

# Volumetric Analysis of Abnormal Region in MR Brain Images



Nikhil Gala, Kamalakar Desai, Deepak Patkar

**Abstract:** MRI is known as one of the best imaging modality used for neuro image analysis. Detection of abnormality regions in Brain image is critical due to its complex structure, which can be accurately analyzed with MRI. Several methods and segmentation algorithms have been proposed in the past to extract the abnormal region however there is further scope of increasing the segmentation efficiency. In this work abnormality region in brain is extracted with region based and edge based hybrid segmentation methods and thus obtained region is rendered for volumetric analysis. This analysis is used for depth measurement and localization of abnormal region accurately. Apart from this analysis mainly provides the information about the abnormal region distribution and its connectivity with other regions.

**Index Terms:** Volumetric analysis, abnormal region extraction, segmentation, rendering

## I. INTRODUCTION

The three dimensional analysis of brain provides the depth information unlike in the case of 2D image slice. The 3D analysis has turned out to be more essential in various fields like product designing, automobile industry, medical image analysis and many others. The manual creation of these three dimensional images consume lot of time and labor and therefore the production cost is too expensive. In order to overcome the above mentioned limitations several methods of automatic 3D reconstruction are under research and investigations.

In general this reconstruction are categorized as active and passive, in the first approach a huge labor is required thereby the cost of implementation is too expensive and the later requires automatic algorithms that require less equipment and labor leading to the reduction in cost of implementation. So, this work can be treated as one of the passive categorized attempt for three dimensional reconstruction approaches of brain abnormal regions. Clustering algorithms do not use training data but still perform the functions as done by classifier methods.

Due to non-usage of training data, they are termed as unsupervised methods. The alternate process of segmenting the image and identifying and characterizing the property of each class needs to be done iteratively since there is no training data available. Thus it can be said that using the available data, clustering methods will train themselves. Segmentation of image, decision making process, assessing various pattern analysis, combination or grouping data with similar attributes and conditions involving machine-learning like data mining, retrieval of documents and pattern classification are some of the areas in which clustering is useful.

An efficient and improved brain tumor detection algorithm was developed by Rajeev Ratan, Sanjay Sharma and S. K. Sharma developed algorithm for brain tumor detection which is more efficient and it mentions the use of multi-parameter MRI analysis and the tumor cannot be segmented in 3D unless and until 3D MRI image data set is available [1].

As mentioned in [2] Abbas and Farshad have proposed 3D image segmentation that aims to identify the clusters in image and further classify the same. It is found that 20% reduction in memory that is utilized along with reduction in processing time while using Jacquard's coefficient for classification.

Combination of two approaches is proposed by Hooda and Verma in [3]. It mentions of implementing the clustering approach and region growing approach. They have proposed the region growing approach with the k-means and fuzzy C-means clustering approaches which has helped in identification of accurate location of the abnormal tissue.

A combination of morphological operators implemented along with co-clustering algorithms has been suggested for the extraction of brain tumor region in [4] by Satheesh et al. As a start to this process of extraction of tumor, the T1 – weighted images are applied with the mathematical morphological operations. These morphological operators eliminate the non-brain regions and other tissues that may including skull, cerebrospinal fluid (CSF), tissues depicting fat and muscles from the MRI slices. This process helps in making the segmentation process more robust. Removal of skull and fat regions is an important step as it may interfere in the actual segmentation process and makes the segmentation algorithm less efficient. Post morphological operation the extracted brain region is exposed to the co-clustering algorithm. Incorporating active contour models, clustering approach and some morphological operations was suggested by Reyes et al. in [5], which is ROI based abnormal segmentation. An efficiency of 88.2% could be attained by this method.

Revised Manuscript Received on October 30, 2019.

\* Correspondence Author

**Nikhil Gala\***, Department of Electronics & Telecommunication, Mukesh Patel School of Technology Management & Engineering, NMIMS University, Mumbai, India.

**Dr. Kamalakar Desai**, Academic and Technical Advisor, Guru Gobind Singh College of Engineering & Research Centre Nashik, India

**Dr. Deepak Patkar**, Director Medical Services, Head –Department of Imaging, Nanavati Super Speciality Hospital, Mumbai, India.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](http://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

This efficiency can be further improved.

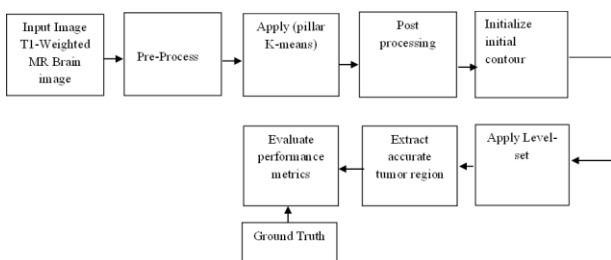
Further to this, we can detect exact tumor size and location from the MR scans by following the hybrid method of segmentation. Kimmi et.al in [9], presented one such hybrid segmentation method which involves threshold segmentation, watershed segmentation, edge detection and morphological operators.

