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MINING NEURODEGENERATIVE MOTOR SYMPTOMS OF PARKINSON'S DISEASE USING POSTURE SENSOR DATA

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Abstract: Parkinson Disease (PD) occurs due to the loss of dopamine in the brains thalamic section that results in unconscious or oscillatory movement in the body. Normally Doctors diagnosis the PD disease clinically with their expertise and experience. But most of the time immoral diagnosis and treatment are reported. For this, patients need to take number of tests for diagnosis, but the time, these all tests still not sufficient to diagnosis Parkinson Disease effectively. This work emphasis on classify the severity of PD or idiopathic Parkinsonism. Firstly, this work is proposed to apply some data mining technique to select the best attributes (according to the posture datasets). In second step, selected attribute was trained using motor evaluation UPDRS data and the algorithm is applied for the best attribute. Unified Parkinson Disease Rating Scale (UPDRS), captures numerous aspects of PD that include Mentation, Behaviour and Mood, Activities of Daily Life (ADL), Motor Examination and Complications of Treatment. For discovering the best classifiers Support Vector Machine-Sequential Minimal Optimization (SVM-SMO) algorithm is used. The accuracy is improved using algorithm. Data mining models is to monitor the sequence of gait features, which may eventually lead to earlier diagnosis of rising neurological disease for healthcare community.

Keywords: Parkinson's Disease (PD), Dopamine, Thalamic section, Posture, UPDRS.

I.INTRODUCTION

For the analysis and monitoring of Parkinson Disease (PD), a key requirement is that analysis of disease stages and severity. The severity may be quantitative, reliable and replicate able. This technology has the potential to much improve both clinical diagnosis and management in PD. PD is then crucial to identify and to extract the information of clinical relevance from the large amount of available data. The data captured by these wearable sensors need basic knowledge about the processing and machine learning algorithms to transfer information into scientifically and clinically. [1]

The records consider store motion data from wearable sensors and clinical information i.e., clinical data, scores, tests. The main goal is to develop data mining tools which can provide quantitative information to the clinician in the field of movement disorders. This work will focus on motor impairment in PD. The main objective motor symptoms of PD are tremor, slowness of movements, uncontrolled movements. The data mining techniques that can manage the available information and extract quantitative knowledge are lacking.

1.1 DATA MINING

Originally data mining was considered as the step of data analysis in the process of knowledge discovery from databases (KDD); now the two concepts (data mining and KDD) are usually used as meaning. Data mining can be defined as "the nontrivial pulling out of implicit earlier unknown and potentially practical information from records" [2]. The technique of data mining, such as data processing, feature extraction, feature selection, development of an algorithm, interpretation and evaluation, are shown in Figure 1.

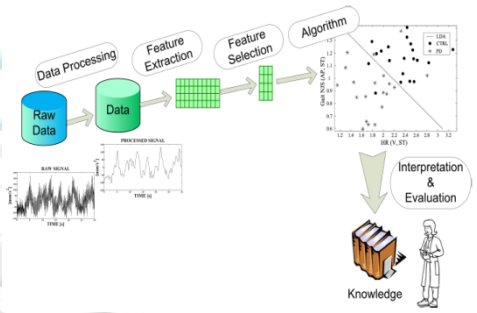

Figure 1: The data mining process

Data mining is a very broad field at the intersection of statistics, machine learning, and pattern recognition. The data mining techniques that were used in this work are machine learning algorithm. Machine learning algorithms are supervised learning and unsupervised learning. The supervised (e.g. there are two groups of subjects to discriminate and there is information a priori on the class label of each subject) and unsupervised (e.g. no a priori instruction/knowledge, the technique is used to find groups of subjects characterized by all the same patterns). Supervised techniques can be divided into classification and regression: classification is the process of finding a function (algorithm) that categorizes data collection (e.g. healthy vs pathological). Regression is used to get a function that models mathematical data values rather than discrete class labels. Unsupervised techniques are used to extract understandable patterns and associations in the data. Among them, clustering can be used to find homogeneous patterns in the data and to generate class labels. [2] A data mining technique that can be both unsupervised and supervised. The feature selection is used to extract from the data and informative patterns discarding useless or unnecessary

information. This technique can improve the performance, the clarity of the outcome of the results. The relevant algorithm is used to extract data for better outcome.

