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Survey of Brain Tumor Segmentation on MRI Images

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Abstract **Early human brain tumor diagnosis and radiotherapy planning can be aided with human brain segmentation based on digital image processing algorithms. In literature, Lot of papers are published on brain tumor segmentation. But brain tumor segmentation is still a challenging issue in medical imagery even with the help of Magnetic Resonance Images (MRI). This paper makes an analysis of brain tumor detection methods which are published recently, to aid the pathologists and computer programmers to sharpen their knowledge in brain tumor segmentation. This segmentation analysis brings forth a comparative study on five recent papers depend on the standard analytic measures. This paper is an advanced survey work on brain tumor segmentation to help young researchers to proceed with brain tumor segmentation research. This paper acts as an analysis tool to measure the merits and demerits of brain tumor segmentation algorithms**.

Keywords — **Brain MRI Images, tumor detection, tumor segmentation, medical imaging, preprocessing, dimensional view**

I. INTRODUCTION

Brain tumor segmentation is one of the key needs in preplanning of surgical treatments which may assist the pathologists to reach success in surgical operations on brain. Nowadays brain tumor operations are performed in manual way in hospitals which consumes more time. Manual brain tumor delineation is difficult and heavily depends on the individual operator which may not be an advisable one. The multi sequence images obtained simultaneously from MRI scanner and complementary information in the tumor area can help to analyze tumors by pathologists [3] [7] [8].

The main challenges of brain tumor segmentation are its various sizes, shapes and appearance at different locations. The deformation of surrounding structures in the brain due to mass effect or edema also complicates the brain tumor segmentation. The artifacts and noise are other obstacles in brain tumor segmentation [9] [10]. Hence there is an urgent need to design or develop a semi-automatic-segmentation or automatic-brain-tumor-segmentation approach with acceptable quality in its performance. This paper analyses and compares the recent developments on brain tumor segmentation based on different analytic metrics and research categorization to help the researchers.

The tumor detection process of labeling each pixel in an image that they share the same characteristics is spelled by the paper [11] which makes segmentation using Genetic algorithm. The author Rajesh C. Patil [12] describes a threshold based tumor detection method which creates a binary segmented image from grayscale image. Deepthi Murthy [13] has also published a paper in this concept. A. Lekshmi [14] accomplishes the tumor segmentation based on fuzzy C means method. The other papers which follow these techniques are [15] [16]. The watershed algorithm is also based on the same technique [17].

II. BRAIN STRUCTURE AND TUMOR TYPES

The brain is the most important organ in the body. The brain is a soft, spongy mass of tissue. It is protected by the bones of the skull. It controls the 5 senses, as well as the ability to speak and move. The right side of the brain controls the left side of the body. The left side of the brain controls the right side of the body. There are three major parts of the brain which control different activities:

i) **Cerebrum**: It is the largest part of the brain. It controls reading, thinking, learning, speech, and emotions.
ii) **Cerebellum**: It controls balance and complex actions like walking.
iii) **Brain Stem**: The brain stem connects the brain with the spinal cord. It controls hunger, thirst, breathing, body temperature, and blood pressure.

There are many different types of cells in the brain. The thinking cells and the brain activity cells are known as ‘*neurons*’. The other cells in the brain take care of the neurons and they are known as ‘*glial cells*’.

Tumor is defined as the abnormal growth of the tissues, which is a cluster of abnormal cells growing in the brain. It can be malignant or benign. Benign cells are non cancerous and malignant cells are cancerous. Benign brain tumor grows slowly, has distinct boundaries, and rarely

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spreads. Malignant brain tumor grows quickly, has irregular boundaries, and spreads to nearby brain areas. Malignant tumors are classified into two types. They are primary and secondary brain tumors. The primary brain tumors are tumors that start in the brain. Secondary (Metastatic) brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. The symptoms of brain tumor depend on the tumor area, type, and location. Symptoms may be caused when a tumor presses on a nerve or damages a certain area of the brain. The most common symptom of brain tumors is headaches, because of the pressure that the tumor places on the brain. Seizures or convolutions can occur because the tumor may irritate the brain. The Fig. 1 depicts the structure of brain tumor.