Nikhil Gala, and K.D. Desai in [6] presented a three dimensional brain image reconstruction methodology which is very much helpful in predicting the depth of any abnormality in the image and also proposes an active contour based approach for the extraction of the abnormal (tumor) region. The extracted regions are modeled using Iso-surface 3D view models.

Yang and others in [10] proposed simultaneous image segmentation. This image segmentation method was having additional step of moderate bias correction. Here the authors have presented a new model in the level set formulation for gray images and then split Bergman method for fast minimization has been implemented. They also applied the algorithm for pseudo color transformed images and compared the results with earlier Chan-Vese model and others. So in this paper, a hybrid method of segmenting the abnormal regions from MR brain images is proposed. The method also estimates the volume of the tumor and then compares that with the reading provided by the radiologist.

**II. HYBRID APPROACH FOR ABNORMAL BRAIN REGION EXTRACTION**

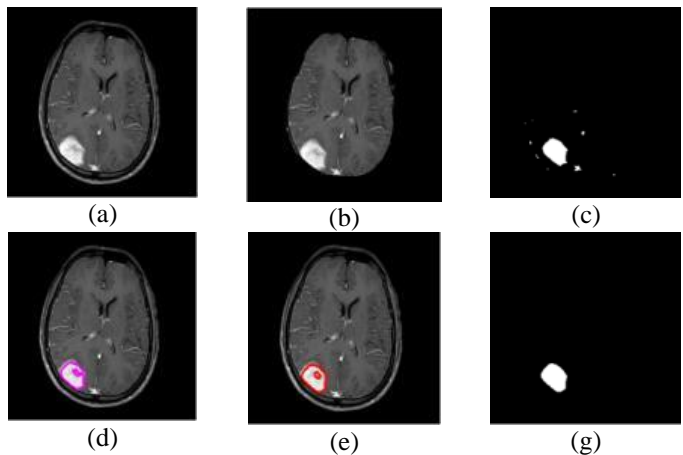
In this work we are proposing the hybrid approach which is an integration of edge based segmentation algorithm and region based segmentation algorithm. In this method, the MRI scans of type T1-weighted are exposed to pre-processing stages which helps in the removal of the skull and fat regions. After the pre processing stage, Pillar K-means clustering algorithm is applied to the MR image which is presented in [7]. There may be presence of segmentation blobs in the output after this clustering algorithm. The over segmentation ratio is higher as observed during the implementation of this Pillar K-mean algorithm. To moderate this effect of over segmentation, the boundary of this extracted abnormal region obtained as an output of the Pillar K –mean algorithm is then further fed as an initial contour for level set approach. In this paper we have implemented the skull removal method as suggested by Satheesh et.al in [4] at the pre-processing stage.



**Figure 1 : Proposed block diagram for tumor extraction**

The algorithm for pillar algorithm is presented in our previous article [7] [11], appropriate post processing operations such as median filtering or hole filling is performed to minimize the segmentation blobs thus obtained clustered output is considered. A contour is drawn all along

the boundary of the abnormal region obtained from Pillar K –mean algorithm which is treated as initial contour for level set iteration process [7] [12]. The outputs at each stage is shown in figure 2



**Figure 2 : (a) Input Image (b) Skull removed Image (c) Clustered output (d) Initial contour of level-set (e) output after 100 iterations (f) Final image segmented (g) Final image segmented**

The input image figure 2(a) is directed for skull removing process. The region in the image depicting the skull is removed as shown in figure 2(b), it is stated by many authors (eg: [4]) that presence of skull leads to degradation in segmentation performance. This image obtained in 2(b) is applied for Pillar K-means approach and clustered region shown in figure 2(c) is extracted whose boundaries after post processing is considered as the initial contour as shown in figure 2(d). For the evolution process in level-set method the initialized contour is iterated for 100 iterations where the discontinuity components are mitigated and thus obtains figure 2(e), figure 2(g). The extracted region is compared against the ground truth image provided by experts (radiologists) and the performance of the algorithm with several metric is evaluated.

**III. 3D VOLUME ESTIMATION**

In this work the segmented regions are stacked together and rendered to project the 3D view of the abnormal region. Higher number of slices helps in reconstruction of a clearer and more reliable 3D tumor. Since the number of slices of MR scans with tumor present in it are limited, we need to apply some technique to predict intermediate slices from the real or actual slices. This can be made possible using method of interpolation which is proposed and it helps to increase the number of slices for further improvement in the reconstruction of the 3D tumor image. In the MRI slices obtained the gap between the consecutive slices is greater than the distance between the adjacent pixels that are present within the slice.

The 3D view can be visualized using the Iso-surface models [13], which is three-dimensional equivalent of an Iso-line. An Iso-surface can be understood as surface within a fixed volume of space and includes points that have the constant value.



It can be termed as a level set of a continuous function in the 3D space. In medical imaging, Iso-surfaces may be used for visualization of anatomy of internal organs, bones, or other structures of a particular density in a 3D CT scan, etc.