1.2 Parkinson's Disease

Parkinson's Disease (PD) is a neurodegenerative disorder which affects mostly older people (1 out of 100 over 75 year [3]). It is characterized by the progressive loss of dopaminergic neurons [4].Its main motor symptoms are:

- tremor (vibration to hands, arms, legs or jaws);
- muscle rigidity (stiffness);
- bradykinesia (slowness of voluntary movements);
- Postural and balance impairment.

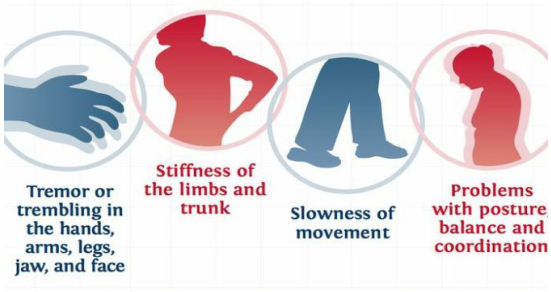

Figure 2: Symptoms of PD

These symptoms have a negative impact in quality of life, can severely limit motor abilities, and lead to adverse events such as falls.

Pharmacological remedy based on dopaminergic medications can minimize or reduce most of the symptoms but after prolonged periods of treatment it is normal to develop motor complications like:

- **dyskinesia**: involuntary movements;
- **dystonia**: involuntary muscle contractions;
- **Fluctuations of symptoms severity**: abrupt transitions from periods when the medication is effective (ON-periods) and periods when the symptoms are high although the subject is under medication (OFF-periods).

As it was shown here motor impairment have many different characteristics in PD.

1.3 Clinical Evaluation of Motor Impairment in Parkinson's disease

In the clinical field the evaluation of the motor impairment in PD s limited to the use of scales and questionnaires. The Unified Parkinson's Disease Rating Scale (UPDRS) [5] is the most widely used clinical scale to estimate PD symptoms.

1.3.1 Clinical Scales

UPDRS has four sections:

- mentation, behavior and mood;
- activities of daily living;
- motor examination;
- complications of therapy

Sections 1, 2, and 4 are based on the "history" of the subject. Section 3 is also referred as the motor section of UPDRS or motor UPDRS1: it is based on the examination by the clinician. This rating scale evaluates the severity of PD symptoms in a 5-points scoring system (0 for no symptom and 4 for a marked severity of the symptom). Figure 3 represents the UPDRS section.

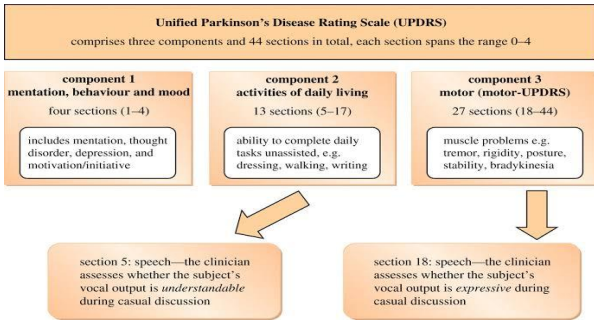

Figure 3: UPDRS Section

There is another clinical level that is the **Hoehn and Yahr (H&Y) scale** [5]. The scale included stages 1 through 5 to point out the growing level of disability. To get better the low resolution of the scale, a customized H&Y scale that includes 0.5 increments was obtainable and has been adopted broadly in the clinical field [6]. H&Y (both original and modified) level suffers from the same problems of UPDRS. Stableness of the H&Y and UPDRS scales include their wide. In this work the term motor UPDRS will be used. Figure 4 represent a Hoehn and Yahr scale.