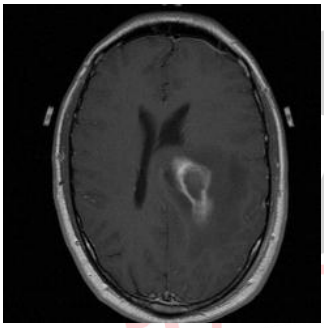

Fig.1. Structure of brain tumor.

III. SURVEY ON BRAIN TUMOR SEGMENTATION

This paper makes a survey on brain tumor segmentation to get more knowledge on tumors and tumor-detection-methods for medical research persons. To build a comparative study, this paper uses the following five methods.

- Brain tumor segmentation based on tumor cut method [1]
- Brain tumor segmentation based on multi fractal texture estimation [2].
- Brain tumor segmentation based on local independent projection based classification [3].
- Brain tumor segmentation based on 3- dimensional intracranial structure deformation features [4]
- Brain tumor segmentation based on convolutional neural networks [5]

A. Brain tumor segmentation using tumor-cut (BTS-TC)

AndacHamamci et al. [1] report a brain tumor segmentation method for contrast enhanced MR images. This method is designed specific to radio surgery applications. The name of this method is tumor cut method. This method can be considered as a practical tool for segmentation of solid tumors. The basic concept of this method is cellular automata (CA) based seeded tumor segmentation. The contrast enhanced T1 weighted magnetic resonance images are the input of this method and the volume of interest and seed selection is standardized. The connection establishment on CA based segmentation is performed to solve the shortest path problem. The state or transition function of CA is modified to compute exact shortest path solutions. This method designs a parameter to adapt the heterogeneous tumor segmentation.

The level set method is employed by tumor probability map which is served by the CA to make the spatial smoothness. In this method the user should draw a line through the cancer object as initial seed. An additional algorithm is also designed to differentiate necrotic enhancing tumor tissue content.

This method works based on user's line drawing over the largest visible diameter of the tumor. The VOI is selected depending on the user's line and the seeds of foreground and background. Tumor possibility map is generated using the two strength maps. The level set surface is initialized as 0-5 and the map is used to evolve the surface which converges to the final segmentation map. The necrotic regions of tumor are segmented using CA based on necrotic seeds.

The simulation is conducted using two real tumor databases: one from hardware tumor repository and another from clinical database of tumors at radiation oncology department of ASM. The feature dimension is depended on bounding box dimension. The accuracy of this method is upto 90%. The merit of this method is the fast execution due to theparallel implementation of BTS-TC method. Another advantage is that it has robustness with various tumor types. It also has less computational cost. The demerit of this method is that it is a semi-automatic method not a full automatic one. Another demerit of this method is that it has not dealt with any other tumor growth measurement scheme. This method can assist clinicians and researchers in radio surgery planning.

B. Brain tumor segmentation based on multi fractal texture estimation (BTS-MFTE)

The author Atiq Islam et al. [2] describe a tumor detection method for human brain tumors. The multi-fractal texture estimation concept is used in this paper. This method proposes a stochastic model for addressing tumor texture in brain tumor MRI images. This method is the type of patient independent brain tumor segmentation. The Multi-fractional Brownian motion (mBm) is utilized to formulate the brain tumor texture. The Ada-boost algorithm is extended to reach the tumor segmentation by making alteration on assigning weights to component classifiers. This method conducts analysis using BRATS2012 dataset. The Ada-Boost classification helps to classify patterns for detection and training.

This method fuses the fractal and MultiFD features for automatic tumor segmentation in brain MRI. The texton

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features are also used in this method. The overall flow diagram in depicted in Fig.2.

The standard preprocessing steps are performed to enhance the MR Images. The Fractal, Texton and Intensity features are extracted and they are applied on tumor segmentation. The Ada-Boost classifier is employed to absorb the features as input and make output as tumor-and- non-tumor regions.

The preprocessing steps involve the actions such as realign and unwrap slices within a volume and co-register slices from different modalities. The other two preprocessing steps are 'correct MRI bias field using SPM8 toolbox' and 'correct bias and intensity in homogeneity across the entire slice'.

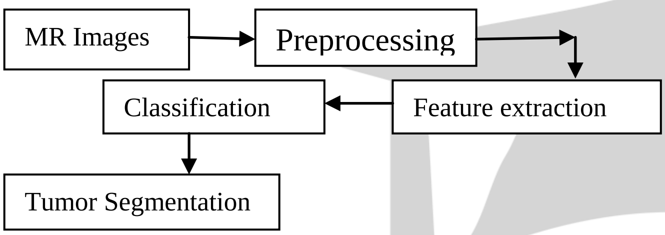

Fig.2. Overall flow diagram for BTS-MFTE method.

