International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 14, No.1 (Sep-2023)

http://dx.doi.org/10.12785/ijcds/140161

Cerebral Cortex Segmentation from MR Brain Images based on Contouring Technique to Detect Alzheimer's Disease

Sivanesan Rajangam[1] **and Kalavathi Palanisamy**[2]

[1,2]*Department of Computer Science and Applications, The Gandhigram Rural Institute (Deemed to be University), Tamilnadu, India*

Received 08 Nov. 2022, Revised 14 Jul. 2023, Accepted 31 Jul. 2023, Published 01 Sep. 2023

Abstract: Magnetic Resonance Images (MRI) are extensively used for medical diagnosis to detect various dementia by analyzing the whims in the brain tissues of the human brain. The popularly known dementia is Alzheimer's Disease (AD), and dissection of brain tissue acts a vibrant role to diagnose AD. One such brain tissue is Cerebral Cortex (CC) or Cortical Thickness (CT), which is majorly used for pathological studies, CC/CT segmentation is the most significant part of diagnosis. This paper reveals the importance of segmenting the cerebral cortex to detect AD. In this method, the segmentation is done in three processes; the first step is to find the cerebral hemispheres, the second step is segmenting the CC in each hemisphere by employing a contour-based approach and in the thirdly, the CC is segmented based on the histogram statistics and intensity profile of the segmented region by contouring technique. Earlier approaches for AD detection are based on brain tissue like white matter and gray matter segmentation. This Proposed method segments CC and yields acceptable results to detect AD in pathophysiological images and the results of this method is evaluated with brain images of IBSR_18 and ADNI using Jaccard (Jac), Dice (Dc) similarity measures, Dissimilarity Jaccard (dJac) and with Sensitivity (Sen), Specificity (Spc) quantitative measures.

Keywords: Magnetic Resonance Imaging (MRI), Brain Tissues, Cerebral Cortex (CC), Contour, Brain Hemisphere, Alzheimer's Disease (AD) Detection.

1. INTRODUCTION

MRI plays an inevitable role in biomedical research and clinical diagnosis. MRI is used to generate detailed two and three-dimensional images of a living subject with the help of an MRI scanner. The wide propagation of MRI techniques has led to ever-increasing imaging applications and massive new biomedical research and findings in clinical sciences. The MRI scanner significantly produces vibrant brain images that help the doctors to diagnose a disease including Multiple Sclerosis, Dementia, Seizures, Brain tumor, Schizophrenia, Parkinson's and Alzheimer's Disease, etc. MRI not only supports diagnosing the disease but also helps for further treatment planning of diagnosed disorders. Segmentation of brain tissues in the brain image is a foremost task in neurodegenerative diseases, especially segmentation of the Cerebral Cortex is of fascinating interest to neuroscientists. It is one of the most tedious and needy segmentation chores in brain image segmentation. CT is the distance between the inner and outer surface of the brain. Outer surface refers to the boundary of Gray Matter (GM) and Cerebral Spinal Fluid (CSF), inner surface refers to Gray matter (GM) and White Matter (WM) boundary is illustrated in Figure 1 CC varies from 2mm - 4mm in different ranges of the brain regions [1]. Segmenting the cerebral cortex or measuring cortical thickness is the most essential task for both normal and abnormal neuro anatomy to detect the disease. Depending upon the cortex's region, the cortical thickness varies with substantial variation between the hemispheres of the same brain and the individual brains. Benedicto et al.[2] developed a topographic segmentation technique for parcellations of CC reliably; also, it detects the subtle morphometric impairments or abnormal patterns in cortical subregions. The functional cortical ab-

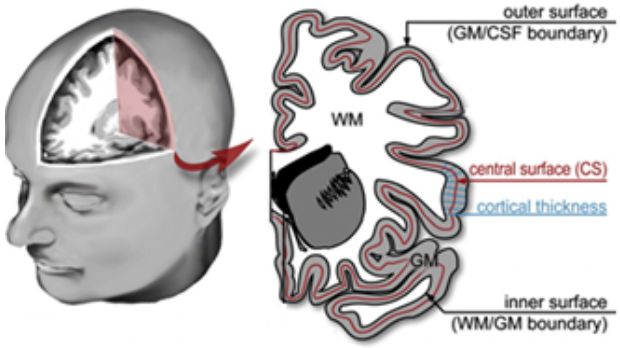


Figure 1. Illustration of Cortical Thickness in Coronal view [Courtesy (https://en.citizendium.org/wiki/Brain_morphometry)]