STAGE 0	No signs of disease
STAGE 1	Unilateral disease
STAGE 1.5	Unilateral plus axial involvement
STAGE 2	Bilateral disease, with no impairment of balance
STAGE 2.5	Mild bilateral disease, with recovery on pull test
STAGE 3	Mild to moderate bilateral disease; some postural instability; physically inde
STAGE 4	Severe disability; still able to walk or stand unassisted
STAGE 5	Wheelchair-bound or bedridden unless aided

Figure: 4 Hoehn and Yahr (H&Y) scale

1.4 Data Mining on Data from Wearable Sensors in Parkinson's Disease

The wearable sensors can provide a high amount of data to analyse, different motor tasks: data mining techniques can help to extract meaningful patterns from these available databases. The dataset of Parkinson's patient are available from the Parkinson's Progression Markers Initiative (PPMI) and data mining operation is applied for this data.

1.2 Objective

The main focus of this work is the classifying the datasets to determine if a person is affected by PD or not. This work is an attempt to introduce a classification approach using **Support Vector Machine-Sequential Minimal Optimization (SVM-SMO)** algorithm to categorizes PD affected people with the help of data collected from the wearable sensor and it's hard to diagnosis.

II.LITERATURE STUDY

Currently, clinical PD diagnosis is primarily based on clinical history and physical examinations. Examples of these applications are the works from [Keijsers et al 2006] [8] where neural networks are used to predict the UPDRS scores of dyskinesia and to detect ON-OFF states; the work from [Patel et al 2009] [9] where support vector machines are used to

forecast UPDRS scores of bradykinesia, tremor, and dyskinesia. These revisions provide support of the feasibility and of using wearable sensors to automatically evaluate some of the motor symptoms in PD. Different physicians may give results based on variable rating scales such as Unified Parkinson's Disease Rating Scale (UPDRS) and Intermediate Scale for Assessment of PD (ISAPD). These rating scales are individual and qualitative, sometimes making interpretation or association difficult (Martinez-Martin et al. 1994) [10]. While these diagnosis techniques(Single-photon emission computed tomography (SPECT)) have been proven to be effective at accurately diagnosing PD, greater than 50% of the dopaminergic neurons are lost by the time that a patient is clinically diagnosed with PD, making early-stage detection not easy and critically essential for neuroprotective efforts (Gil and Manuel 2009)[11].

GeetaYadav and Yugal Kumar [12] have developed a statistical model which analyses Gait Rhythm in Patients with Parkinson′s Disease. The model proposed by these authors identifies the people affected by the PD more accurately. Also, predictive model for PD identification is extending. Three classification algorithms are used tree classifier, statistical classifier and support vector machine. Based on the accuracy and specificity, the performances of PD are analyzed. Among the three classifiers, SVM and tree classifier produce high accuracy. The statistical classifier correctly identifies the number of people who are all affected by PD; the result of accuracy is increased. SVM and Tree classifiers require additional functionalities because of variation in specificity. Whereas, in statistical classifiers, specificity are almost the same and further investigation is not necessitated.

These challenges are further exacerbated by the variations in PD symptoms and motor complications (referred to as motor fluctuations) among different people, hereby potentially dipping the quality of the resulting diagnosis. Another example is to have sensor-based systems placed on the upper and lower limbs of each subject so as to measure the hand motor and gait functions (Barth et al. 2012)[13]. Furthermore, these data collection techniques require physical contact with the patient, which may affect the manner in which the patient responds.

Gracy et al., [14] have discussed the four types of classifiers namely, Naïve Bayes, random tree, J48 and decision tree. WEKA tool is used to run the above classifiers. The performance is evaluated from the factors like shivering hands, legs, arms or jaws and emotional changes. The accuracy of above classifiers is shown using confusion matrix. A confusion matrix gives information about the actual and predicted values of classifiers. Among these classifiers, random tree provide 84% of accuracy. The proposed technique (Big Data) handles large amount of data with optimum accuracy.