The fractal and MultiFD features are simplified into its single features for each. The texton feature count is 48. In this work block division value is 8x8. The modified supervised Ada-Boast classifier is trained to differentiate tumor from the non-tumor tissues. In this work T1, T2 and FLAIR modalities are used. The advantages of this method are: a) easily attached with 3D feature based segmentation b) patient independent model c) automatic model.

The demerit of this method is that it suffers when it faces large set data because Ada-Boost is a linear type classifier.

C. Brain tumor based on local independent projection (BTS-LIP)

The author Meiyan Huang et al. [3] expresses a brain tumor segmentation methodology for early tumor diagnosis and radiotherapy planning. The main challenge of brain tumor segmentation is addressed by the complex characteristics such as high diversity in tumor appearance and ambiguous tumor boundaries. Magnetic system and segmentation are treated here as clarification issue. Each and every voxel are characterized as various classes based on Local Independent Projection base classification (LIPC) method. The calculation of LIPC method is picked up from Locality property that has local anchor embedding. The MICCAI 2012 and MICCAI 2013 database are used to conduct simulation. The BRAIS 2012 database also aids to make simulation in brain tumor. The flow chart of the BTS-LIP method in depicted in Fig. 3. The BTS-LIP method includes four major divisions such as preprocessing, feature extraction, tumor segmentation and post processing. A Multi-resolution framework is introduced to diminish the computational cost.

The Preprocessing steps includes N3 algorithm to remove the bias field artifacts. The intensity values at the 1% and 99% qualities are extracted for brain region which involves tumors, edema and brain tissues. The parameters for linearly scale voxel intensities are fixed to the range [0, 100]. Thus the three stage preprocessing is performed in this work. This feature extraction is performed by selecting intensity values in a patch (w) around a voxel and rearranged as a feature vector. The block size of feature processing is w3x4 due to 4 modalities. The LIPC method segments the brain tumor image. The post processing scheme works based on the concept that each classified edema region must have a voxel near the classified tumor regions within some small

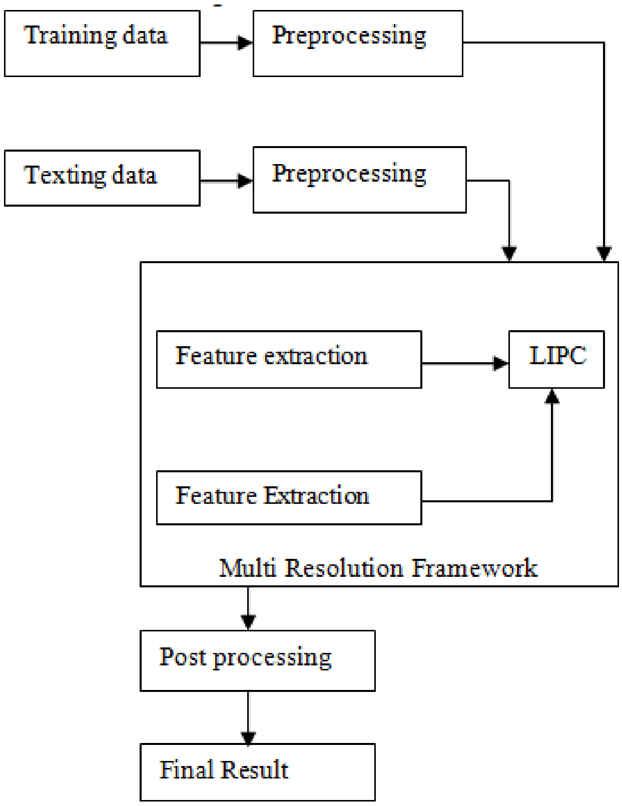

Fig.3. Flow chart of the BTS-LIP method.

distance. The connected component algorithm and mathematical morphology methods are helped to refine the classified edema regions by extracting the edema regions which are connected atleast one of the tumor regions.

The proposed method's advantage is that it makes a natural smoothness on segmented images. The other advantages are: a) automatic tumor segmentation b) executes on multi-resolution framework c) less computational cost. The demerit of this method is that it needs four modalities to segment brain tumor.

