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A Robust Algorithm for Diagnosis of Schizophrenia Using Multimodal Features from MRI Scans

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Abstract*— Schizophrenia is a mental disorder characterized by abnormal social behavior and failure to recognize what is real. Common symptoms include false beliefs, unclear or confused thinking, hearing voices ,reduced social engagement, and emotional expression, and a lack of motivation.Schizophrenia is a severe and disabling mental illnesses which has no well-established, non-invasive diagnosis biomarker. Currently, due to its symptom overlap with other mental illnesses (like bipolar disorder) it can only be diagnosed subjectively, by process of elimination.This research paper automatically diagnose subjects with schizophrenia based on multimodal features derived from their brain magnetic resonance imaging (MRI) scans.Two modalities of MRI scans are used to obtain these features: functional and structural MRI. The objective of this research is how to optimally combine this type of multimodal information and select features that enhance the diagnosis of schizophrenia .Our paper consists of five sections. First section explains the introduction of our topic, second section describes the related work, third section explains the research gap, fourth section explains the proposed algorithm to diagnose schizophrenia and fifth section describes the conclusion.

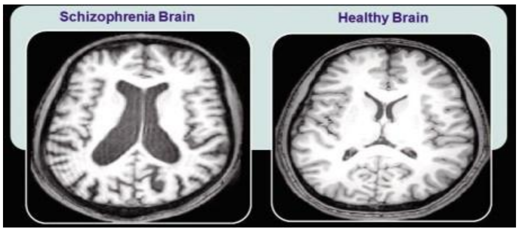
***Keywords*— Support Vector Machine, MRI, ANOVA, Functional MRI, ICA, GIFT**

I. INTRODUCTION

Schizophrenia is a mental disorder characterized by abnormal social behavior and failure to understand reality [8].Common symptoms include false beliefs, unclear or confused thinking, hearing voices, reduced social engagement and emotional expression, and a lack of motivation. People often have additional mental health problems such as anxiety disorders, major depressive illness or substance use disorder. Symptoms typically come on gradually, begin in young adulthood, and last a long time. The cause of schizophrenia is believed to be a combination of environmental and genetic factors. Possible environmental factors include certain infections, parental age, and poor nutrition during pregnancy. Males are more often affected than females. About 20% of people do well and a few recover completely if this disease found early.

Magnetic resonance imaging (MRI) is a best technique of examining the human body. MRI is used to explain and characterize the neural architecture of the human brain. MRI scanner employs a magnetic field and radio waves to generate exhaustive images of the human brain. MRI is a medical imaging techniques used to investigate the overall structure of healthy and schizophrenic brain. MRI data is most relevant in the studies of a head, specifically, for tracking disease of brain and other brain related problems.

Our objective is to diagnose schizophrenia using multimodal features of MRI scans. Now-a-days, there are no automated tools developed for diagnosis of schizophrenia. In this paper, we surveyed many papers to get the optimal technique or algorithm. We are combining the features of MRI that is Functional MRI and Structural MRI to get the best method.



II. RELATED WORK

Although a number of recent studies have examined functional connectivity at rest, few have assessed differences between connectivity both during rest and across active task paradigms. Therefore, the question of whether cortical connectivity patterns remain stable or change with task engagement continues to be unaddressed.Cetin et al. collected multi-scan fMRI data on healthy controls (N=53) and schizophrenia patients (N=42) during rest and across paradigms arranged hierarchically by sensory load. They measured functional network connectivity among 45 non-artifactual distinct brain networks. Then, They applied a novel analysis to assess cross paradigm connectivity patterns applied to healthy controls and patients with schizophrenia. To detect these patterns, They fit a group by task full factorial ANOVA (Analysis of Variance) model to the group average functional network connectivity values. There approach identified both stable (static effects) and state-based differences (dynamic effects) in brain connectivity providing a better understanding of how individuals' reactions to simple sensory stimuli are conditioned by the context within which they are presented. There findings suggest that not all group differences observed during rest are detectable in other cognitive states. In addition, the stable differences of heightened connectivity between multiple brain areas with thalamus across tasks underscore the importance of the thalamus as a gateway to sensory input and provide new insight into schizophrenia.[4]