Volume of brain tumor can be calculated using the frustum model. In this model, we calculate the area of the object of interest in each slice of MR scan. This frustum model is applied for calculating the brain tumor volume for two sequential or consecutive slices with Area  $A_i$ . The formula given below is used to calculate the tumor volume

$$est. Vol = \sum \frac{h}{3} * (\sum A_i + (\prod A_i)/2)$$

In the above equation (1) the variable “h” represents the sum of slice thickness and slice spacing, the spacing and thickness in the present work is considered based on recommendation of the radiologist and Fabian Balsiger in [14] and “ $A_i$ ” is the area of  $i^{th}$  slice. Below table states the different spacing and thickness that has to be considered in various aspects.

**TABLE I : PROTOCOL FOR MRI FOR WEIGHTING ALONG WITH THEIR SLICE THICKNESS AND SPACING**

	Weightin g (W)	Contrast	Slice thickness/ spacing in mm
Sagittal	T1-W	-	5/6
Axial	T1-W	-	4/4
Axial	T2-W	-	5/4
Sagittal	T2-W Flair	-	5/6
Axial	T1-W	Gadolinium	4/4
Sagittal	T1-W	Gadolinium	5/6
Corona	T1-W	Gadolinium	4/4

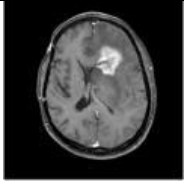
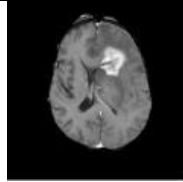
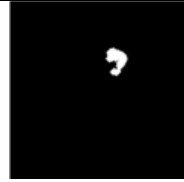

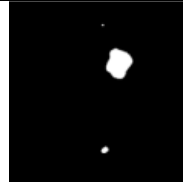

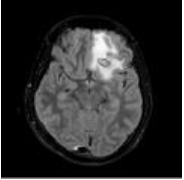
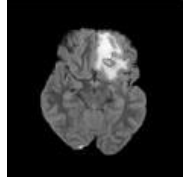




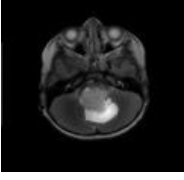
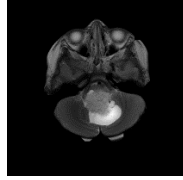
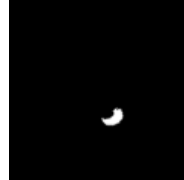
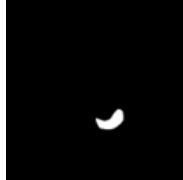

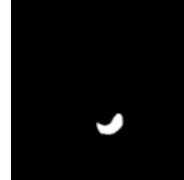
1			
---	--	--	--

In this work, all the images that were used in experiments were considered to be Axial type with T1-weighted and Gadolinium contrasted, hence as stated in the above the thickness and spacing of 4mm/4mm is adopted.