III.BACKGROUND STUDY

In existing system, clinical data are collected and dense representation of PD features in a single value in the database which will be accurately estimated, since so much information regarding his condition is represented by a single value. This is why a Decision Support System (DSS) that assists Hoehn & Yahr stage estimation was estimated in the previous work. In contrast to previous works, the DSS does not rely in rule-based approaches, but takes advantage of data mining and machine learning techniques. A classification algorithm is trained using a set of UPDRS-III data and new instances can then be automatically classified to provide insights and suggestions to facilitate clinical decision. Although DSS algorithms based on data mining techniques have been developed for a variety of biomedical applications. The main advantage of using data mining techniques is that they allow the development of DSS algorithms without requiring any prior medical knowledge, but only a class-discriminative set of features instead. In addition, it is easier to examine the potential benefits of combining other, non-motor symptoms such as the other three parts in UPDRS, in the Hoehn & Yahr stage estimation.

IV.METHODOLOGY

In this work, wearable sensor is used to collect the data. To overcome the limitations; discussed in the previous section, the proposed data mining driven methodology employs machine learning techniques that reduce subjective biases (resulting from human physical examination) and identifies PD features that may be relevant in detecting early stage PD. The sensors that capture posture data, and subsequent classification algorithm i.e., SVM-SMO employed on the acquired data, detect posture features relevant to PD. Figure 5 represents the overall methodology which is based on extracting correct PD motor features and related features to detect PD posture patterns. The methodology is partitioned into four steps.

Step 1: Outlines the manner in which patient posture data is acquired and stored for subsequent data mining/knowledge discovery (DATA ACUQUISTION).

Step 2: It involves data cleaning and feature dimension reduction. (DATA PREPROCESSING)

Step 3: The process of data mining and knowledge discovery is introduced in, where the multiple machine learning algorithms are used to examine the pre-processed data using SVM-SMO. (DATAMINING ALGORITHMS)

Step 4: Evaluates the model performance using the machine learning algorithms and outlines the possible outcomes for the methodology and it to be integrated into a healthcare organism. (EVALUATION)

Figure 5: Proposed methodology of PD

A. *Data Acquisition*

The data sample is captured from sensor in every 33ms, a data sample that is captured by representing patient posture position data from each of the 20 nodes. The *sensors that capture/collect data, when the patient starts walking towards the sensor, the data are collected every 33ms. The skeleton part of the patient is collected by the sensor which is taken as*

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raw data that are stored in the database it is represent in Figure 6. The hardware is capable of fine-tune the 20 node locations, based on varying degrees of human personality (range, shape, height, etc.).

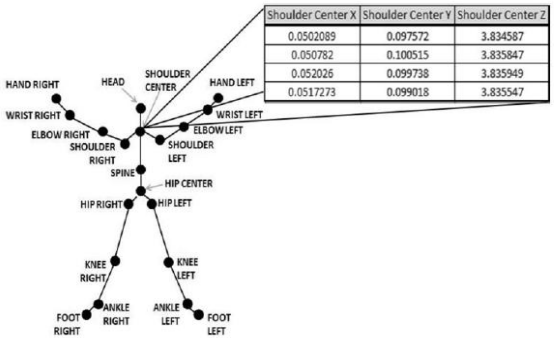


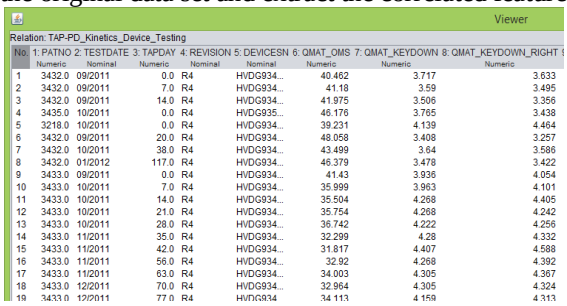
Figure 6: Skeleton image of a person with 20 nodes and example data from Shoulder Centre node

Dataset

The dataset of PD are available from the PPMI repository and samples acquired from study participants of Parkinson's patient. The data set consists of kinetic device testing which contain the data related to posture data of 32 patients who affected by PD. Figure 7 represents the dataset of PD.