E-mail address: rajangamsivanesan@gmail.com, pkalavathi.gri@gmail.com

normalities provide pathophysiology of brain illness. A 4D segmentation method [3] to resolve unnecessary temporal variations in segmented cortical thickness utilized local intensity information to report the heterogeneous intensity. Spatial cortical thickness limitation to sustain the cortical thickness within a coherent range, and it also conquers the artificial variations. Cardoso et al.[4] anticipated a local adaptive algorithm to segment the cortical thickness, due to the presence of noise, non-uniformity, intensity and partial volume effects, the segmentation has not been done correctly. To overcome this, they established three post-processing steps to avoid segmentation bias; a novel modification in prior information, explicitly partial volume was introduced to enhance sulci and gyri and they used the locally erratic Markov Random Field (MRF) models. Dale et al. [5] compile some of the automated procedures to obtain exact reconstructions of the cortical surface. The automated Talairach registration process was used to calculate the transformation matrix from a T1-weighted image. The intensity normalization was done to steam line the corrupted susceptible artifacts to enhance the segmentation after the normalization procedure. A surface tessellation was used to construct the white matter for each hemisphere and finally they built the cortical surface volumes. A Surface Assisted Parcellation (SAP) system [6] conserves the morphologic and topographic distinctiveness of the individual cerebellum and representation of functional and structural data on the cerebral cortex for volumetric analysis[7] It allows the computation of topographical measurements of cortical thickness for segmentation and data generated from semi-automated volumetric and manual sources. It permits interoperation among surface-based topographic analysis and volume-based topographic analysis. It encompasses many segmentations systems functionality. According to the functional composition of cerebral cortex Rademacher et al[8] developed a structure for parcellation and it has been pragmatic on human brain MR images. It supports investigations of hemispheric quantitative and asymmetries in cognitive impairment and provides a revision of computational methodology and classic systems models. The anatomical detail is also supplied for structure-function correlations needs and it is preferably suited for the 3D individual functional and anatomic data. A computer-assisted algorithm executes parcellation routine in wieldy time[9] The topographic parcellations of the human neocortex conserve the individual brain based on MR brain images. The algorithm goes with the flow of three parcellation steps; first step is the specification of anatomic landmarks, in the second step the cortex is divided into parcellation units, and in the third step it assigns names to parcellation units. This method was executed in T1 weighted brain MR images. A new approach in voxel-based estimation technique estimates grey matter volume and the cortical thickness without using surface meshes described in [10]. The histogram-based swarm optimization technique proposed by Priya and Kalavathi [11] used to segment the brain tissues and they employed the same method for AD detection. Lerch et al [12] investigated the automated cortical thickness measurements to analyze the AD patients. The thickness maps are analyzed using three discriminant techniques; linear analysis, quadratic analysis, and logistic regression, to separate patients. To avoid overtraining of the discriminants, they performed the leave-one-out-cross-validation procedure. The cortical thickness distribution in patients suffering from Motor Neuron Disease (MND) was examined by Machts et al[13]. The Cortical Thickness (CT) measures were extracted for the prefrontal, premotor, motor, and occipital, and the study demonstrates that the CT is thinner in MND patients. Tuan et al.[14] developed a histogram technique and an adaptive region expansion method for segmenting 3D MRI images of the skull, scalp, and brain. This model was developed for doctors to use automated segmentation of 3D MRI images of the skull, scalp, and brain to help in the diagnosis of a range of infections and traumas. Cuingnet et al.,[15] performed three classification tests namely Elderly Control(CN) vs AD, CN vs Mild Cognitive Impairment converters (MCIc) and MCIc vs Mild Cognitive Impairment non converters (MCInc) on ADNI database to obtain the performance and they evaluated the performances of ten approaches on the same database. The authors in [16] aimed to determine how significantly classification accuracy could be enhanced through the integration of information gathered through different structural MRI analysis methods. It estimates the hippocampus volume and tissue volume via manifold learning. Nebel et al.[17] addressed the knowledge gaps in gauging sex and gender differences by identifying twelve significant subjects requiring additional research in this field of study based on the AD field on sex and gender differences. These are typically four stages in AD detection and classification, including noise removal, AD part extraction from brain features associated with MRI images, and classifier retention. The main focus of Thompson et al.'s[18][19] work was a discussion of their methodologies for mapping structural changes in the brain. This approach was employed to figure out the profile of brain aberrations in previous studies on dementia and other neurological conditions. They described a subject- and time-based cortex data comparison and pooling tool in this work, coupled with a cortical pattern matching and image analysis pipeline. The Alzheimer's Association [20][21][22]focuses on how the use of biomarkers can influence the way AD is diagnosed as well as estimates of the disease's prevalence and incidence. Alzheimer's dementia affects 5.5 million Americans, based on statistics. This creative approach could promote earlier detection of an illness and result in an improved understanding of the prevalence and incidence of AD. The benefits of making an Alzheimer's diagnosis early in the disease's course, while modest cognitive impairment is being caused by the disease. Their understanding of the disease has advanced from manifestation-based methods with the finding of AD biomarkers in recent years. Hala Ahamed et al. [23] take MRI scans for structural information and PET (Positron Emission Tomography) for functional information for fusing the images using early fusion (Laplacian Re-Decomposition) and late fusion (Canonical Correlation Analysis) by taking

the advantages of PET & MRI to classify the Alzheimer's Disease. Active contours are of two types one is Parametric Active Contours (PAC) and another is Geometric Active Contours (GAC). The contours are obsessed with reaching the object edge. Parametric active contours depend much on curve parameters and are expressed as curve function. Geometric active contours efficiently handle the topological change and do not require the curve parameterization [24]. In order to initialize the contour properly, the contour-based segmentation is enhanced with ensemble strategy and it is attained through maximizing the weighted mutual information [25]. Many of the existing methods for AD detections were dealt with segmenting mainly the brain tissues such as White Matter and Gray Matter. Whereas, very few researches have concentrated on Cerebral Cortex in the brain image, even though the segmentation process of this region is deemed to be very complex. However, the Cerebral Cortex is the premier region which will be affected due to AD. Therefore, any AD detection methods need to focus on this region for early detection. Hence, the prime contribution of this research article is to introduce a new methodology for the early detection of AD based on the morphological changes in the Cerebral Cortex region in Magnetic Resonance Images. In this proposed method we utilized parametric active contour to detect the edge of the CC region by considering the curved nature of its appearance for the earlier detection of AD. This article is disciplined in the following sections, section 2 reveals a comprehensive explanation about the methodology and materials, section 3 illustrates the results obtained with the proposed method and section 4 fleetingly provides the conclusions.

2. Material and Methods

The construction of the proposed method is shown in the following Figure 2; the first process of this method is preprocessing, the input image to confiscate the skull and the non-brain portions from the brain region. Then, it segments the Left Hemisphere (LH) and Right Hemisphere (RH) of the skull-stripped brain image, using the automatic segmentation of the cerebral hemisphere method[26]. Then the edges of the cerebral cortex are identified in each segmented left and right hemispheres. The identified edges of the cerebral cortex are segmented using contouring technique from the hemispheres of the given brain.

A. *Preprocessing – Skull Stripping*

Preprocessing is the initial and essential step in medical image segmentation and analysis. In order to produce the efficient results, in our proposed method, skull stripping is used as a preprocessing process to remove the non-brain portions of the brain like muscles, fat, skins, eyeballs etc. from the original MR brain scan. Skull stripping is the quite requisite preprocessing part in medical image segmentation to get accurate results [27]. The popular tool BET (Brain Extraction Tool) from FSL [28], is a widely used tool to segment the brain portion in T1 weighted brain images. The traditional method is unable to extract the brain portion

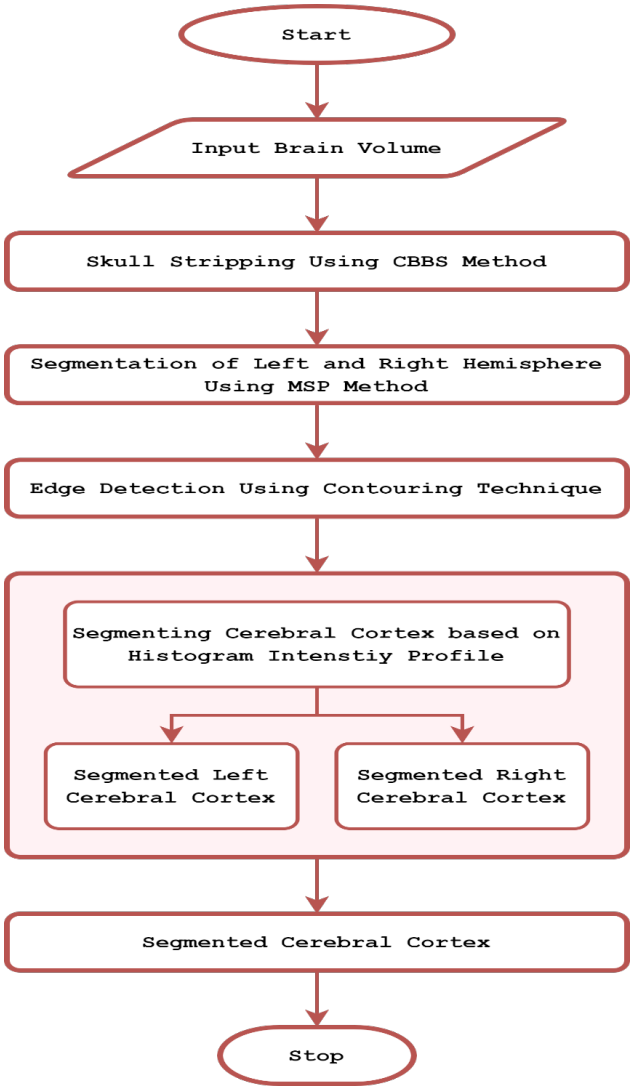
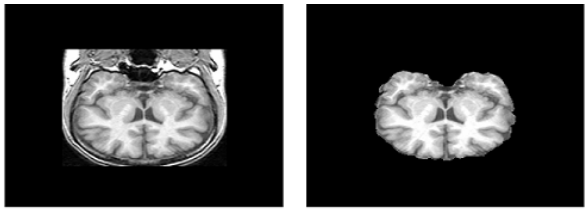


