A Comparative Study of FMRI Data Analysis Techniques

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Abstract: *Neuroimaging tools and methods have been developed to study brain functionality to enhance our understanding of the brain. State vector machine (SVM) and linear discriminant analysis (LDA) are the two different techniques used for the analysis of FMRI data. In this paper we will study these two techniques, one of which is used for the prediction of vulnerability of major depression and the other one is used for the analysis of Alzheimer's disease and lie detection. Further we will compare them on the basis of various parameters and will discuss about the technique which can lead to better results.*

Keywords: FMRI, Neuroimaging.

I. Introduction:

Brain is most fascinating and least understood organ in the human body. For decades, scientists have tried to find the relationship between behavior, memory, thought, consciousness and the physical body. In recent years, there has been a strong development in the techniques for monitoring of a working brain. One of the most important points for FMRI in investigating human brain function relies on the fact that brain function is spatially segregated, i.e. there is localization of specific functions are at various sites.FMRI can identify and map these functional specializations at high spatial resolution. With the advancement in the research technology and use of neuroimaging tools, FMRI emerges as a very prominent tool for

analysis of human brain. FMRI can give high quality visualization of activity location in the brain resulting from any stimulation. It therefore allows the study of how the healthy brain functions, how it is affected by various diseases and how it recovers after any damage.

II. Neuroimaging Algorithms

a) LDA Algorithm

For predicting an individual's vulnerability to major depression (MD), Functional magnetic resonance imaging (FMRI) signature has shown a high potential towards it. Here linear discriminant analysis (LDA) algorithm has been used to address the problem. The results demonstrate that guilt-selective changes in the functional connectivity of anterior temporal lobe are sufficient to distinguish between both the remitted MD group and control group with high accuracy (78.3%) [1].

b) SVM Algorithm

for the analysis of Alzheimer's disease and lie detection they utilizes support vector machine(SVM) algorithm and predicts the outcomes of the processed data. The support vector machine (SVM) attempts to learn a model from data by finding the largest margin hyperplane that separates data from different conditions (e.g. baseline/activation) or groups (e.g. patients/controls). The results showed that the accuracy of the linear SVM for the

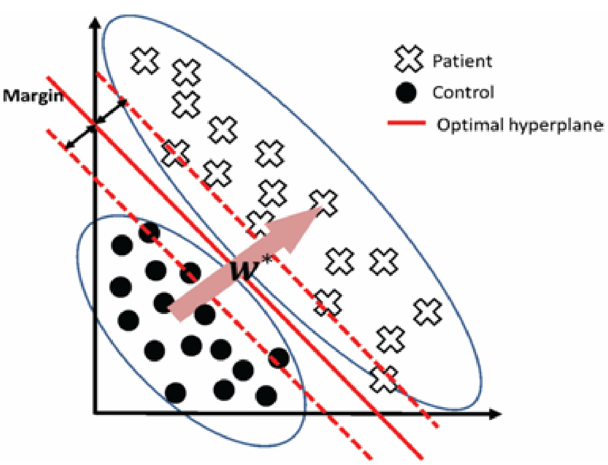
Alzheimer's disease dataset was 86% and for the lie detection dataset it was 84% [2].

III. Result and Discussion

Linear discriminant analysis (LDA) and support vector machine (SVM) are the two different techniques that have been used by the above two authors. One for the prediction of vulnerability of major depression (MD) and other for the analysis of Alzheimer's disease and lie detection. The basic idea behind the two techniques lies on the fact that how they separates the different datasets from each other [3].

In the prediction of major depression vulnerability, LDA separates the datasets from each other by drawing a line between them in 3D space whereas in case of Alzheimer's disease and lie detection, SVM draws a hyper plane between the datasets to distinguish between them.

SVM finds the closest points between the patient and control group and draws a line 'w' connecting them. Finally it draws a hyper plane that bisects the line 'w'. It is shown in fig 1,



By doing this, it maximizes the possible margin between the two groups and this leads to a better distinction between control group and patient group.

By using LDA, João R.Sato et al use more number of voxels to classify the data. This in turn acquires more memory space and hence becomes more time consuming to compute the outcomes. Comparing to this Bilwaj Gaonkar and Christos Davatzikos exploits SVM which uses less number of voxels to achieve similar classification accuracies. Therefore acquires less memory space, less time consuming and more efficient method for FMRI data analysis.

SVM Advantages:-

- It can be used for higher dimensions.
- It is a discriminative model.
- It has both linear and non-linear classifiers.
- It minimizes hinge loss.

Both LDA and SVM techniques can be used for FMRI data/image analysis. LDA uses a line to separate the datasets. By using a line, there can arise a problem of data overlapping between the two territories. On the other hand SVM uses a plane for the same purpose and maximizes the margin between the two datasets. Therefore it minimizes the chance of interference between the datasets and hence increases the accuracy.

Parameters	SVM	LDA
concept	Extracts the information which is sufficient for classification	Mostly focus on extracting all discriminative information available.
Voxels	Uses less voxels to achieve similar classification accuracies	Uses significantly more voxels to classify the data.
Stability	more stable	Less stable
Cost	Cost efficient	Expensive
Accuracy	Alzheimer's disease- 86% Lie detection- 84%	Major depression- 78.26%

Table1- Comparison between SVM (state vector machine) and LDA (linear discriminant analysis) approach for FMRI data analysis.

Conclusion:

In this article, the two techniques are compared on the basis of certain parameters. The study shows that SVM has got some advantage over LDA for the analysis of FMRI data. A comparison between two techniques is shown in table 1.

IV. References

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