B. Data Pre-processing

Data pre-processing is an important phase to avoid the mistakes or bias in the analytical results. The dataset may include noises such as inconsistent notation. The data collection is complete, the data is cleaned to reduce noise in the original data set and extract the correlated feature set.


Viewer

Relation: TAP-PD_Kinetics_Device_Testing

No.	1: PATNO	2: TESTDATE	3: TAPDAY	4: REVISION	5: DEVICESN	6: QMAT_OMS	7: QMAT_KEYDOWN	8: QMAT_KEYDOWN_RIGHT
	Numeric	Nominal	Numeric	Nominal	Nominal	Numeric	Numeric	Numeric
1	3432.0	09/2011	0.0	R4	HVDG934...	40.462	3.717	3.633
2	3432.0	09/2011	7.0	R4	HVDG934...	41.18	3.59	3.495
3	3432.0	09/2011	14.0	R4	HVDG934...	41.975	3.506	3.356
4	3435.0	10/2011	0.0	R4	HVDG935...	46.176	3.765	3.438
5	3218.0	10/2011	0.0	R4	HVDG934...	39.231	4.139	4.464
6	3432.0	09/2011	20.0	R4	HVDG934...	48.058	3.408	3.257
7	3432.0	10/2011	38.0	R4	HVDG934...	43.499	3.64	3.586
8	3432.0	01/2012	117.0	R4	HVDG934...	46.379	3.478	3.422
9	3433.0	09/2011	0.0	R4	HVDG934...	41.43	3.936	4.054
10	3433.0	10/2011	7.0	R4	HVDG934...	35.999	3.963	4.101
11	3433.0	10/2011	14.0	R4	HVDG934...	35.504	4.268	4.405
12	3433.0	10/2011	21.0	R4	HVDG934...	35.754	4.268	4.242
13	3433.0	10/2011	28.0	R4	HVDG934...	36.742	4.222	4.256
14	3433.0	11/2011	35.0	R4	HVDG934...	32.299	4.28	4.332
15	3433.0	11/2011	42.0	R4	HVDG934...	31.817	4.407	4.588
16	3433.0	11/2011	56.0	R4	HVDG934...	32.92	4.268	4.392
17	3433.0	11/2011	63.0	R4	HVDG934...	34.003	4.305	4.367
18	3433.0	12/2011	70.0	R4	HVDG934...	32.964	4.305	4.324
19	3433.0	12/2011	77.0	R4	HVDG934	34.113	4.159	4.313

Figure 7: Dataset of PD

C. Data Mining Algorithms

In this work most popular classification algorithms are evaluated. Our objective was to achieve average estimation errors below 7%. This value conservatively approximates the inter rater variability that marks the use of the Unified Parkinson's Disease Rating Scale, the medical scale utilized in this study to assess the severity of symptoms and motor complications [15].

SVM-SMO classifier

Estimating data features for all the sensors utilized in the work produce large feature sets. In direct work [16], [17], projection algorithms, classification techniques, and measures of quality were used to assess the suitability of the accelerometer-based feature sets to estimate the harshness of tremor, bradykinesia, and dyskinesia. A promoted outcome of our work, decide to develop a classifier to estimate the strictness of Parkinsoniam symptoms and motor complications based on data feature; SVM is used because the success of this approach in many classification problems and reveal good overview performance [18]. The specific SVM execution, adopted relies on the one-versus-rest approach to tackle the multiclass classification trouble. Three different kernels (i.e., exponential, radial basis, and polynomial kernels) were utilized and results were compared.

Sequential minimal optimization (SMO) is an algorithm for solving the quadratic programming (QP) problem that arises during the working out of support vector machines. SMO is far and widely used for training support vector machines.