Figure 2. Process flow of the proposed method

accurately when the input brain volume is affected with various imaging artifacts such as intensity inhomogeneity, partial volume effect etc., hence, we used a method Contour Based Brain Segmentation (CBBS)[29] which could separate the brain portion accurately irrespective of the appearance of various imaging artifacts. The skull stripped image for a sample selected brain input image is shown in Figure 3.

B. *Brain Hemisphere Segmentation*

Brain cerebral hemisphere dissection is frequently required for countless bio-medical and neuro-scientific bids because the utmost of the brain structures has a two-sided morphology and functional laterality. Brain hemispheres look symmetric, but naturally, it has differences. The two hemispheres are coupled by a profuse band of neural filaments identified as the corpus callosum. Usually, we are not attentive to these two hemispheres that play the different



(a) (b)

Figure 3. (a) Input Image (b) Skull Stripped Image Using CBBS method

protagonists in day-to-day functions. Once the brain is divided into two halves it may use to diagnose various brain disorders like seizures, dementia etc., because these kind of brain disorders are associated with brain hemispheres, the symmetry of the brain reveals the standard healthy and unhealthy states of the brain and also easy to identify the morphological changes. In this proposed method the second process is to separate the brain portion into left and right hemisphere, we used a robust method which separates the hemisphere of the brain automatically by identifying Mid Sagittal Plane (MSP) for asymmetric analysis of brain images [30]. This method is particularly developed for T1, T2 and Flair weighted images, according to the MSP region of the brain the hemisphere is separated. The curve fitting approach is used to fit the curve in the identified points, in which the second order polynomial is used and is expressed as

$$y_i = s_0 + sx_i + s_2 x_i^2 \tag{1}$$

where, i is the number of curve points, x_i and y_i are the data points. By solving the below matrix the coefficients s_0, s_1, s_2 of second order polynomials are computed,

$$\begin{bmatrix} r & \sum x_i & \sum x_i^2 \\ \sum x_i & \sum x_i^2 & \sum x_i^3 \\ \sum x_i^2 & \sum x_i^3 & \sum x_i^4 \end{bmatrix} \begin{bmatrix} s_0 \\ s_1 \\ s_2 \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum x_i y_i \\ \sum x_i^2 y_i \end{bmatrix} \tag{2}$$

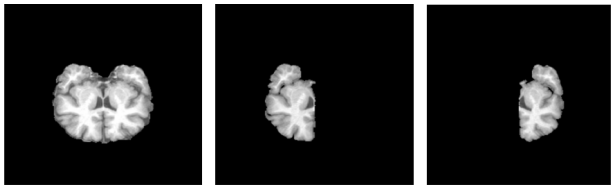
where, r is the number of curve points identified for curve fitting, $\sum x$ represents x values sum, $\sum xy$ represents the sum of all x and y values. The following Algorithm 1 gives a brief explanation about the process of this method. The curve points for curve fitting are identified by setting the Region of Interest (ROI) in the middle of the skull stripped image. By default, it identifies three points; start, middle and end points.The remaining curve points are identified by the black pixels in the binarized ROI region. The segmented Left Hemisphere (LH) and Right Hemisphere (RH) for a sample skull stripped images are shown in Figure 4.

C. Segmentation of Cerebral Cortex

Segmenting the cerebral cortex is an astonishingly non-trivial task, in pathological study CC has been acknowledged to vary in anorexia nervosa, epilepsy, dementia, Multiple Sclerosis, Schizophrenia, mental retardation and Alzheimer's Disease (AD). Though CC is a minuscule tissue spread over in brain morphometry, it is responsible for cognition of humans. It sounds a significant part in

Algorithm 1 Cerebral Hemisphere Segmentation

Input : Skull stripped Brain Images
Output : Segmented Left Hemisphere (LH) and Right Hemisphere (RH)
Step 1: Read the brain image I.
Step 2: Identify the curve points in I.
Step 3: Using the second order polynomial detect the MSP in the defined ROI by curve fitting method.
Step 4: Segment the brain image I into LH and RH based on the detected MSP.



(a) (b) (c)

Figure 4. Hemisphere Segmentation (a) Skull Stripped Image (b) Left Hemisphere (c) Right Hemisphere

discernment, language, responsiveness, perception, memory and attention. AD is connected to cognitive impairment, once the person is diagnosed with AD, then the human brain literally faces changes in brain structure especially in brain tissues like WM, GM, CSF and CC. Generally, CC is constructed with six distinct layers connected to each other, the shrinkages occurring between the layers leads to cognitive impairment. CC segmentation from MR Images is helpful to assess the AD in the medical field. In this proposed method we used contour models to segment the CC from brain images. Contour models designate the object boundaries or any other image features to form a parametric curve [31]. This model has potential in solving the broad cases of segmentation, and it primarily works to detect outline of the object. Usually, the contour is obtained by slicing the surface with a horizontal plane. A contour is a 2D plot which is drawn after obtaining the contour points in the one-dimensional curve and is expressed as

$$C(i, j) = C_j, \qquad j = 1, 2, 3, \ldots, N_l \tag{3}$$

where, CJ is the plotted matrix and is given as a constant and, Nl is the number of contour levels. The curve with constant C is called the contour of C.Equation 3 is non-linear, it has multiple solutions, it may produce a set of multiple, non-connected curves. These non-connected curves are then approximated by finding the linear approximation of C(i,j) [18]. The detection of CC begins with finding the closed region in each of the segmented left and right hemisphere. Figure 5, illustrate the contour detection in the segmented left hemisphere of a sample MRI brain slice. From this it is necessary to extract the CC region alone from the identified contours.

