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ANALYSIS OF BRAIN MORPHOMETRY USING IMAGE SEGMENTATION

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Abstract:- Computational neuroanatomy is an emerging field of powerful applications in neuroscience which promises an automated methodology to characterize neuroanatomical configuration of sMRI brain scans. This paper presents the current status of research in brain morphometric analysis. This papers primary objective is to help the researchers in understanding the current status of literature in brain moprhometry analysis and to help in understanding different tools being currently used and different measures of performance for the classification tool.

Keywords:- C-means; Classification; Clustering; Image Segmentation; Marphometric; Neuroanatomy.

I. INTRODUCTION

The human body is an extremely complex system. Getting data about its static and dynamic properties gives massive amounts of knowledge. The use of images is the most effective way to manage, present and interpret the vast quantities of that information in the clinical medicine and in the supporting biomedical research compare to the CT MRI is having superior contrast properties and important in diagnosis imaging techniques for early abnormalities of brain and used to study the changes in tissues and organs so many of the researchers are used to study the Magnetic resonance imaging (MRI) Anatomical structure of brain is more important, analysed by segmenting human brain macroscopic structures used for analysing brain disorders and to understand the brain degeneration, and brain trauma, and other condition of the brain. Brain morphometric analysis and markers are used for diagnosis the brain disorders individual anatomical slices of brain image is used to analyse brain hyper metabolism and hypo metabolism using image segmentation. Regional connectivity in diffusion tensor image is also enabled by Anatomical segmentation of image data.The morphometric methods are used to characterize and identify the brain structural difference correlated with the disease severity with brain structural shape. Neuroanatomical difference between brains is carried in good way as it is having development of improved resolution in images acquire and processing algorithms. MRI is the one of the sophisticated imaging technique to investigate neurological disorders such as Alzheimer, Schizoperia, autism, dyslexia and turner syndrome. By relating the normal brain with diseased brain

using Computer based diagnosis system medical image segmentation is the primary processing mechanism and it is more complicated and challenging one due to the intrinsic nature of the images. Most of the image segmentation techniques follow the region growing, clustering and thresholding mechanism are been proposed for image segmentation. Brain image intensities are distributive so it is very difficult to apply threshold technique so it is combining with the other segmentation methods to make it successful to segment the image. There are different statistical methds to make the segmentation of the image more accurate such as fuzzy C-mean clustering, and Expectation-maximization algorithms.As stated in earlier image segmentation is most important stage in image and data pre processing stage a sophisticated classification algorithm is purely depend on the feature extraction from the pre processed image that is get segmented. Segmentation play major role in determining accuracy of system. To cluster data in data set different classification algorithms are adopted to perform statistical clustering mechanism unsupervised classification is used such as self organizing group methods are used for clustering the image pixels or grouping the pixels. So to enhance the accuracy of any classification tool for automated analysis of better morphology it is imperative for us to design better algorithms and better algorithms invariably should have better segmentation techniques.

For neuro imaging analysis computerised automated classification methods are used. Neighbourhood information of image intensities is used for multi resolution approaches to find the change in brain volume. Computer aided techniques are used for study the texture change in image intensity and gray matter concentration change, Weakness in the sub cortical structures. Brain analysis is mainly depend on Voxel based analysis such as VBM (Voxel based Morphometry) for sMRI. For voxel based morphometry brain image is registered in a common 3-Dimensional space space and mass univarite on each voxel statistical tests are performed to find the significant changes. Sensitivity of these approaches is limited to different spatial complex and involve a combinational different brain structure voxels. Computerized automatic classification is commonly used in neuroimaging. Based on multi resolution techniques it is possible to detect the several significant changes in brain volume based on neighbor information it is possible to detect the texture change in signal intensity gray matter variation in sub cortical limbic. VBM is mainly used in sMRI. Where the statistical analysis is performed on registering the images on common stereotaxic space and then performs analysis to detect the group differences. It is difficult task because It have combination of different voxel structures to overcome univarient analysis Support vector mechanism is used for this may successfully applied to different individual classifications. MRI images are

interpreted by visualizing the films but due to shortage of efficient radiologists and have large no of MRI images to be analyse It maly lead labor, cost expensive and inaccurate in the analysis of the MRI more over if more no of MRI images are analysed then human eye can not perceive small variations so it need a automatic computerized analysis system.Researchers have approached Brain morphometry analysis and some of the tools and measures that are currently being used for the said analysis. Different analysis discusses in brief about kind of tools being presently used for brain morphometry analysis and presents an overview about how the performance of the classification should be analyzed.

