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Analysing the Performance of Support Vector Machine Algorithm in Predicting Parkinson's Disease

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Abstract: Parkinson's disease (PD) is a neurodegenerative measure disease where the symptoms steadily develop start with an insignificant a slight shaking movement in one hand and a feeling of stiffness in the body and it became worse over time. Dopamine is most notably involved in helping us feel preference as part of the brain's reward system. It acts as a message between the parts of the brain and nervous system that support control and co-ordinate body movements. As dopamine generally neurons in the parts begin to experience difficulty in speaking, writing, walking or completing another simple task. Virtually, 90% pretentious people with Parkinson have tongue disorders. It affects over 6 million people worldwide. At present there is no conclusive result for this disease by non-specialist clinicians, particularly in the early stage of the disease where identification of the symptoms is very difficult in its earlier stages. The future predictive analytics outline is a combination of K-means clustering and Decision Tree which is used to improvement visions from patients. By using machine learning methods, the problem can be explained with negligible error rate. The investigated approach serves as a guide in determining the diagnosis and in planning the appropriate by a loss of nerve cells in the part of the brain.

Keywords: performance; machine; analysing; support; vector;

INTRODUCTION:

The Parkinson's disease gene prediction can be considered as a classification task with two labels. We use Support Vector Machine (SVM) algorithm to solve this bi-classification problem. For 2 classifications, SVM constructs a hyperplane or set of hyperplanes in a high-dimensional space to classify genes with different labels. SVM is useful in solving classification as well as regression problem statements. In the classification problem, two classes are separated or classified by a hyperplane. SVM creates two marginal lines along with a hyperplane having some distance so that they will be easily linearly separable for both the classification points. Tremors are common, but the disorder may also source stiffness or slowing of movement. Nerve cells in this part of the brain are responsible for making a chemical called dopamine. Machine learning methods are presence gradually practical in the healthcare sector. As its name implies, machine learning agrees for a computer program to learn and extract meaningful depiction from data in a semi-automatic manner. For the diagnosis of PD, machine learning models have been practical to a crowd of data modalities, including handwritten patterns. In recent years, the number of publications on the application of machine learning to the analysis of PD has increased. While earlier studies have reviewed the use of machine learning in the diagnosis and valuation of PD, they were partial to the scrutiny of motor symptoms, kinematics, and wearable sensor data. Diagnosis is clearly a difficulty in PD management, and an effective screening process, particularly one that doesn't require a clinic visit, would be beneficial. Since PD patients exhibit characteristic vocal features, voice recordings are a useful and non invasive tool for diagnosis. If machine learning algorithms could be applied to a voice recording dataset to accurately diagnosis PD, this would be an effective screening step prior to an appointment with a clinician. Actually, this sort of binary classification problem is common in many areas of medical diagnosis, and techniques that work well within one domain are likely to be applicable to others. The primary dataset used in this development is from the UCI Machine Learning Repository [BL13], and comprises data from voice tapes of 23 subjects with Parkinson's disease and 8 control subjects. There are a total of 195 recordings, from which 22 different voice portion features have been taken out. Each example also contains a subject identifier and a binary classification quality which specifies whether or not the subject has PD.

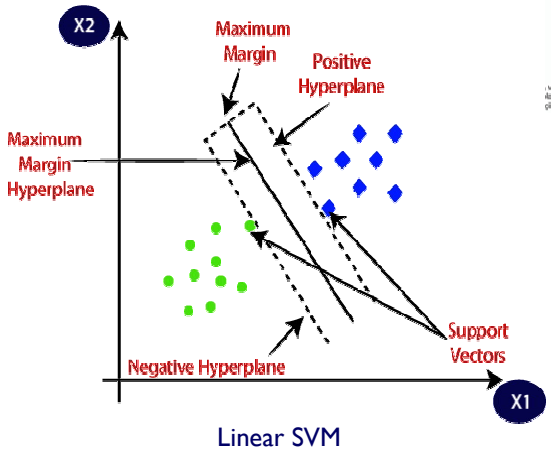
SUPPORT VECTOR MACHINE

Support Vector Machine or SVM is one of the most versatile Supervised Learning algorithms, which is used for Classification as well as Regression problems. But, primarily, it is used for Classification problems in Machine Learning.