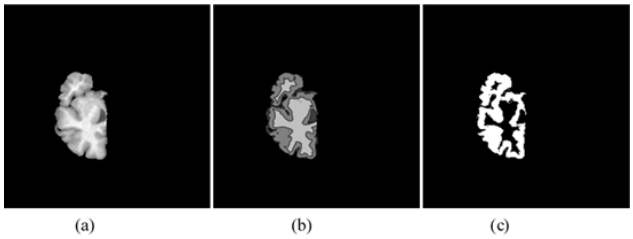


Figure 5. Contour detection (a) Segmented Left Hemisphere (b) Contoured Image (c) Segmented Cerebral Cortex

D. Selection of CC Region

The edifice for selection of peaks and segmenting the CC region from intensity profile and histogram statistics is depicted in the following Figure 6; the skull-stripped brain slice is given as input and the brain is divided in two hemispheres. After hemisphere segmentation, the process of histogram generation and peak identification takes place, according to the peaks position the CC region is segmented. In order to extract the CC alone in the contoured hemisphere image, we have computed the threshold value based on the histogram statistics and the intensity profile of the segmented regions. We found four peaks in the histogram of filled contour image which contains four regions including the background and are named as P1, P2, P3 and P4. The region in the filled contour detects CC, GM, WM and the background. By default, the first peak P1 is the background region, so we considered the remaining peaks P2, P3 and P4 of the histogram as shown in Figure 7, Figure 8 & Figure 9. Let G1, G2 and G3 are the grayscale values of the identified peaks P2, P3 and P4 respectively. We considered the second largest value among G1, G2 and G3 as the CC region. Because, as per the intensity profile of the brain tissue, the first maximum gray scale indicates WM. The middle gray scale indicates CC and the GM is marked in the region with the least value excluding the background intensity. The following examples show the identification of cerebral cortex in different scenarios of image intensity profile and peaks as illustrated in Figure 7,Figure 8 & Figure 9. In the Figure 7 the identified peaks from the histogram of an image as P1, P2, P3 and P4, first peak always be a background and let the P2 as G1, P3 as G2 and P4 as G3, among these, the G2 is considered as CC region. Similarly, in the Figure 8 the identified peaks from the histogram of an image as P1, P2, P3 and P4, and let the P2 as G1, P3 as G2 and P4 as G3, among these gray scale values, we consider G1 as CC region. Here, in the Figure 9the identified peaks from the histogram of an image as P1, P2, P3 and P4, and let the P2 as G1, P3 as G2 and P4 as G3, among these gray scale values we consider G3 as CC region. The steps involved in this process are described in Algorithm 2.

E. Datasets Used

1) Dataset - 1

In this proposed method, NITRC (NeuroImaging Tools & Resources Collaboratory) – IBSR (Internet Brain Segmentation Repository) – 18 normal [32] is used to examine the proficiency of the proposed method. It also contains the expert segmentation outcomes to analyze the performance of the proposed method.

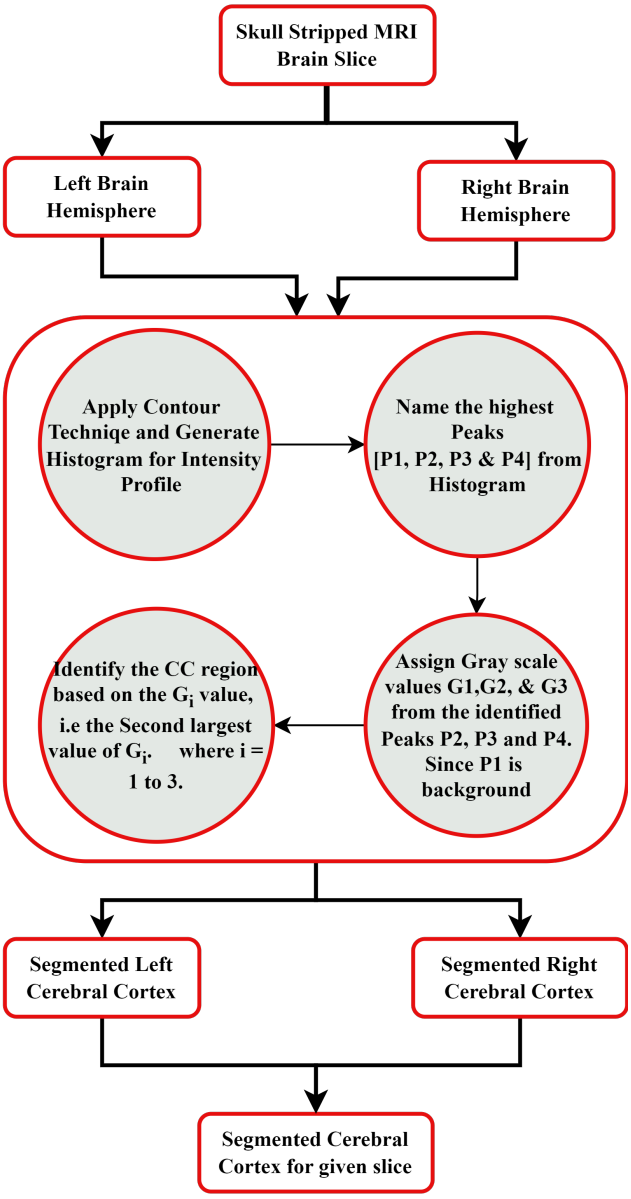


Figure 6. Process of Peak Selection and CC Segmentation

2) Dataset - 2

This dataset, which includes T1-weighted fast field echo MRI scans of Cognitive Normal (CN) and Alzheimer Disease (AD) images, was collected from the Alzheimer's Disease Neuroimaging Initiative (ADNI) [32].

F. Performance Metrics Used

The similarity measures are computed to find the accuracy of the proposed method. Jaccard (Jac) coefficient [33] is a similarity measure, also known as Jaccard Index used