Optimization problem

Consider a binary classification problem with a dataset (x_1, y_1), … (x_n, y_n), where x_i is an input vector and $y_i \in \{-1, +1\}$ is a binary label corresponding to it. A soft-margin support vector machine is trained by solving a quadratic programming trouble, which is expressed in the dual form as follows:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j K(x_i, x_j) \alpha_i \alpha_j,$$

subject to:

$$0 \le \alpha_i \le C, \quad \text{for } i = 1, 2, \ldots, n,$$

$$\sum_{i=1}^{n} y_i \alpha_i = 0$$

where C is an SVM hyper parameter and $K(x_i, x_j)$ is the kernel role, both provided by the user; and the variables α_i are Lagrange multipliers

.Algorithm

SMO is an iterative algorithm for solving the optimization problem described above. SMO breaks this problem into a series of smallest possible sub-problems, which are then solved logically. Because of the linear equality limit involving the Lagrange multipliers α_i, the minimum possible problem involves two such multipliers. Then, for any two multipliers α_1 and α_2, the constraints are summary to:

$$0 \le \alpha_1, \alpha_2 \le C,$$
$$y_1 \alpha_1 + y_2 \alpha_2 = k,$$

and this reduced step can be solved analytically: one requests to find a minimum of a one-dimensional quadratic function. k is the negative of the sum over the rest of terms in the equality constraint, which is stable in each iteration.

The algorithm proceeds as follows:

1. Discover a Lagrange multiplier α_1 that violates the Karush–Kuhn–Tucker (KKT) situation for the optimization trouble.
2. Pick a succeeding multiplier α_2 and optimize the pair (α_1, α_2).
3. Repeat steps 1 and 2 until convergence.

When all the Lagrange multipliers satisfy the KKT conditions (within a user-defined tolerance), the problem has been resolved. Although this algorithm is assured to come together, heuristics are used to choose the pair of multipliers so as to accelerate the rate of convergence. This is significant for large data sets since there are n(n-1) possible choices for α_i and α_j.

The advantage of SMO is numerical QP optimization is avoided entirely here. Instead of this, solving for two Lagrange

multipliers can be done analytically in SMO. Thus, the inner loop of the algorithm can be expressed in a short amount of C code, rather than invoking an entire QP library routine. Although, more optimization sub-problems are work out through SMO, but each sub-problem is so fast that overall QP problem is solved quickly. Another advantage is that SMO doesn't require extra matrix at all. Since no matrix algorithm are used in SMO, so very large SVM training problems can fit inside of the memory of an ordinary personal computer or workstation.

There are two constraints for solving two Lagrange multipliers.

- One is Bound Constraints $0 \leq \leq C$
- Second one is Equality

D. Evaluation

The results for the classification algorithms and feature selection approaches, Classification performance is evaluated using 10-fold cross- validation. UPDRS-III scores are converted to the original version of five Hoehn & Yahr stages, since this scale is used in PPMI. Specificity, positive predictive value, and accuracy metrics are estimated for each stage separately.

Visualization of the attributes

The figure 9 shows a histogram for the attribute distributions for a single selected attribute at a time, by default this is class attribute.. X-axis denotes the feature values. The feature value ranges according to the respective feature range. These ranges are split using mean value. Y-axis denotes the number of people lie in- between that ranges.