The area of the SVM algorithm is to make the best line or decision boundary that can separate n-dimensional space into classes so that we can easily put the new data point in the correct sort in the future. This best decision limit is called a hyperplane. SVM chooses the extreme points/vectors that help trendy creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

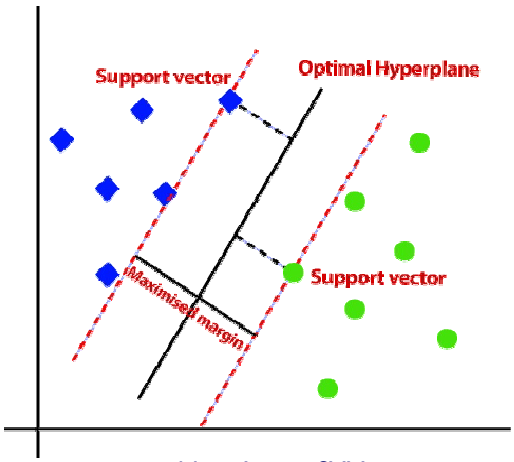
Types of SVM:
SVM can be of two types:

Linear SVM:
Linear SVM is used for linearly severable data, which means if a dataset can be categorised into two classes by using a single straight line, then such data is termed as linearly severable data, and classifier is used called as Linear SVM classifier.

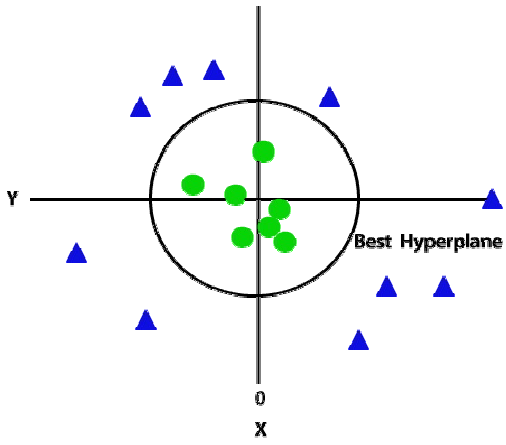


Linear SVM

Non-linear SVM:



Non- Linear SVM



Non-linear SVM

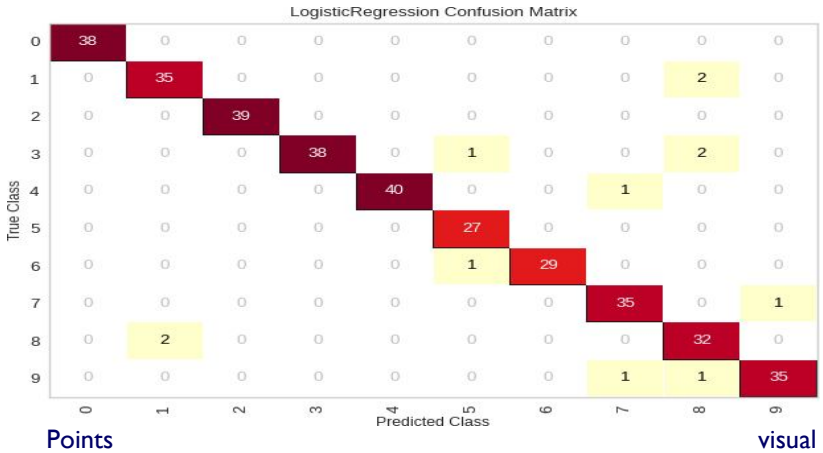
Non-Linear SVM is used for non-linearly distributed data, which means if a dataset cannot be categorised by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier. To separate these data points, we need to add one more dimension. For linear data, we have used two dimensions x and y, so for non-linear data, we will add a third dimension z. It can be calculated as:

$$z=x^2+y^2$$

PERFORMANCE METRICES:

Confusion Matrix:

The Confusion Matrix visualizer is a Score Visualizer that takes a fitted scikit-learn classifier and a set of test X and y values and returns a report showing how each of the test values expected classes compare to their actual classes. Data scientists use confusion matrices to translate which classes are most easily confused. visualizer is a Score Visualizer that takes a fitted scikit-learn classifier and a set of test X and y values and returns a report showing how each of the test values predicted classes compare to their actual classes. Data scientists use confusion matrices to understand which classes are most easily confused.