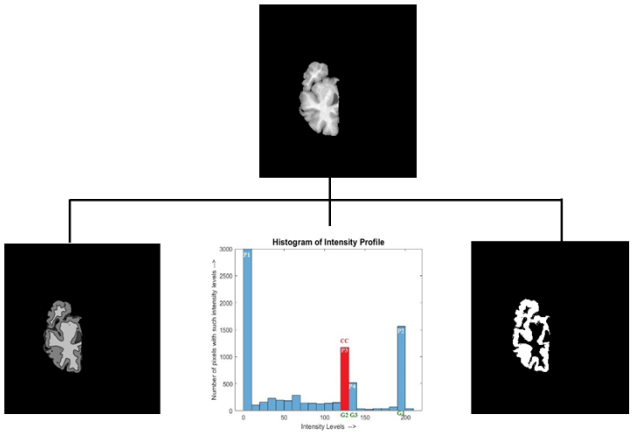


Figure 7. Identifying CC region, third peak considered as CC

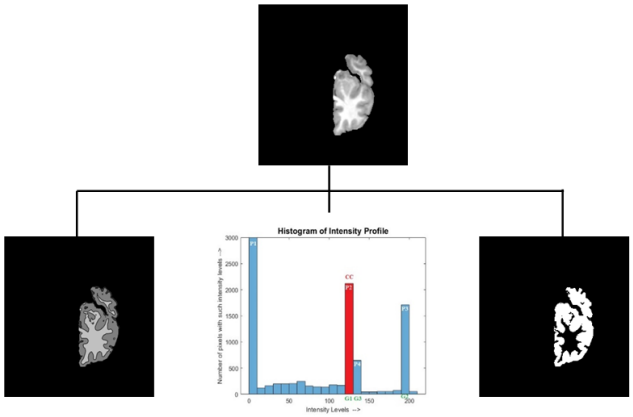


Figure 8. Identifying CC region, second peak considered as CC

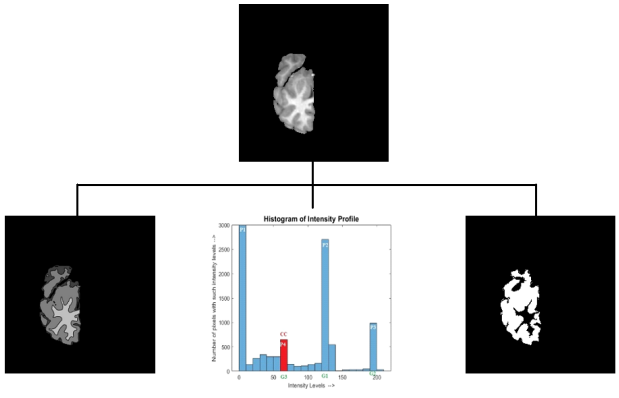


Figure 9. Identifying CC region, fourth peak considered as CC

Algorithm 2 Segmentation of Cerebral Cortex in brain hemispheres

Input : Segmented hemisphere
Output : Extracted Cerebral Cortex
Step 1 : Read the segmented Left Hemisphere (LH) and segmented Right Hemisphere (RH)
Step 2 : Detect all the connected edges on LH and RH using contouring techniques.
Step 3 : Obtain the Left Cerebral Cortex (LCC) and Right Cerebral Cortex (RCC) based on the histogram statistics and intensity profile of the segmented regions obtained by contouring technique.
Step 4 : Let Histogram Statistics are denoted as Peaks namely P1, P2, P3 & P4.
Step 5 : Let G1, G2, & G3 are gray scale values of P2, P3 and P4 respectively, since P1 is Background.
Step 6 : Select the second maximum among G1, G2 and G3 as CC regions.
Step 7 : Combine both segmented LCC and RCC as a single image.

to assess the resemblance and assortment of two images. Jac is calculated by Equation 4 as given below:

$$Jac(M,N) = \frac{|M \cap N|}{|M \cup N|} \tag{4}$$

Dice (Dc) coefficient [33] is a similarity measure known as Sorensen index and is also used to assess the resemblance of two images. The following Equation 5 is used to calculate Dc value.

$$Dc(M,N) = \frac{2|M \cap N|}{|M| + |N|} \tag{5}$$

In both the Equation 4 and Equation 5, M denotes the cerebral cortex in the segmented LCC and RCC gained by the proposed method, N denotes the LCC and RCC brain image obtained from the hand stripped image.

$$dJac(M,N) = 1 - \frac{|M \cap N|}{|M \cup N|} \tag{6}$$

dJac (dJ) denotes [33] the dissimilarity between the two images, here the dissimilarity is measured between the normal slices and AD slices of brain MR images to detect AD for clinical observation. The quantitative measure Sensitivity (Sen) [34] finds the proportion that are acceptably identified positive and is denoted by

$$Sen = \frac{TP}{TP + FN} \tag{7}$$

Similarly, Quantitative measure Specificity (Spc) [34] is the proportion that are acceptably identified negative and is calculated by

$$Spc = \frac{TN}{TN + FP} \tag{8}$$

where in Equation 6 and Equation 7 TP, FP, TN and FN represent True Positive, False Positive True Negative and False Negative respectively.

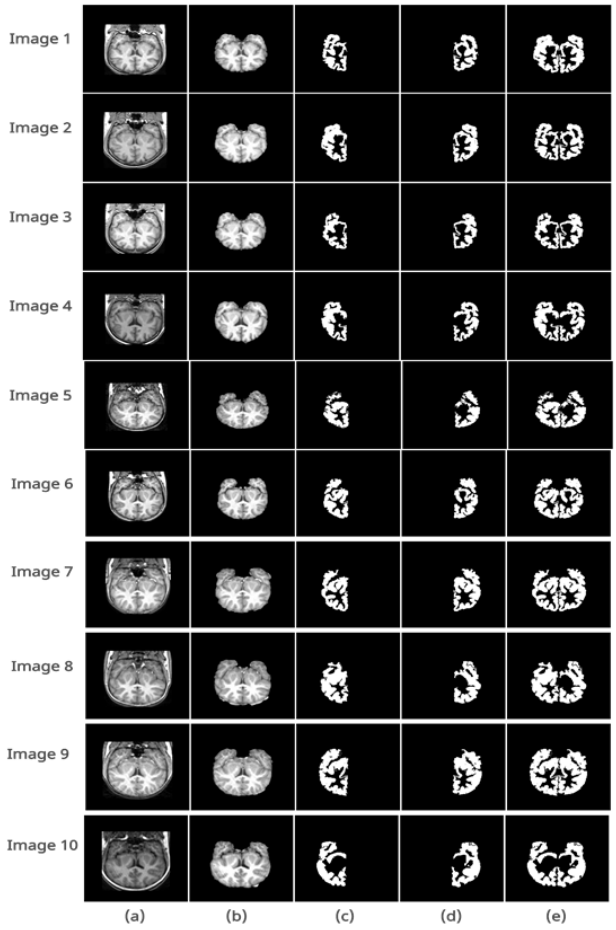


Figure 10. CC Segmentation results of Proposed Method (a) Original image (b) Skull Stripped Image (c) Segmented LCC (d) Segmented RCC (e) Complete Cerebral Cortex in the whole brain slice

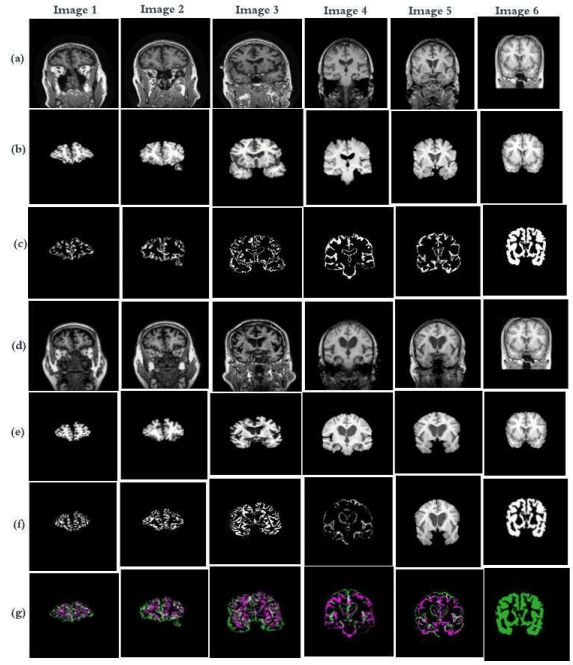


Figure 11. Segmentation of CC to detect AD (a) Normal/Cognitive Normal image (b) Segmented Hemisphere of image of (a), (c) Segmented CC in image (b), (d) AD affected/Normal input image, (e) Segmented hemisphere of image (d), (f) Segmented CC in image (e), (g) Overlapped Segmented CC of image in (c) and (f). [Green color denotes CC of the healthy slice; pink color denotes CC in the corresponding AD/Normal slice]

