
Value
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
Days
azimuth.mean
azimuth.absolute.deviation
azimuth.standard.deviation
azimuth.max.deviation
pitch.mean
pitch.absolute.deviation
pitch.standard.deviation
pitch.max.deviation
roll.mean
roll.absolute.deviation
roll.standard.deviation
roll.max.deviation



Evaluation

Features aggregated for each day where features are: x.absolute.deviation + x.standard.deviation + x.max.deviation + y.absolute.deviation + y.standard.deviation + y.max.deviation + z.absolute.deviation + z.standard.deviation + z.max.deviation + x.mean+ y.mean + z.mean+ accl+ absolute.deviation +standard.deviation +max.deviation +PSD.250 + PSD.500+ PSD.1000+ PSD.2000+ azimuth.mean+ azimuth.absolute.deviation+ azimuth.standard.deviation+ azimuth.max.deviation + pitch.mean + pitch.absolute.deviation + pitch.standard.deviation + pitch.max.deviation + roll.mean + roll.absolute.deviation + roll.standard.deviation + roll.max.deviation

We use weka for various classification algorithms. The result of the ten fold cross validation is presented along with the confusion matrix.

Naïve Bayes

This classifier can work on both categorical and numerical data. A distribution is assumed over the random variables (features) and parameters are learned from data. The parameters for the distribution learned for all features constitute the Naïve Bayes model. This model can be used to classify new instance.

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	100	66.6667 %
Incorrectly Classified Instances	50	33.3333 %
Kappa statistic	0.3005	
Mean absolute error	0.33	
Root mean squared error	0.5636	
Relative absolute error	66.4128 %	
Root relative squared error	113.068 %	
Coverage of cases (0.95 level)	71.3333 %	
Mean rel. region size (0.95 level)	53.3333 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.362	0.074	0.806	0.362	0.5	0.802	control
	0.926	0.638	0.63	0.926	0.75	0.802	PD
Weighted Avg.	0.667	0.378	0.711	0.667	0.635	0.802	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	25	44
PD	6	75

Bayes Net

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	112	74.6667 %
Incorrectly Classified Instances	38	25.3333 %
Kappa statistic	0.4834	
Mean absolute error	0.2836	
Root mean squared error	0.4615	
Relative absolute error	57.0711 %	
Root relative squared error	92.5825 %	
Coverage of cases (0.95 level)	90.6667 %	

Mean rel. region size (0.95 level) 73 %
Total Number of Instances 150

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.638	0.16	0.772	0.638	0.698	0.78	control
	0.84	0.362	0.731	0.84	0.782	0.78	PD
Weighted Avg.	0.747	0.269	0.75	0.747	0.743	0.78	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	44	25
PD	13	68

Decision Stump

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances 109 72.6667 %
Incorrectly Classified Instances 41 27.3333 %
Kappa statistic 0.4334
Mean absolute error 0.367
Root mean squared error 0.4444
Relative absolute error 73.8445 %
Root relative squared error 89.141 %
Coverage of cases (0.95 level) 98.6667 %
Mean rel. region size (0.95 level) 97.6667 %
Total Number of Instances 150

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.507	0.086	0.833	0.507	0.631	0.677	control
	0.914	0.493	0.685	0.914	0.783	0.677	PD
Weighted Avg.	0.727	0.306	0.753	0.727	0.713	0.677	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	35	34
PD	7	74

J.48 Decision Tree

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	109	72.6667 %
Incorrectly Classified Instances	41	27.3333 %
Kappa statistic	0.4539	
Mean absolute error	0.2913	
Root mean squared error	0.5098	
Relative absolute error	58.6165 %	
Root relative squared error	102.2601 %	
Coverage of cases (0.95 level)	76.6667 %	
Mean rel. region size (0.95 level)	59 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.754	0.296	0.684	0.754	0.717	0.722	control
	0.704	0.246	0.77	0.704	0.735	0.722	PD
Weighted Avg.	0.727	0.269	0.731	0.727	0.727	0.722	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	52	17
PD	24	57

Random Forest
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	116	77.3333 %
Incorrectly Classified Instances	34	22.6667 %
Kappa statistic	0.5486	
Mean absolute error	0.2893	
Root mean squared error	0.3793	
Relative absolute error	58.2237 %	
Root relative squared error	76.0892 %	
Coverage of cases (0.95 level)	100 %	
Mean rel. region size (0.95 level)	89.6667 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.826	0.272	0.722	0.826	0.77	0.877	control

	0.728	0.174	0.831	0.728	0.776	0.877	PD
Weighted Avg.	0.773	0.219	0.781	0.773	0.774	0.877	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	57	12
PD	22	59

Random Tree

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	119	79.3333 %
Incorrectly Classified Instances	31	20.6667 %
Kappa statistic	0.5827	
Mean absolute error	0.2067	
Root mean squared error	0.4546	
Relative absolute error	41.5883 %	
Root relative squared error	91.1965 %	
Coverage of cases (0.95 level)	79.3333 %	
Mean rel. region size (0.95 level)	50 %	
Total Number of Instances	150	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.754	0.173	0.788	0.754	0.77	0.79	control
	0.827	0.246	0.798	0.827	0.812	0.79	PD
Weighted Avg.	0.793	0.213	0.793	0.793	0.793	0.79	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	52	17
PD	14	67

Logistic Regression

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	120	80 %

Incorrectly Classified Instances 30 20 %
Kappa statistic 0.5948
Mean absolute error 0.2007
Root mean squared error 0.4469
Relative absolute error 40.3876 %
Root relative squared error 89.6445 %
Coverage of cases (0.95 level) 80 %
Mean rel. region size (0.95 level) 50.3333 %
Total Number of Instances 150

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.739	0.148	0.81	0.739	0.773	0.83	control
	0.852	0.261	0.793	0.852	0.821	0.843	PD
Weighted Avg.	0.8	0.209	0.801	0.8	0.799	0.837	

=== Confusion Matrix ===

Predicted =>	Control	PD
Control	51	18
PD	12	69

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