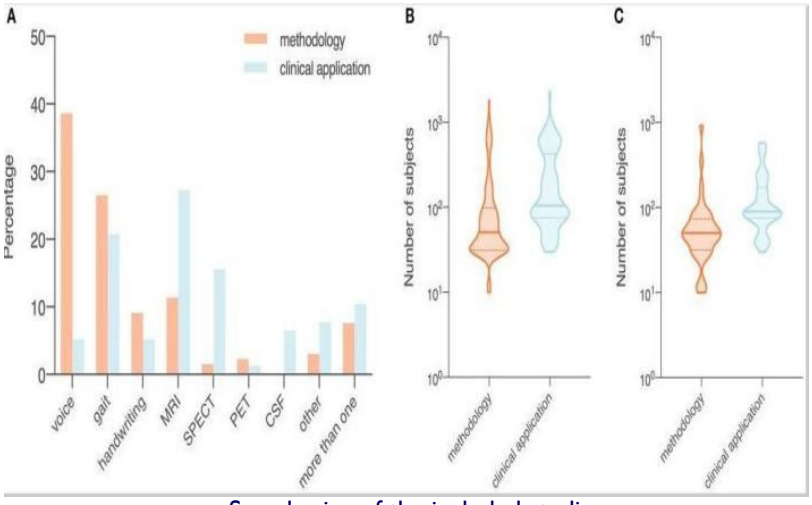


Points visual data

ACCURACY SCORE:

In machine learning models accuracy plays an important role. Accuracy is a mirror of the effectiveness of our model. Not even this accuracy tells the percentage of correct predictions. It is just a mathematical term, Sk learn provides some function for it to use and get the accuracy of the model. Accuracy score, Classification report, confusion matrix are some of them. In this blog, we will understand the accuracy, the mathematical background of accuracy and how to predict it with hands-on code.

$$Accuracy = \frac{Correct\ Predictions}{All\ Predictions} = \frac{TP + TN}{TP + TN + FP + FN}$$

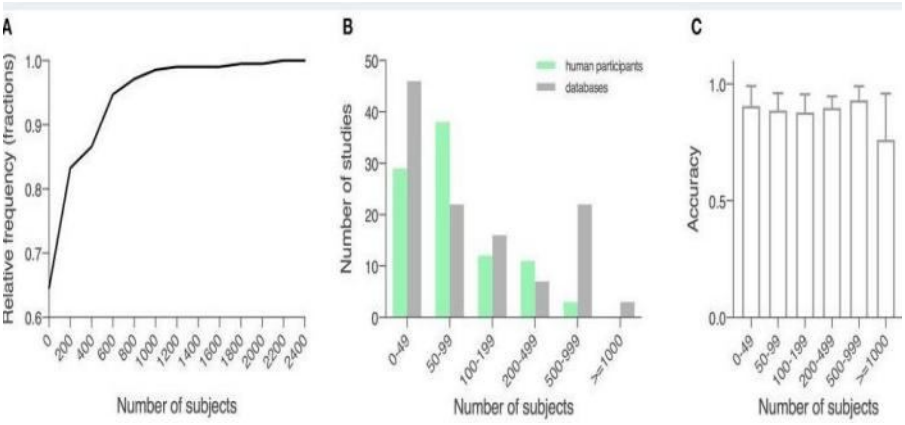


Sample size of the included studies

A. Cumulative relative frequency graph depicting the frequency of the sample sizes studied.
B. Histogram depicting the frequency of a sample size of 0–50, 50–100, 100–200, 200–500, 500–100, and over 1,000 for studies using locally recruited human participants and studies using previously published open databases. Green, studies using locally recruited human participants; gray, studies using data sourced from public databases.
C. Model performance as measured by accuracy in relation to sample size, shown in means (SD).

CONCLUSION:

In future work, we plan to increase our subject pool and utilize optimal features election strategies under MIL frameworks for developing robust person-specific models. These techniques can potentially be adapted to various other physiological sensing and monitoring applications as well. A machine learning approach that works to identify mitochondrial impairments, a potential mechanism underlying the pathogenesis of Parkinson disease (PD), accurately.



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