3. Results and Discussion

The proposed method is employed on IBSR-18 and ADNI dataset, the selected sample T1 weighted images from IBSR-18 and the corresponding segmented results are shown in Figure 10. It shows the original image chosen from the dataset in column (a) of Figure 10, the skull stripped image using CBBS method is given in column (b) of the same figure. The segmented cerebral cortex of both left and right hemisphere images are given in the column (c) and (d) of Figure 10 respectively. The combined cerebral cortex of both left and right hemisphere are shown in Figure 10

Table Ishows the performance analysis of the proposed method for the images shown in Figure 10, and Table II shows the performance analysis of all the volumes of IBSR_18 data set which contains expert segmented or ground truth volumes. This table contains Jaccard (Jac), Dice (Dc) similarity measures and Sensitivity (Sen), Specificity (Spc) quantitative values for Left Cerebral Cortex (LCC) and Right Cerebral Cortex (RCC) individually. This method produces acceptable results for all the brain im-

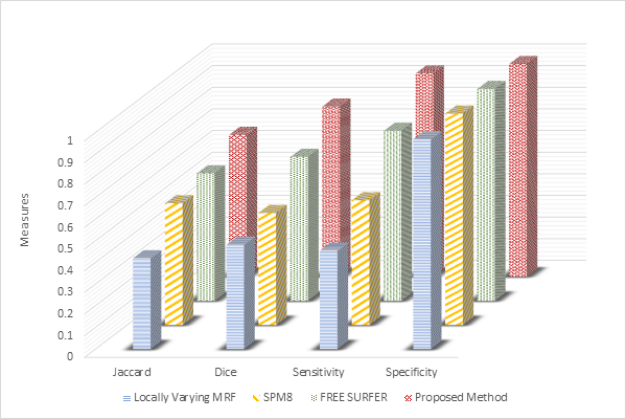


Figure 12. Comparison of the proposed method with the existing methods

TABLE I. Computed Jaccard (Jac), Dice (Dc), Sensitivity (Sen) and Specificity (Spc) by the proposed method for the images shown in Figure 10

	Jac		Dc		Sen		Spc	
Brain Images	LCC	RCC	LCC	RCC	LCC	RCC	LCC	RCC
Image1	0.621	0.602	0.766	0.751	0.949	0.949	0.987	0.987
Image2	0.702	0.771	0.825	0.803	0.944	0.944	0.987	0.987
Image3	0.784	0.725	0.812	0.841	0.957	0.957	0.987	0.987
Image4	0.704	0.713	0.826	0.833	0.946	0.946	0.995	0.995
Image5	0.525	0.623	0.688	0.767	0.950	0.950	0.984	0.984
Image6	0.674	0.610	0.799	0.758	0.939	0.939	0.990	0.990
Image7	0.614	0.640	0.761	0.780	0.933	0.933	0.987	0.987
Image8	0.704	0.731	0.870	0.873	0.945	0.945	0.976	0.976
Image9	0.640	0.632	0.780	0.774	0.914	0.914	0.985	0.985
Image10	0.613	0.675	0.760	0.806	0.931	0.931	0.980	0.980
Mean	0.598	0.611	0.717	0.726	0.855	0.855	0.896	0.896
SDev	0.071	0.059	0.050	0.040	0.012	0.012	0.005	0.005

*LCC-Left Cerebral Cortex, RCC- Right Cerebral Cortex, SDev-Standard Deviation

TABLE II. Computed Jaccard (Jac), Dice (Dc), Sensitivity (Sen) and Specificity (Spc) by the proposed method for the dataset IBSR_18 volume

	Jac		Dc		Sen		Spc	
Brain Volume	LCC	RCC	LCC	RCC	LCC	RCC	LCC	RCC
IBSR_1	0.621	0.602	0.766	0.751	0.949	0.949	0.987	0.987
IBSR_2	0.725	0.731	0.765	0.745	0.921	0.921	0.967	0.967
IBSR_3	0.702	0.771	0.825	0.803	0.944	0.944	0.987	0.987
IBSR_4	0.548	0.561	0.698	0.688	0.921	0.921	0.974	0.974
IBSR_5	0.652	0.725	0.812	0.841	0.957	0.957	0.987	0.987
IBSR_6	0.687	0.628	0.712	0.782	0.924	0.924	0.982	0.982
IBSR_7	0.704	0.713	0.826	0.833	0.946	0.946	0.995	0.995
IBSR_8	0.698	0.719	0.768	0.783	0.921	0.921	0.998	0.998
IBSR_9	0.525	0.623	0.688	0.767	0.953	0.953	0.984	0.984
IBSR_10	0.528	0.589	0.835	0.875	0.965	0.965	0.981	0.981
IBSR_11	0.674	0.61	0.799	0.758	0.939	0.939	0.99	0.99
IBSR_12	0.647	0.614	0.772	0.782	0.958	0.958	0.948	0.948
IBSR_13	0.614	0.64	0.761	0.78	0.933	0.933	0.987	0.987
IBSR_14	0.704	0.731	0.87	0.873	0.945	0.945	0.976	0.976
IBSR_15	0.625	0.795	0.845	0.862	0.948	0.948	0.99	0.99
IBSR_16	0.64	0.632	0.78	0.774	0.914	0.914	0.985	0.985
IBSR_17	0.629	0.658	0.754	0.735	0.924	0.924	0.982	0.982
IBSR_18	0.613	0.675	0.76	0.806	0.931	0.931	0.98	0.98
Mean	0.641	0.668	0.780	0.791	0.939	0.939	0.982	0.982
SDev	0.061	0.067	0.050	0.050	0.015	0.015	0.011	0.011

ages, and some of the images yield very accurate results when compared to the expert segmented images. The mean value of LCC and RCC for the computed sensitivity and specificity are 0.939 and 0.982 respectively. This indicates that our proposed method produced acceptable segmented results. An average of 0.641 for LCC and 0.668 for RCC as Jac and 0.780 for LCC and 0.791 for RCC as Dc average similarity values were produced by the proposed method for cerebral cortex segmentation of the whole brain volumes. An analysis on Cortical Thickness (Cerebral Cortex) is essential to identify various brain disorders in addition to the dissection of brain tissues in brain images[35]. Table III. illustrates the comparative analysis of the proposed method with existing methods namely Locally varying Markov Random Field (MRF), Statistical Parametric Mapping (SPM)8 and Free Surfer. Locally varying Markov Random Field (MRF)[36] have been widely used for computer vision problems, Statistical Parametric Mapping (SPM)8 is designed to analysis the brain data[37] and Free Surfer is a structural and functional MRI analysis software for neuroimaging data[38]. The comparison result shown in Figure 12 depicts that the proposed method produces better

TABLE III. Performance analysis of the existing and the proposed methods in terms of Jac, Dc, Sen and Spc for LCC & RCC regions

Methods		Jac	Dc	Sen	Spc
LOCALLY VARYING MRF	LCC	0.419	0.483	0.455	0.970
	RCC	0.422	0.482	0.456	0.971
SPM8	LCC	0.559	0.512	0.577	0.976
	RCC	0.565	0.523	0.575	0.977
FREE SURFER	LCC	0.602	0.695	0.865	0.979
	RCC	0.576	0.635	0.706	0.979
Proposed Method	LCC	0.641	0.780	0.939	0.982
	RCC	0.668	0.791	0.939	0.982

TABLE IV. Computed Dissimilarity Jaccard (dJac) to detect AD for the images shown in Figure 11

Brain Images	dJac		Clinical Observation
	LCC	RCC	
Image1	0.335	0.307	AD
Image2	0.356	0.341	AD
Image3	0.286	0.243	AD
Image4	0.562	0.528	AD
Image5	0.587	0.589	AD
Image6	0.000	0.000	Normal

results than the existing methods.