D. Brain tumor segmentation based on intracranial structure deformation features (BTS-ISDF)

A brain tumor segmentation method is described by the author Shang-Ling Jui et al. in the paper [4]. This method improves feature extraction component based on 3-Dimentional Intracranial Structure Deformation features.

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This feature improves the brain tumor segmentation accuracy because of the extraction of relevant features is of significant importance for brain tumor segmentation. The Lateral Ventricular (LAV) deformation is measured using 3 dimensional non-rigid registration and deformation modeling. The ever increasing amount of brain MR Image data has granted new opportunities for pathologists to analyze and processing of image data. This method aids diagnosis, treatment and monitoring the brain tumors for pathologists.

This method uses dynamically created template LaVs by considering the speciality of brain hemisphere symmetry. This method aligns and models LaV deformation via 3-D view. The Artificial Neural Network (ANN) and Support Vector Machine (SVM) is handled to segment the brain tumor segmentation. The flow diagram of this method is depicted in the Fig. 4.

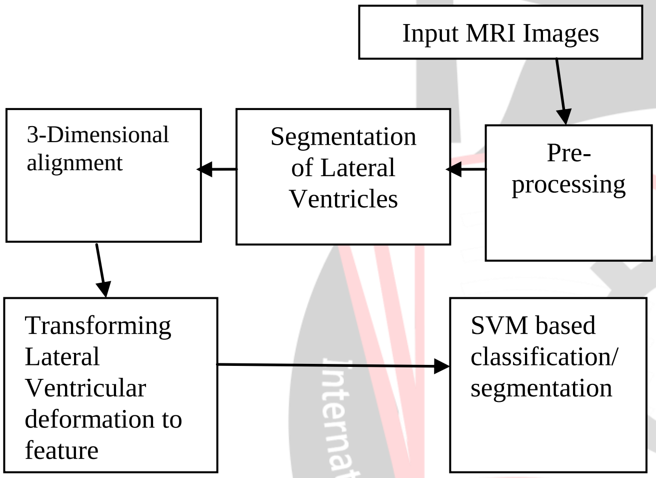

Fig.4. Flow diagram of BTS-ISDF method.

The feature extraction process includes three major divisions such as Segmentation of lateral ventricles, 3-Dimentional alignment and Feature transformation. The cerebrospinal fluid (CSF) tissue separation is done by Fuzzy C means (FCM) method. The specific group of CSF pixels is identified based on the intensity property from MRI images. The segmentation can be formed by using a mask in the brain followed by a filter for removing small isolated CSF pixels. The deformation modeling is applied through the alignment from control points generation and control points registration.

The LaV deformation feature extraction is obtained by 3-Dimensional nonlinear warping followed by displacement of each voxel generated from the warping process. This process combination of other two processes which are 3-Dimensional nonlinear Warping and Displacement of data. The user own database with eleven cases is used to test the simulation. The merit of this method is that it can be adapted with any classifier to segment brain tumors. The accuracy provided by this method 94%. The feature dimension of this method is Image Height*Image Width. The demerit of this method is that it has no robust against noise environment.

E. Brain tumor segmentation based on Convolutional Neural Network (BTS-CNN)

The author Sergio Peteira et al. [5] report a brain tumor segmentation approach based on Convolutional Neural Network (CNN). This method is associated with 3x3 size small kernels which are the gifts to design a deeper architecture. The over-fitting problem of CNN is avoided using fewer numbers of weights in the network. Intensity normalization is used in this method as a processing work to enhance the performance of CNN. The BRAT2013 database is used to conduct simulation and the BTS-CNN method reaches the first position on success. The BRATS 2015 database challenge is also faced by the BTS-CNN method and attains second position on success of brain tumor segmentation. This method is the best suited to preplanning of GLIMOS brain tumor which has highest mortality rate. This method uses MRI Images as input to segment brain tumors. The smaller kernels reach more convolution layers while having the same receptive field of bigger kernels. For example, two 3x3 cascaded convolution layers have the same effect of applying 5x5 kernels but with fewer weights. The intensity normalization method solves the heterogeneity caused by multi-site multi-scanner acquisitions of MRI. This method considered both spatial and structural variability in brain tumors to get segmentation.