Allen et al. describe a simple data-driven approach to assess Functional Connectivity(FC) based on techniques like k-means clustering of windowed correlation matrix, sliding time-window correlation and spatial independent component analysis. They used GICA to split resting state data into functionally homogenous regions. They used the series of sliding windows to estimate the Time-varying FC . The resulting FC time series is used to determine brain regions with variable connections. They identify patterns of FC that reoccurs in time and across subject, using k-means clustering. They said these clusters as “FC states”. These FC states are very effective as compared to large-scale networks. These time varying FC is also used in the functional coordination between different neural systems.[5]

Segall et al. used the Gray Matter(GM) measures . GM consists of neuronal and glia cell bodies. They saw a reduction in GMD(Grey Matter Densities) as age increases. They used the GM to understand the both structural and functional connectivity. They investigate the spatial correspondence between structure and function. They applied spatial independent component analysis to both GMD maps and to resting state fMRI. These decomposed components were than compared by spatial correlation. They show correspondence between a single structural component and several resting-state functional components. They used the Multivariate approach, SBM(Source Based Morphometry), and found GM structural relationships several areas in brains where structure and function corresponds. They also concluded that age has a significant effect on structural components.[6]

Allen et al. established a baseline from which diagnostic should easily done. They also able to reduce unnecessary testing and able to optimizes sensitivity. They also identify the effect of age and gender on the resting-state networks(RSNs). They collected the data from the same scanner and preprocessed that data using automated analysis pipeline based in SPM (Statistical Parametric Mapping). These RSNs were evaluated in terms of three outcome measures: time course spectral power , spatial map intensity and functional network connectivity. They identify the substantial effect of age on all three measures. They also identify the smaller gender effect but found stronger intra-network connectivity in females and more inter-network connectivity in males. They provide the powerful and useful baseline for future investigations of brain networks in health and disease.[7]

Schizophrenia has often been conceived as a disorder of connectivity between components of large-scale brain networks. Lynall et al. tested this hypothesis by measuring aspects of both functional connectivity and functional network topology derived from resting state fMRI time series acquired from various peoples. They identify that people with schizophrenia, strength of functional connectivity was significantly decreased; whereas diversity of functional connections was increased. They correlated the Functional connectivity and topological metrics. They concluded that people with schizophrenia tend to have a less strongly integrated, more diverse profile of brain functional connectivity, associated with a less hub-dominated configuration of complex brain functional networks.[15]

Schizophrenia is hypothesized to involve disordered connectivity between brain regions. Currently, there are no direct measures of brain connectivity; functional and structural connectivity used separately provide only limited insight. Simultaneous measure of anatomical and functional connectivity and its interactions allow for better understanding of schizophrenia-related alternations in brain connectivity. Separate functional and anatomical connectivity maps were calculated and combined for each subject. Global, regional, and voxel measures and K-means network analysis were employed to identify group differences and correlation with clinical symptoms. Combining two measures of brain connectivity provides more comprehensive descriptions of altered brain connectivity underlying schizophrenia.[16]

Kumari et al. used Magnetic Resonance Imaging tools in there framework. MRI is most valuable tools used in surgical and clinical surgery. Radiologist then examine the Magnetic Resonance Imaging to identify the presence of defective tissues. MRI may contain both normal and abnormal tissues. Further these separated abnormal tissues are inspected for brain tumor.There proposed method used the PCA for feature extraction from MRI data. These features are further classified using SVM. They used the dataset consists of 256 X 256 pixels, T2-weighted MRI brain images.They study the brain MRI of 60 pateints and found that 45 images were abnormal and remaining were normal.They found that there method were computationally effective and yielded good result.[18]

Sindhu et al. used the Brain MRI for detecting Brain Tumor. They used image processing techniques. There proposed methodology consists of four stages. They were image preprocessing , image segmentation ,feature extraction and classification.They improved the performance of detecting brain tumor in MRI by using image processing and neural network techniques. They surveyed more than 25 research papers for reviewing methods used particularly brain tumor in MRI.[19]

There Paliwal et al. proposed method were used to identify the region of interest in the brain using Discrete Wavelet Transform based image decomposistion algorithm.They related the different brain activations to different brain functions and disorders by using MRI and EEG signals. They de-noising the image using wavelet transform and further feature extraction is used to classify the medical images.They proposed the different methods used for feature extraction in MRI scans.They improved the classification performance with the help of different classifiers, also compare the different classification techniques and get the best results.[20]