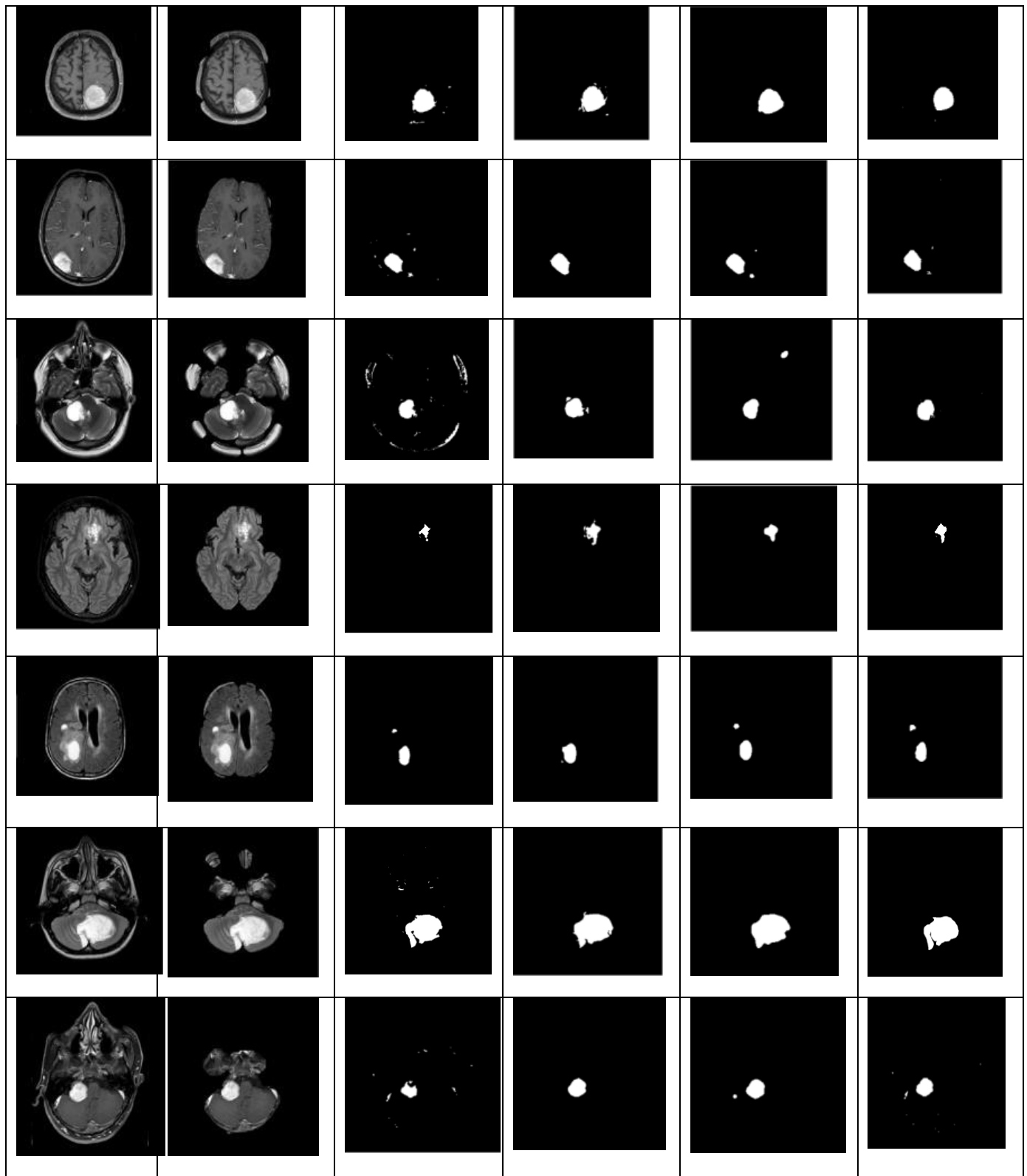
**IV. EXPERIMENTAL RESULTS**

To justify the method presented in this work a total of 3840 MRI slices were collected which are of 30 patients each of 128 slices. From this huge set, Axial T1-weighted, contrast images created using the contrast agent gadolinium were separated for each patient using Radiant Dicom Viewer available at [15]. The images separated were processed with the proposed methodology; the script development for the implementation is done using Matlab 2018 a version tool on Intel i7 dual core processor with 8GB RAM.

For the evaluation of performance, the method is subjected for multiple metrical analysis with respect to ground truth image provided by expert (radiologist). The metrics are Similarity Index (SI), correct detection ratio (CDR) and for calculating the performance in terms of segmentation error we have the total segmentation error (TSE) which is a sum of under segmentation error (USE) and over segmentation error (OSE), these were mentioned in [7]. The results are tabulated below

Input Image	Skull removed	Pillar	Pillar +GVF	Pillar + Level-set	Ground Truth
					
					
					





**Figure 3 : Figure 3: Column 1: Input Image, Column 2: Skull removed image, Column 3: Pillar Output, Column 4: Pillar +GVF output, Column 5: Pillar+ level set, Column 6: Ground truth**

In this paper, a total of 10 patients' data out of 30 patients' data is randomly chosen and presented; it can be observed from the table II, III, IV the metrical analysis of the methods used for extracting the abnormal regions. It is observed that the proposed Pillar + Level set approach attains a similarity index of 0.886 which is around 2% more than other two methods, similarly correct detection ratio is improved by 1.5% while the average error is decreased by 2.5%. When the

volume is estimated with all three methods using the equation (1), the proposed method could achieve a minimum difference of 1.03 which is almost half of the difference of two other methods, which states that around 2 pixels are differed



from the ground truth radiologist analysis which is good achievement. Table V gives the performance analysis of the proposed Method (Pillar + Level Set) which clearly indicates our proposed method is performing better with respect to SI, CDR, TSE. Table VI depicts the volumetric analysis of 5

patients with 3D volume visualization and slice-o metric view analysis of the abnormal regions.

**TABLE II : METRICAL ANALYSIS OF THE PILLAR K-MEANS ALGORITHM**

S.no	Patient Name	SI	CDR	USE	OSE	TSE	Estimated Vol (cm <sup>3</sup> )	Vol by radiologist (cm <sup>3</sup> )	Difference of Vol (cm <sup>3</sup> )
1	Subject 1	0.834	0.805	0.135	0.1941	0.3291	24.97	26.05	1.07
2	Subject 2	0.853	0.816	0.097	0.183	0.28	33.69	27.58	6.11
3	Subject 3	0.654	0.5018	0.0313	0.4981	0.538	76.33	78.2	1.87
4	Subject 4	0.8099	0.7016	0.0308	0.2984	0.3293	40.12	42.98	2.85
5	Subject 5	0.922	0.899	0.05	0.1	0.15	44.07	45.32	1.25
6	Subject 6	0.763	0.856	0.399	0.1436	0.5426	11.21	9.94	1.27
7	Subject 7	0.857	0.932	0.24	0.067	0.308	22.82	24.51	1.69
8	Subject 8	0.897	0.9105	0.119	0.089	0.208	103.86	104.94	1.09
9	Subject 9	0.938	0.922	0.044	0.077	0.122	144.86	145.64	1.4
10	Subject 10	0.847	0.817	0.1109	0.182	0.293	33.71	30.24	3.47
	<b>AVERAGE</b>	0.838	0.816	<b>0.125</b>	0.183	0.31	53.56	53.54	2.2