II.REVIEW OF LITERATURE

sMRI and V.B.Morphometry used to study the use full Region, that used to study the structural ROI of neuro imaging data, that employ to compare the number of patients and report short fall in temporal and pre frontal lobe [8], in the superior temporal gyrus[7], along with amygdale and hippo campal and para hippo campal gyrus and lateral ventricles enlargement. Structural MRI is used for early stage of schizophrenia [13]. Along with the above factors there are many factors that lead to make the disease to begin with different processes, due to the matter of hereditary factors, misusing antipsychotic drugs during treatment [17]. Change in gray matter density changes over time may develop schizophrenia, at temporal lobes [8]. fMRI is used to examine the on comparing the normal brain and schizophrenia brain on function of cognitive network abnormalities are reported in particularly implicating the prefrontal cortex. These techniques produce most constant and interesting results, ROI methods are important to predefine brain regions but not possible to capture the patterns distributed and brain abnormalities. Voxel Based Morphometry is a computational morphometry, it cannot capture individual deviation from the standard one machine learning in the direction of notice the correlation of medical application and unity of MRI. Machine learning algorithms are applied and analysed in fMRI and Structural MRI [14],[16]. Machine learning is also used for diagnose the neurological and psychiatric disorders [11] as dementia [9],[10][5], depression [11],[6], and schizopheria[7],[12],[11].Pattern reorganization make the interface the status of heath and individual level and study for clinical decision making. Schizophrenia has been studied by neurological image techniques such as sMRI, fMRI, used to identify the structural abnormalities [3],[15].Structural change of brain pattern comparing with healthy and diseased person is characterized by extracting biomarker and morph metric information. Biomarkers are classified based on the application . BM (Biomarkers) are theorises from modified images such as GM concentration of brain maps the data from High resolution T1 MRI Brain Image those are registered on reference space in order to perform volumetric analysis. To analyse the total brain it need thousands of voxel biomarkers.

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In order to examine the structural change due to various diseases Volumetric analysis is used as a most important mechanism for investigate the different brain disorders. Alzihmers Disease patients and Mild Cognitive impairment patients are classified using High-dimensional VBM, [9], [10], [2], [1]. Classification of AD and front temporal demented is carried by Automatic voxel-based classification [9], [10]. Finding Region of interest of brain structure volume of brain structure is adopted in complement to the VBM. . Medial temporal and hippocampal atrophy are sensitive to AD biomarkers [2], [11].Biomarkers include the volumetric pixels include cortical thickness, cortical folding pattern, longitudinal volume change not decide how fully automated volume based morpometry is accurately diagnosis the disease compare to Voxel based Morphometry. [1] the change due to AD in hippocampus volume estimation in early stage by full brain Voxel based Morphometry. NeuroQuant gives statistical information about Volume of medial temporal lobe region change in AD patient between early and controls match with the clinical data. Total brain volumetric information is used to classify anatomical changes. In real time application large dimensional limits the accuracy of the classifier due to its high dimensionality. Volumetric information of brain tissues or structures are affected by disease and age it a large dimensional data is available as a block box for interoperating voxel based classifier in spatial pattern.

III.BRAIN MORPHOMETRY TOOLS

This section reviews some of the brain mophometry tools being widely used in neuro imaging and analysis. SPM (Statistical Parametric Mapping) is popular neuro imaging analysis software that implements a VBM pipeline. The incoming MRI images are first convert into probability map using pipeline mechanism it include Gray matter probability, by Bayesian segmentation algorithm. GM map get smoothen and perverted to mention space to compare voxel slice by voxel slice. DARTEL Algorithm is used for optimize the Gray matter and white matter probability maps.The most widely used VOlBM is Surfer software. It have the features of pipeline description that used for segment and measure volumes. But it as limitations of computationally complex, pipeline operation typically takes several hours, restricted to use in clinical routine. Multi template also have more computational complexity.Another algorithm available now a days is Morpho Box, it has less computational complexity than surfer that perform segmentation of brain anatomy in to 2 steps one it label the volume of brain tissues that no atlas based mechanism at this stage, second by segmenting the brain tissues collecting from first step map and mixed to form a local image intensity model.