Kumari et al. proposed a method to extract the optimal features of brain tumor using MRI. There proposed system consists of three parts: preprocessing , segmentation and feature extraction. They used the best methods for all these parts. They used the median filtering for preprocessing for removing the noise , K-means clustering algorithms for segmentation and to recognize the tumor shape and size by using edge detection method.They found that median filter is best among mean filter ,weiner filter and gaussian filter for removing the noise in the image and further found that partitioned clustering like K-means is faster then heirarichal clustering and also found good result by using GLCM (Gray Level Co-occurrence Matrix) and Gabor feature extraction techniques for feature extraction.[21]

Lehana et al. worked on improving the quality of biomedical images using Aura Transform because these MRI are very useful to extract exact images . There were lots of mathematical methods are used. The objective is to extract maximum useful information from these images related proper functioning of the brain. In there proposed method, they used the aura based technique for enhancing the qulaity of MRI scans of the human brain.The relative distribution of pixel intensities with respect to a predefined structuring element is called Aura. The Aura matrix is formed by local distribution of pixel intensities of te given texture. By applying Aura transform, they get the significant results as compared to existing systems.[22]

Bandhopadhay et. al. proposed a system for segmentation of MRI scans by using a system of image registration and fusion theory . There system is relatively fast for diagnosis of the brain tumor as compared to existing systems. There proposed system consists of three parts. First part consists of registration of multiple MRI scans of the brain along with adjacent layers of brain. In second part, these images were further processed to get high quality image for segementation. Finally , K-means algorithm with dual localization methodology is used for segmented image. They showed some good result on given data and found significantly good segmented data as compared to existing data.[23]

Joseph et al. proposed a framework used to detect brain tumor in MRI scans. They first collected MRI scans, then they convert it into grey scales.Noise in the images were removes using median filter .Then this image was segmented using k-means clustering algorithm. Further they applied propose morphological filtering to that segmented image.They found good result by applying this framework.[24]

III. RESEARCH GAP

Recent studies have clearly demonstrated that schizophrenia is a brain disease. Our research will automatically detects subjects with schizophrenia and schizoaffective disorder based on multimodal features derived from the magnetic resonance imaging (MRI) data. Two modalities of MRI scans are used to obtain these features: functional and structural MRI. The objective of this research is how to optimally combine this type of multimodal information and select features that enhance diagnosis. Recent imaging studies employing methods of multivariate statistics and machine learning revealed an opportunity to detect schizophrenia using biological features.The above things encourages the multidisciplinary research of image-based computer aided diagnostic tools that will hopefully improve early diagnosis of schizophrenia.

IV. PROPOSED ALGORITHM

Step 1 : Data collection and Preprocessing

The data consist of two sets of information collected by different imaging modalities: Functional Network Connectivity (FNC, [5]) and Source-Based Morphometry (SBM, [6]) loadings. The FNC will derived from functional magnetic resonance imaging (fMRI) scans, and can be seen as a functional modality feature describing the subject's overall level of 'synchronicity' between brain areas. SBM loadings are derived from structural MRI scans, and they indicate the concentration of grey matter in different regions of the subject's brain

Step 2 : Group ICA

Group independent components analysis will performed using the GIFT(Group ICA of fMRI Toolbox). Data will decomposed into functional networks using spatial ICA. Spatial ICA applied to fMRI data identifies temporally coherent networks by estimating maximally independent spatial sources, referred to as SMs(Spatial Maps), from their linearly mixed fMRI signals, referred to as TCs(Time Courses).

Step 3 : Feature Identification

All structural components will visually inspected by some viewers and the GM composition of each component will evaluated. We will using the method of [7] to select a subset of functional components from rs-functional components. These structural and functional components are combine for further classification.

Step 4 : Classification using SVM

Support Vector Machine are used to investigate the data between normal and schizophrenic patient. There are two sets i.e. one for training and second for testing. SVM is the best method to distinguish between normal and schizophrenic patient.

V. CONCLUSION

We surveyed many research papers to get best solution to automatically diagnose schizophrenia using machine learning. We have studied many image processing techniques to get the requirements and properties in detection of schizophrenia in brain. It was observed that our proposed algorithm is relatively less computationally expensive, simple, and promising. This algorithm is best to predict brain abnormalities more effectively and more efficiently. We believe that, this article can give valuable understanding into this significant research topic and encourage new research. In the next phase of our work, we will plan to develop a new algorithm and compare their result with the existing algorithm for better results.

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