**TABLE III : METRICAL ANALYSIS OF PILLAR + GVF**

S.no	Patient Name	SI	CDR	USE	OSE	TSE	Estimated Vol (cm <sup>3</sup> )	Vol by radiologist (cm <sup>3</sup> )	Abs Diffe of Vol (cm <sup>3</sup> )
1	Subject 1	0.846	0.891	0.213	0.107	0.322	25.71	26.05	0.74
2	Subject 2	0.867	0.912	0.19	0.087	0.278	37.26	27.58	9.68
3	Subject 3	0.696	0.98	0.87	0	0.872	74.95	78.2	3.25
4	Subject 4	0.879	0.9935	0.264	0.006	0.271	44.63	42.98	1.66
5	Subject 5	0.914	0.941	0.117	0.058	0.174	49.34	45.32	4.02
6	Subject 6	0.723	0.856	0.056	0.424	0.482	10.7	9.94	0.76
7	Subject 7	0.886	0.955	0.2	0.044	0.244	26.43	24.51	1.92
8	Subject 8	0.834	0.858	0.199	0.148	0.341	103.28	104.94	1.66
9	Subject 9	0.931	0.984	0.13	0.015	0.145	144.78	145.64	0.78
10	Subject 10	0.879	0.796	0.014	0.203	0.2183	30.35	30.24	0.11
	<b>AVERAGE</b>	0.845	0.912	0.225	0.109	0.334	54.74	53.54	2.45

**TABLE IV : METRICAL ANALYSIS OF PILLAR + LEVEL-SET APPROACH**

S.no	Patient Name	SI	CDR	USE	OSE	TSE	Estimated Vol (cm <sup>3</sup> )	Vol by radiologist (cm <sup>3</sup> )	Abs Diffe of Vol (cm <sup>3</sup> )
1	Subject 1	0.855	0.924	0.234	0.0756	0.312	25.38	26.05	0.67
2	Subject 2	0.851	0.897	0.209	0.102	0.311	28.55	27.58	0.97
3	Subject 3	0.887	0.992	0.243	0.007	0.25	77.13	78.2	1.07

4	Subject 4	0.913	0.997	0.185	0.002	0.188	41.32	42.98	1.66
5	Subject 5	0.94	0.961	0.083	0.038	0.121	44.25	45.32	1.07
6	Subject 6	0.835	0.752	0.048	0.247	0.296	10.05	9.94	0.11
7	Subject 7	0.874	0.944	0.21	0.055	0.271	23.22	24.51	1.29
8	Subject 8	0.927	0.939	0.087	0.06	0.141	103.88	104.94	1.07
9	Subject 9	0.931	0.968	0.111	0.03	0.142	144.56	145.64	1.08
10	Subject 10	0.882	0.83	0.052	0.169	0.221	31.55	30.24	1.31
	<b>AVERAGE</b>	<b>0.886</b>	<b>0.92</b>	0.146	<b>0.078</b>	<b>0.225</b>	52.98	53.54	<b>1.03</b>

TABLE V : PERFORMANCE OF PROPOSED APPROACH

Sr.No	Segmentation Approach	SI	CDR	USE	OSE	TSE
1	<b>Pillar - K Mean</b>	0.84	0.82	<b>0.13</b>	0.18	0.31
2	<b>Pillar + GVF</b>	0.85	0.91	0.23	0.11	0.33
3	<b>Pillar + Level Set</b>	<b>0.89</b>	<b>0.92</b>	0.15	<b>0.08</b>	<b>0.23</b>

Fig. 4, 5 and 6 shows graphical representation of key performance parameters like SI, CDR, TSE for Pillar- K Means, Pillar + GVF and proposed approach method Pillar + Level Set. As seen from Fig. 7 the proposed approach gives better performance when average value of SI, CDR and TSE are compared. The better values obtain are put in bold in Table 5.