This method is designed with 3 stages such as preprocessing, classification and post-processing. The preprocessing step corrects the intensity so that same tissues reach same intensity through intensity normalization. After normalizing the MRI images, the mean intensity value and standard deviation across all training patches are extracted.

The application of convolutional layers consists of convolving signal-or-image with kernels to generate feature maps. The weights of the kernels are fixed atrun-time using back-propagation to enhance the characteristics of the input. The small weights with small kernels property make the CNN easier to train. The neighborhood information is processing using kernels which is the key source of context information. The CNN is consisted by the following key modules.

- Initialization
- Activation function
- Pooling
- Regularization
- Data augmentation

The CNN segments the brain tumor by processing training and testing. Some false segmentation can be done as a tumor at small volume and this small volume clusters can be removed based on a specified threshold. The advantages of this method are; a) automatic segmentation

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b) reliable method c) usage of small size 3x3 kernels d) avoid over-fitting in CNN. The demerit of this method is that a hard threshold is used in the post-processing section.

IV. ANALYSIS AND DISCUSSION

The reviewed results are analyzed and tabulated in tables and depicted via graphs.

Table 1: Analysis on preprocessing, feature and Segmentation

Methods	Publication	Year	Pre-processing	Features	Segmentation method
BTS-TC [1]	IEEE Transaction on medical Imaging	2012	User line based VOI selection	Intensity based patches	Level set
BTS-MFTE [2]	IEEE Transaction on Biomedical Engineer	2013	4stage method	Fractal multiFD and texton	Modified Ada-Boost
BTS-LIP [3]	IEEE Transaction on Biomedical Engineer	2014	*N3 algorithm *brain region extraction *linear-scaling of voxel intensity	Patch based intensity	LIPC
BTS-ISDF [4]	IEEE intelligent systems	2016	Not reported	Intracranial structure	SVM
BTS-CNN [5]	IEEE transaction on medical imaging	2016	Intensity normalization	Pixels based intensity	CNN

Table 2: Analysis on block size used, merits and demerits

Methods	Block Size	Merits	DeMerits
BTS-TC [1]	Not reported	*Fast execution *Robustness with various tumor types *Less computational cost	*Semi automatic method
BTS-MFTE [2]	8x8	*Easily adopt with 3D texture based segmentation.	*Suffers with large set training data.
BTS-LIP [3]		* Patient independent type. *automatic model.	
BTS-ISDF [4]	Not reported	* Automatic tumor segmentation executes on multi-resolution framework. *less computational cost	Need of 4 modalities
BTS-CNN [5]	Dynamic 3x3	*Adapted to any classifier *Automatic segmentation *Reliable method *Small 3x3 kernels *Avoid over-fitting in CNN	Not robust to noisy environment Hard threshold is required in post processing

The feature count property is expressed by the table 3 and Fig. 5. Also database count is expressed in Fig.6. The BTS-CNN method occupies more features than other methods. The BTS-MFTE method occupies fewer features than other methods. The BTS-LIP method uses more database than other method. The BTS-MFTE and BTS-ISDF methods use only one database.

This BTS-ISDF method provides higher accuracy in brain tumor segmentation than other methods. The BTS-TC method is the second-best method in case of accuracy and the BTS-MFTE is the least performance method. These accuracy based results are expressed by Table 3 and Fig.7.

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Table 3: Analysis on Feature count, database used and Accuracy

Methods	Feature used	Database used	Accuracy
BTS-TC [1]	121	Hardware tumor database ASM	90%
BTS-MFTE [2]	50	BRAST 2012	81%
BTS-LIP [3]	108	MICCAI 2012 and MICCAI 2013, BRATS 2012	90%
BTS-ISDF [4]	81	Own database with 11 cases	94%
BTS-CNN [5]	192	BRATS 2013 and BRATS 2015	88%