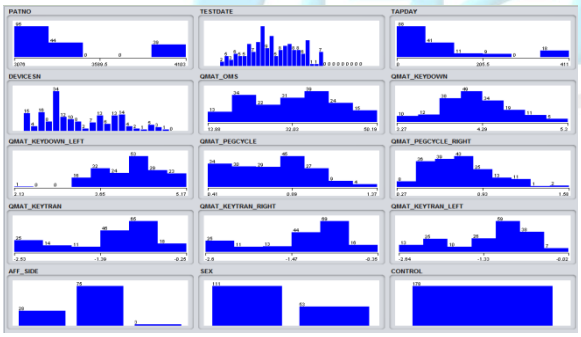


Figure 8: Visualizing all the Attributes

```
Correctly Classified Instances         104               94.5455 %
Incorrectly Classified Instances         6                5.4545 %
Kappa statistic                          0.8678
Mean absolute error                      0.2384
Root mean squared error                  0.3004
Relative absolute error                 81.5447 %
Root relative squared error             79.1302 %
Total Number of Instances              110
Ignored Class Unknown Instances                68

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0.857    0.012     0.960      0.857     0.906      0.878    0.842     0.461     Left
                 0.987    0.156     0.939      0.987     0.963      0.866    0.769     0.629     Right
                 0.750    0.000     1.000      0.750     0.857      0.862    0.856     0.256     Both
Weighted Avg.    0.945    0.114     0.947      0.945     0.944      0.869    0.790     0.572

=== Confusion Matrix ===

  a  b  c   <-- classified as
 24  4  0 |  a = Left
  1 77  0 |  b = Right
  0  1  3 |  c = Both
```

Figure 10:SVM-SMO result

Figure 9: Visualized attributes

v.RESULT AND DISCUSSION

The present results were analyzed to compare the error affecting the estimates of the rigorous of tremor, bradykinesia, and dyskinesia evaluated by using feature sets from data recorded during performance of different motor tasks, using data from the PPMI. These analyses aimed at identifying motor tasks suitable to achieve reliable estimates of the severity of Parkinsonian symptoms or motor difficulty.

Finally, determine the impact of character data features and permutation of data features on the error affecting the estimates provided by SVM. Analyses were performed for each feature type and it is represented in figure 10.

The recent analysis has been using the SVM-SMO model for the Parkinson's disease prediction due to the higher prediction accuracy.

The following graph shows that cost benefit curve in figure 11.

The threshold curve is represented in the figure 12. The ROC curves can be utilized in figure 13 was displayed.

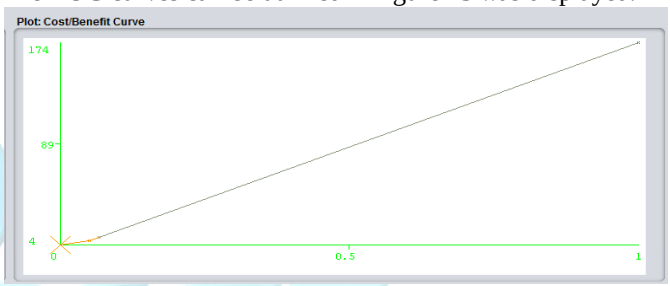


Figure 11: Cost Benefit curve

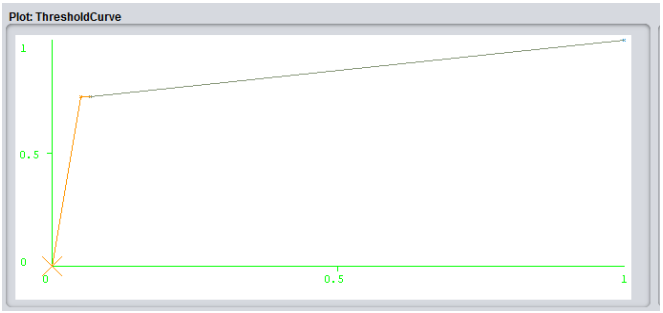


Figure 12: Threshold curve

Figure 13: ROC curve

VI. CONCLUSION

In this paper proposed a classification model using SVM-SMO algorithm, the result range from 94.5455% using PD data. The SVM-SMO algorithm produced better classification and highest accuracy is achieved. For experiments K fold cross validation method is used with different classifiers as well as classification accuracy and error. The mean results of this algorithm represent in terms of classification accuracy & error. SVM-SMO has here performed very well i.e., accuracy 94.5455 and classification error 5.4545. So my future work would be increase the accuracy. In addition, plan to make an Artificial Intelligence on Parkinson Disease Symptom Predictions.

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