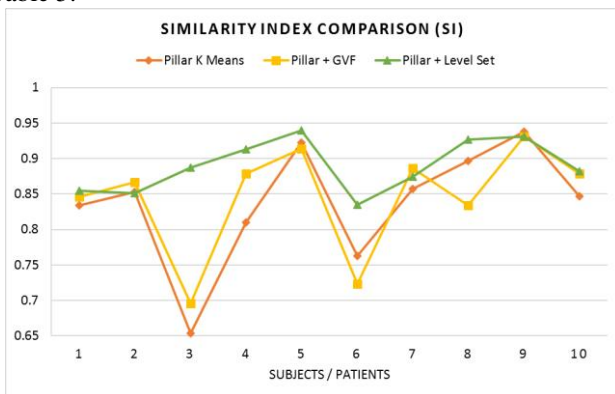


Figure 4: Graph representing Similarity Index Comparison

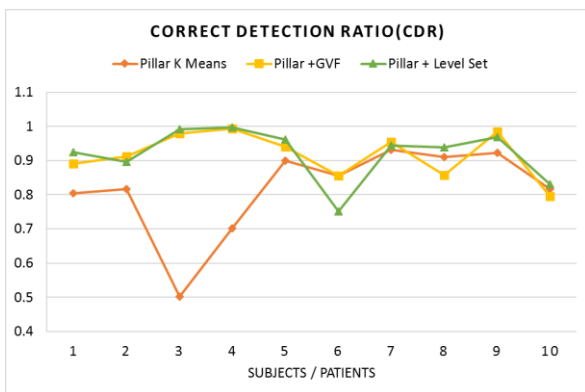


Figure 5: Graph representing CDR Comparison of Pillar - K Mean, Pillar + GV and Pillar + Level Set

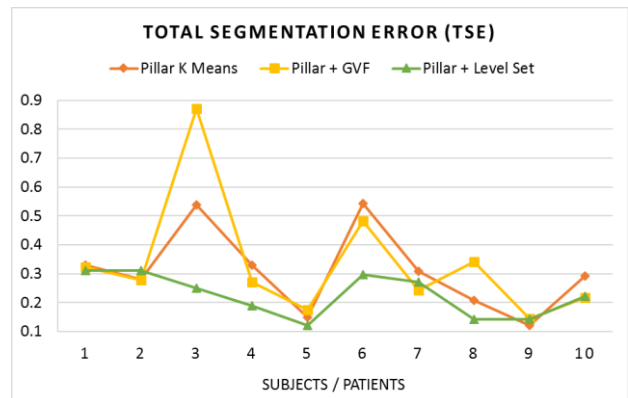


Figure 6: Comparison of Total Segmentation Error

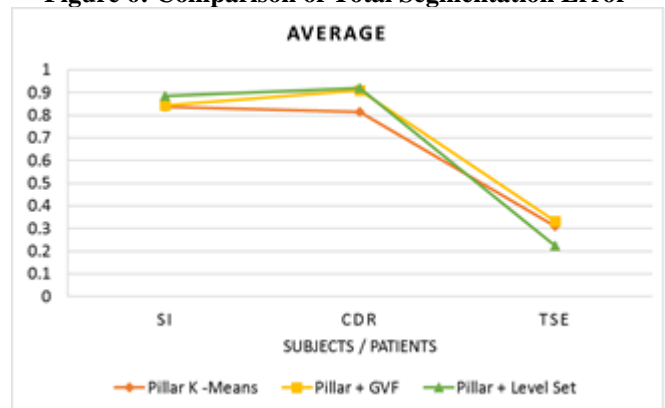


Figure 7 : Comparison Analysis of Pillar- K Means vs Pillar + GVF vs Pillar + Level Set

Fig. 8 provides Graphical representation of actual brain tumor volumes calculated using Pillar- K Means, Pillar + GVF and our proposed method Pillar + Level Set. In the same graph, the brain tumor volumes calculated are compared with the brain tumor volume provided by Radiologist (Ground truth).It can be seen, from the Fig.

9 that brain tumor volume calculated using the proposed approach i.e. Pillar + Level Set provides minimum difference when compared to ground truth thus providing more accurate results.



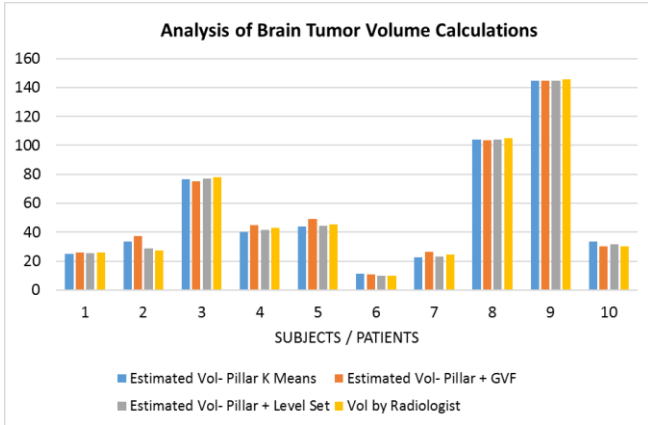


Figure 8 : Graph showing volume calculations for Pillar-K Mean, Pillar + GVF and Pillar + Level Set