We employed the proposed method in Normal and Abnormal*diseased* images from the dataset2 to detect the AD and the corresponding results are shown in the Figure 11. The Figure 11(a) shows the original normal images, segmented hemisphere of same image is given in Figure 11(b), segmented Cerebral Cortex using the proposed method is in Figure 11(c), The Figure 11(d) shows the corresponding AD affected/normal images, segmented hemispheres image of same image in Figure 11(e), segmented Cerebral Cortex using the proposed method is in Figure 11(f), Figure 11(g) illustrates the dissimilarity of the segmented cerebral cortex of normal/cognitive normal and AD affected CC region. Table IV shows the computed value of dissimilarity measures for the images shown in Figure 11. If the segmented CC regions in both the input image and its corresponding Normal/Cognitive image are similar, then the dissimilarity(dJac) is zero. The non-zero value of dJac shows there is a shrinkage in the CC region of the input image when compared to its normal/cognitive normal image. Except for the image 6 of Figure 11, all other images are AD affected images and hence the dJac values are non-zero. The image1 to image5 are taken from the ADNI dataset, it is AD affected images, whereas image 6 is taken from the IBSR dataset which contains normal brain volumes. Thus, our proposed method correctly diagnosed the AD affected regions. Depending upon the computed dJac value we can also analyze the severity of the diseases.

4. Conclusions

An efficient method for automatic segmentation of cerebral cortex in T1-weighted MR brain image is developed in this work. The segmented cerebral cortex is analyzed to detect the brain disorders namely Alzheimer's Disease. The result of this proposed method is compared against the expert segmented images. It clearly indicates an acceptable performance on segmenting the cerebral cortex for detecting the AD. The comparative analysis with the existing methods and tools such as MRF, SPM8 and FREESURFER reveals that the proposed method is superior in segmenting CC regions in MRI brain images. This proposed method is one of the vital approaches to detect AD using MRI brain images. The scope of this research leads to quicker view of misgivings about this disease by the Physician and give acceptable diagnostic solutions. In the future, in addition to early detection, we plan to classify the stages of AD such as Mild Dementia, Moderate AD and Severe AD based on CC region using advanced and learning approaches.

Funding: This work was supported by Science and Engineering Research Board (SERB) File No. EEQ/2016/000375, Department of Science and Technology, Government of India.

Conflict of Interest The authors affirm that they have no financial conflicts of interest

References

[1] C. Hutton, E. De Vita, J. Ashburner, R. Deichmann, and R. Turner, "Voxel-based cortical thickness measurements in mri," *Neuroimage*, vol. 40, no. 4, pp. 1701–1710, 2008.

[2] B. Crespo-Facorro, J.-J. Kim, N. C. Andreasen, R. Spinks, D. S. O'Leary, H. J. Bockholt, G. Harris, and V. A. Magnotta, "Cerebral cortex: a topographic segmentation method using magnetic resonance imaging," *Psychiatry Research: Neuroimaging*, vol. 100, no. 2, pp. 97–126, 2000.

[3] L. Wang, F. Shi, G. Li, and D. Shen, "4d segmentation of brain mr images with constrained cortical thickness variation," *PloS one*, vol. 8, no. 7, p. e64207, 2013.

[4] M. J. Cardoso, M. J. Clarkson, G. R. Ridgway, M. Modat, N. C. Fox, S. Ourselin, A. D. N. Initiative *et al.*, "Load: a locally adaptive cortical segmentation algorithm," *NeuroImage*, vol. 56, no. 3, pp. 1386–1397, 2011.

[5] A. M. Dale, B. Fischl, and M. I. Sereno, "Cortical surface-based analysis: I. segmentation and surface reconstruction," *Neuroimage*, vol. 9, no. 2, pp. 179–194, 1999.

[6] N. Makris, J. E. Schlerf, S. M. Hodge, C. Haselgrove, M. D. Albaugh, L. J. Seidman, S. L. Rauch, G. Harris, J. Biederman, V. S. Caviness, D. N. Kennedy, and J. D. Schmahmann, "Mri-based surface-assisted parcellation of human cerebellar cortex: an anatomically specified method with estimate of reliability," *NeuroImage*, vol. 25, no. 4, pp. 1146–1160, 2005.

[7] J. Caviness, Verne S., J. Meyer, N. Makris, and D. N. Kennedy, "MRI-Based Topographic Parcellation of Human Neocortex: An Anatomically Specified Method with Estimate of Reliability," *Journal of Cognitive Neuroscience*, vol. 8, no. 6, pp. 566–587, 11 1996.

[8] J. Rademacher, A. M. Galaburda, D. N. Kennedy, P. A. Filipek, and J. Caviness, V. S., "Human Cerebral Cortex: Localization, Parcellation, and Morphometry with Magnetic Resonance Imaging," *Journal of Cognitive Neuroscience*, vol. 4, no. 4, pp. 352–374, 10 1992.

[9] B. Fischl, A. van der Kouwe, C. Destrieux, E. Halgren, F. Ségonne, D. H. Salat, E. Busa, L. J. Seidman, J. Goldstein, D. Kennedy, V. Caviness, N. Makris, B. Rosen, and A. M. Dale, "Automatically Parcellating the Human Cerebral Cortex," *Cerebral Cortex*, vol. 14, no. 1, pp. 11–22, 01 2004.

[10] C. Preul, G. Lohmann, M. Hund-Georgiadis, T. Guthke, and D. Y. von Cramon, "Morphometry demonstrates loss of cortical thickness in cerebral microangiopathy," *Journal of neurology*, vol. 252, pp. 441–447, 2005.

[11] P. Thiruvasagam and K. Palanisamy, "Brain tissue segmentation from magnetic resonance brain images using histogram based swarm optimization techniques," *Current Medical Imaging*, vol. 16, no. 6, pp. 752–765, 2020.

[12] J. P. Lerch, "Measuring cortical thickness," *Mc Gill*, p. 154–161, 2001.

[13] J. Machts, A. Cardenas-Blanco, J. Acosta-Cabronero, J. Kaufmann, K. Loewe, E. Kasper, C. Schuster, J. Prudlo, S. Vielhaber, and P. J. Nestor, "Prefrontal cortical thickness in motor neuron disease," *NeuroImage: Clinical*, vol. 18, pp. 648–655, 2018.