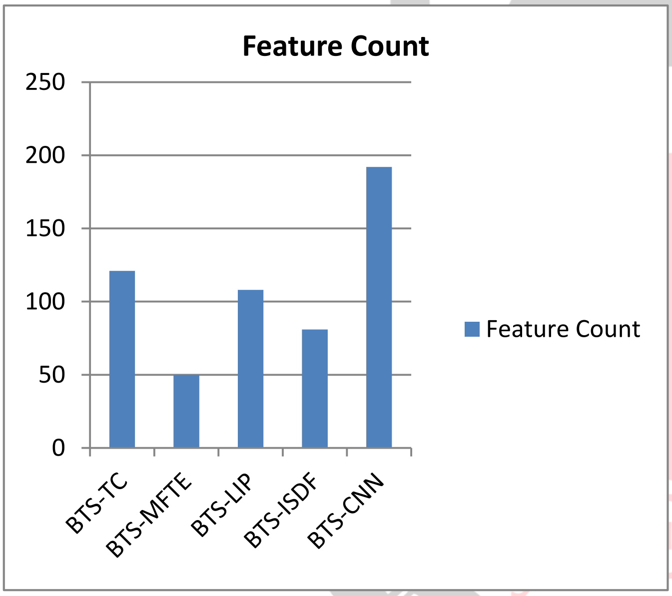

Fig. 5 Analysis chart for feature count for 5 methods

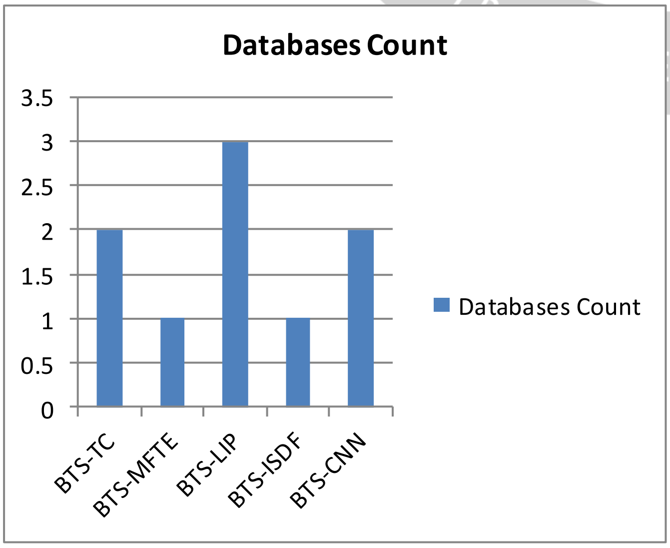

Fig.6. Analysis chart to express database count

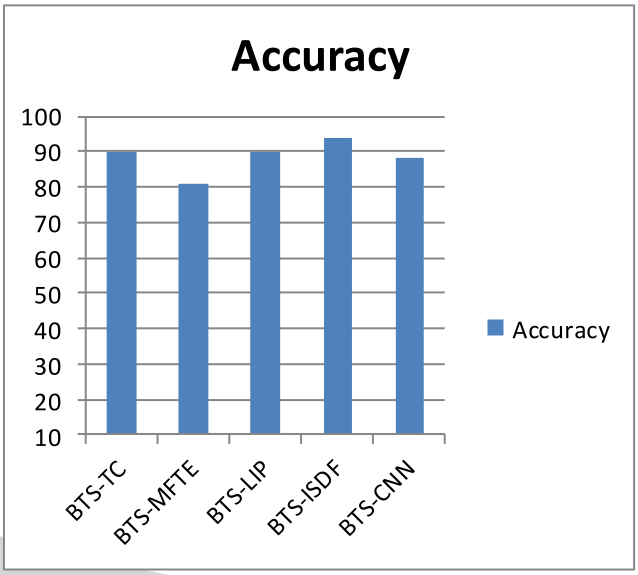

Fig.7. Accuracy analysis chart for five methods.

V. CONCLUSION

Image segmentation is utilized in many biomedical applications. Tumor detection and diagnosis are challenging task and sensitive and hence accuracy and reliability play a key role. This paper reaches a partial survey of various tumor segmentation methods that are part of image processing on Magnetic Resonance images. At first the various methods which are currently used in medical field were extensively studied.

A comparative study is provided on the recent five publishers on tumor segmentation. This analysis compares the performance success of these methods. A brief explanation of each technique which includes tumor area identification and segmentation are provided in this paper. The recent publishing's of tumor detection are analyzed with their own merits and demerits and from this analysis study the young researchers can get knowledge on what method is suitable for a particular type of tumor.

This paper can be helpful for the engineering theories and medical field. The literature studied from this paper concludes that there is no universal system that can detect the tumor accurately regardless of its location, shape and intensity. So in future, better segmentation schemes should be developed to help doctors in analyzing MRI images as the automated system will take less time than manual analysis.

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