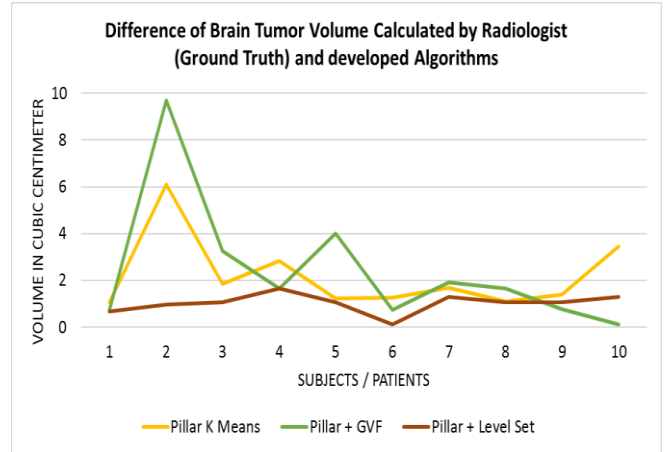
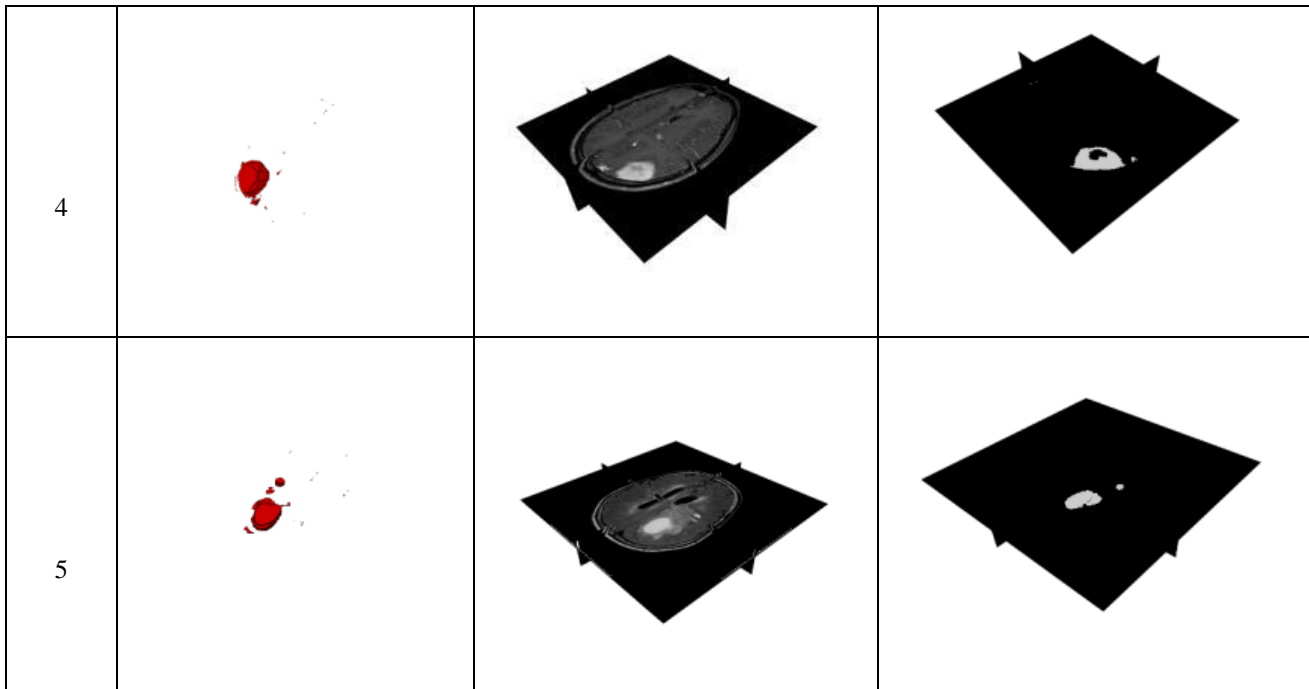


Figure 9 : Graph showing difference in Brain Volume Calculations comparable to Ground Truth

TABLE VI:3D VISUALIZATION AND SLICE-O-METRIC VIEW OF SEGMENTED REGIONS

Patient No:	3D	Slice-o-metric View	Tumor Slice-o-metric
1			
2			
3			



V. CONCLUSION

An effective volume estimation and 3D visualization of MR brain images is presented in this paper. This paper mainly focuses and presents hybrid mode of segmentation for which three methods were presented. The proposed (level set+ pillar) is yielding more accurate and effective results when compared against two other methods in terms of segmentation and volume analysis. The proposed method accurately segments the abnormal region which detects the abnormal region 1.5% accurately than other two, on other hand when volume is estimated its showing a difference of 1.03 with respect to the volume provided by radiologist, this meets the objectives of the research work.

ACKNOWLEDGMENT

Authors would like to thank radiologist Dr. Deepak Patkar, Director-Medical Services and Head – Department of Imaging, Nanavati Super Speciality Hospital, Vile Parle (West), Mumbai for providing the MRI images. We would like to thank for their tremendous efforts in providing the markings for ground truth images and their guidance throughout the research.