[14] T. A. Tuan, J. Y. Kim, and P. T. Bao, "3d brain magnetic resonance imaging segmentation by using bitplane and adaptive fast marching," *International Journal of Imaging Systems and Technology*, vol. 28, no. 3, pp. 223–230, 2018.

[15] R. Cuingnet, E. Gerardin, J. Tessieras, G. Auzias, S. Lehéricy, M.-O. Habert, M. Chupin, H. Benali, O. Colliot, A. D. N. Initiative *et al.*, "Automatic classification of patients with alzheimer's disease from structural mri: a comparison of ten methods using the adni database," *neuroimage*, vol. 56, no. 2, pp. 766–781, 2011.

[16] R. Wolz, V. Julkunen, J. Koikkalainen, E. Niskanen, D. P. Zhang, D. Rueckert, H. Soininen, J. Lötjönen, and A. D. N. Initiative, "Multi-method analysis of mri images in early diagnostics of alzheimer's disease," *PloS one*, vol. 6, no. 10, p. e25446, 2011.

[17] R. A. Nebel, N. T. Aggarwal, L. L. Barnes, A. Gallagher, J. M. Goldstein, K. Kantarci, M. P. Mallampalli, E. C. Mormino, L. Scott, W. H. Yu *et al.*, "Understanding the impact of sex and gender in alzheimer's disease: a call to action," *Alzheimer's & Dementia*, vol. 14, no. 9, pp. 1171–1183, 2018.

[18] S. Hurtz, N. Chow, A. E. Watson, J. H. Somme, N. Goukasian, K. S. Hwang, J. Morra, D. Elashoff, S. Gao, R. C. Petersen *et al.*, "Automated and manual hippocampal segmentation techniques: Comparison of results, reproducibility and clinical applicability," *NeuroImage: Clinical*, vol. 21, p. 101574, 2019.

[19] I. Aganj, G. Sapiro, N. Parikshak, S. K. Madsen, and P. M. Thompson, "Segmentation-free measurement of cortical thickness from mri," in *2008 5th IEEE International Symposium on Biomedical Imaging: From Nano to Macro*. IEEE, 2008, pp. 1625–1628.

[20] A. Association *et al.*, "2017 alzheimer's disease facts and figures," *Alzheimer's & Dementia*, vol. 13, no. 4, pp. 325–373, 2017.

[21] ——, "2018 alzheimer's disease facts and figures," *Alzheimer's & Dementia*, vol. 14, no. 3, pp. 367–429, 2018.

[22] L. C. Harper, "2022 alzheimer's association facts and figures. https://doi.org/10.1002/alz.12638."

[23] H. Ahmed, H. Soliman, S. El-Sappagh, T. Abuhmed, and M. Elmogy, "Early detection of alzheimer's disease based on laplacian re-decomposition and xgboosting," *Computer Systems Science and Engineering*, vol. 46, pp. 2773–2795, 04 2023.

[24] Y.-T. Hsiao, C.-L. Chuang, J.-A. Jiang, and C.-C. Chien, "A contour based image segmentation algorithm using morphological edge detection," in *2005 IEEE International Conference on systems, man and cybernetics*, vol. 3. IEEE, 2005, pp. 2962–2967.

[25] W. Xu, X. Yue, Y. Chen, and M. Reformat, "Ensemble of active contour based image segmentation," in *2017 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2017, pp. 86–90.

[26] P. Kalavathi and V. Surya Prasath, "Automatic segmentation of cerebral hemispheres in mr human head scans," *International Journal of Imaging Systems and Technology*, vol. 26, no. 1, pp. 15–23, 2016.

[27] P. Kalavathi and V. S. Prasath, "Methods on skull stripping of mri head scan images—a review," *Journal of digital imaging*, vol. 29, pp. 365–379, 2016.

[28] Brain extraction tool fsl. [Online]. Available: https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/BET

[29] K. Somasundaram and P. Kalavathi, "Contour-based brain segmentation method for magnetic resonance imaging human head scans," *Journal of computer assisted tomography*, vol. 37, no. 3, pp. 353–368, 2013.

[30] P. Kalavathi, M. Senthamilselvi, and V. S. Prasath, "Review of computational methods on brain symmetric and asymmetric analysis from neuroimaging techniques," *Technologies*, vol. 5, no. 2, p. 16, 2017.

[31] E. Rodríguez, J. Arqués, R. Rodríguez, M. Nuñez, M. Medina, T. Talarico, I. Casas, T. Chung, W. Dobrogosz, L. Axelsson *et al.*,

"We are intechopen, the world's leading publisher of open access books built by scientists, for scientists top 1%," *Intech*, vol. 32, no. tourism, pp. 137–144, 1989.

[32] Nitrc-internet brain segmentation repostitory (ibsr). [Online]. Available: https://www.nitrc.org/projects/ibsr

[33] V. Thada and V. Jaglan, "Comparison of jaccard, dice, cosine similarity coefficient to find best fitness value for web retrieved documents using genetic algorithm," *International Journal of Innovations in Engineering and Technology*, vol. 2, no. 4, pp. 202–205, 2013.

[34] Sensitivity and specificity analysis. [Online]. Available: https://www.xlstat.com/en/solutions/features/sensitivity-and-specificity-analysis

[35] T. Priya and P. Kalavathi, "Hsv based histogram thresholding technique for mri brain tissue segmentation," in *Advances in Signal Processing and Intelligent Recognition Systems: 4th International Symposium SIRS 2018, Bangalore, India, September 19–22, 2018, Revised Selected Papers 4*. Springer, 2019, pp. 322–333.

[36] S. Z. Li, "Markov random field models in computer vision," in *Computer Vision—ECCV'94: Third European Conference on Computer Vision Stockholm, Sweden, May 2–6 1994 Proceedings, Volume II 3*. Springer, 1994, pp. 361–370.

[37] The wellcome centre for human neuroimaging, ucl queen square institute of neurology, london, uk. [Online]. Available: https://www.fil.ion.ucl.ac.uk/spm

[38] Freesurfer. [Online]. Available: https://surfer.nmr.mgh.harvard.edu

Sivanesan Rajangam is a Research Scholar in the Department of Computer Science and Applications in The Gandhigram Rural Institute (Deemed to be University), Tamilnadu India. He has 5 years of teaching and 4 years of research experience. He qualified TN-SET for Assistant Professor in 2017. He worked as Junior Research Fellow (JRF) in the research project funded by Department of Science and Technology, Science Engineering and Research Board (DST-SERB-EEQ) India. His research area focuses on Medical Image Processing and Segmentation.

Kalavathi Palanisamy is Professor in Computer Science and Applications in The Gandhigram Rural Institute (Deemed to be University). She qualified UGC-NET for Lecture ship in 2000. She has 21 years of teaching and 15 years of research experience. The author has more than 80 research articles in various journals and edited volumes. Her research area focuses on Digital Image Processing, Medical Image Segmentation and Analysis, Medical Image Compression and Internet of Things(IoT). She is also serving as a reviewer of many international conferences and various journal in IEEE, Springer, Elsevier etc. The author is a lifetime member of Indian Society for Technical Education (ISTE), New Delhi.