IV. EVALUATION OF CLASSIFICATION PERFORMANCE

Disease Management program concern about the accuracy of diagnosing and Predictive accuracy of disease, that give the efficiency of identify the diseased patients,

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the accuracy is predictive modelling have domain of future health status, risk strarication and cost. Moderan medicine diagnostic test is conforming the existence of syndrome but also rule out the syndrome in healthy Persons. The conventional way is by using 2x2 table. This is recorded as +ve and –ve. Results which are known as dichotomous. By testing the probability of detecting correct diagnosis by inherently statistical validity b test table as true disease person (D+ve) and True non-diseased person(D-ve). These are summarized in 2x2 test matrix table. Row have the information of test result columne gives the dichotomous categories.

TABLE 1: CONTINGENCY DIAGNOSTIC TEST VALUES IN RELATION TO TRUE DISEASE STATUS

		Truth		
Test Values		**Disease (number)**	**Non Disease (number)**	**Total (number)**
	Positive (Number)	A (T+ve)	B (F+ve)	T Test +ve
	Negative (number)	C (F-Ve)	D (T-Ve)	T Test -ve
		T Disease	T Non Disease	Total

A diagnostic test result has four possible outcomes. They are:

4.1 True Positive (Hit): Both test and classified both as positive it is Treated as True +ve (T+ve).

4.2 False Positive (false alarms)*:* it is mistakenly treating the -ve as +ve . In case the test is +ve and it is classified as -ve, it is Treated as False +ve (F+ve).

4.3 False Negative (Misses): In this the +ve item is mistakenly treated as -ve it is represented as False –ve (F-ve).

4.4 True Negative (correct rejections): If Both test and classification is negative, it is mentioned as True –ve (T-ve).

Any assessments of diagnostic performance require some comparisons of diagnostic decisions with 'truth'.A suitable universal method to compute the diagnostic exactness is to state the performance by a single number. The most suitable measurement is the area under the ROC plot (AUROC/ AUC). AUROC gives the inherent validity of the diagnostic test by combining specificity and sensitivity. Utmost AUROC = 1 represent that the test is performed on diseased and non-diseased subject and perfectly diagnosis the disease. The area under ROC is obtained by adding the successive areas of trapezoids instead of collecting ROC points. In order to average the effect between points Trapezoids instead of rectangles as shown in Fig.1.

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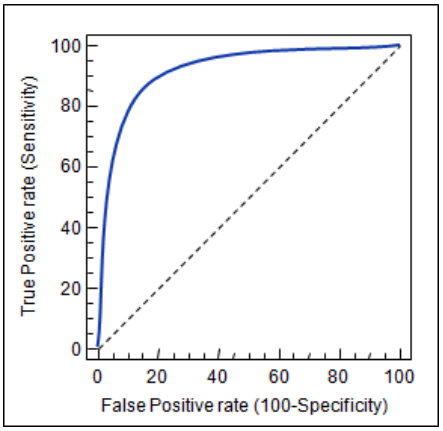

Fig1 : ROC curve

Deciding a good value for AUC depends on the context of individual problem. A rough guideline is to examine the likelihood ratios. The interpretation of the AUC i given in Table 2.

1. TABLE 2. INTERPRETATION RANGE OF ARA UNDER CURVE

Area Under Curve Range	Interpreation
90% to 100%	Excellent
80% to 90%	Good
70% to 80%	Fair
60% to 70%	Poor
50% to 60%	Fail

V.CONCLUSION

This paper explains the importance of brain morphometry analysis and the need to have an automated analysis tools. The paper presents a detailed review of literature stating current status of research and various approaches being employed by different researchers for analyzing neural images. The overview about current tools being used helps the researchers in identifying the methods, limitations and advantages of tools being currently used for brain morphometry. An insight in to performance measures helps to understand how the results for the analysis tool can be categorized and analyzed

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