REFERENCES

1. Rajeev Ratan, Sanjay Sharma, S. K. Sharma, "Brain Tumor Detection based on Multi-parameter MRI Image Analysis". ICGST-GVIP Journal, ISSN 1687-398X, Volume (9), Issue (III), June 2009
2. Abbasi, S, Pour, F. T, "A hybrid approach for detection of brain tumor in MRI images", In Biomedical Engineering (ICBME), 2014, 21<sup>st</sup> Iranian Conference (pp. 269-274). IEEE, 2014
3. Hooda, H, Verma, O. P., & Singhal, T., "Brain tumor segmentation: A performance analysis using K-Means, Fuzzy C-Means and Region growing algorithm". In Advanced Communication Control and Computing Technologies (ICACCCT), 2014 International Conference on (pp. 1621-1626), 2014
4. S.Satheesh, Dr.K.V.S.V.R Prasad, Dr.K.Jitender Reddy, "Tumor Extraction And Volume Estimation For T1-Weighted Magnetic Resonance Brain Images", Global Journal of Computer Science and Technology Neural & Artificial Intelligence, Volume 12 Issue 12 Version 1.0 Year 2012

5. A. M. de los Reyes, M. Elena Buemi, M. N. Alemán and C. Suárez, "Development of a graphic interface for the three-dimensional semiautomatic glioblastoma segmentation based on magnetic resonance images," 2018 Congreso Argentino de Ciencias de la Informática y Desarrollos de Investigación (CACIDI), Ciudad Autónoma de Buenos Aires, Argentina, 2018
6. Nikhil Gala, K.D. Desai, "Three Dimensional MR Brain Image Reconstruction and Interactive Segmentation Based Tumor Region Extraction Using Active Contour Models", International Conference on Science & Engineering for Sustainable Development (2017) Pg. no.279-285
7. Nikhil Gala, Dr. Kamalakar Desai, "Abnormal Region Extraction from MR Brain Images using Hybrid Approach", (IJACSA), Vol. 9, No. 12, 2018
8. S. Abbasi and F. Tajeri Pour, "A hybrid approach for detection of brain tumor in MRI images," 2014 21th Iranian Conference on Biomedical Engineering (ICBME), Tehran, 2014, pp. 269-274
9. Verma, Kimmi, and Shabana Urooj. "Effective evaluation of tumor region in brain MR images using hybrid segmentation." 2014 International Conference on Computing for Sustainable Global Development, INDIA Com), 2014.
10. Y. Yang, R. Wang and C. Feng, "New method for simultaneous moderate bias correction and image segmentation," in IET Image Processing, vol. 13, no. 6, pp. 939-945, 5 2019. doi: 10.1049/iet-ipr.2018.5171
11. Ali Ridho Barakbah ; Yasushi Kiyoki, A pillar algorithm for K-means optimization by distance maximization for initial centroid designation, Computational Intelligence and Data Mining, 2009
12. Chunming Li; Chenyang Xu; Changfeng Gui; Fox, M.D., "Level set evolution without re-initialization: a new variational formulation," Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, vol.1, no., pp.430,436 vol. 1, 20-25 June 2005
13. Bosma, M. K., Smit, J., Lobregt, S.: Iso-surface volume rendering. In Kim, Y., Mun, S. K.(Eds.): Medical Imaging 1998: Image Display, Proc. SPIE 3335. San Diego, CA, 1998,10-19
14. Fabian Balsiger, "Brain tumor volume calculations", thesis submitted to department of biomedical engineering, Linkoping University, China
15. <https://www.radiantviewer.com/> Last Accessed: 20 July 2019.



## ABOUT THE AUTHORS



**Nikhil Gala** received his B.Tech and M.Tech degree in 2002 and 2010 and is currently a research scholar pursuing his Ph.D in the field of Biomedical Image Processing. He is a faculty in the Electronics & Telecommunication department of Mukesh Patel School of Technology Management & Engineering, NMIMS University, Mumbai. He has a total experience of 17 years with 2 years in the industry. His area of interest are signal processing and embedded systems.



**Dr. Kamalakar Desai** received his Ph.D from IIT Mumbai. He is currently the Technical Advisor to the Guru Gobind Singh Group of Institutions. He has served in a leading role as Advisor, Director and Head of Department in many institutes and engineering colleges of repute in India. He has guided several research scholars for their Ph.D degree. His areas of interest are biomedical applications, solar energy applications. Currently he is delivering training workshops in solar energy and its applications thus helping young talent and transforming them into successful entrepreneurs



**Dr. Deepak Patkar** is one of India's leading consultant radiologist. Currently he is the Director - Medical services and Head – department of Imaging at the Nanavati Super Speciality Hospital, Vile Parle, Mumbai, India. He has over 30 years of experience in UK and India. He is the director Telediagnosys Services Pvt Ltd, dealing in Teleradiology with clients in US, Arica and Middle-east. He is also the under graduate and post graduate teacher for d.N.B in Radiology of National board of examination from 2002 till date. He is also a faculty Radiologist for Wipro GE Medical systems and Blue star Medical systems for various academic activities organized all over India. He has several research and indexed publications.