

# Comprehensive Performance Study of Existing Techniques in Brain Magnetic Resonance Imaging for Tumor Detection

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Abstract- The Magnetic Resonance Imaging techniques has been proved to be a powerful tool in the field of medicine. Detection of the presence of tumor on time is important for treatment planning. Brain Magnetic resonance Imaging is fragmented in four consequent phases applied on captured image namely; Pre-processing, segmentation, feature Extraction, Approximate reasoning and classification. We have studied various techniques in Brain Magnetic resonance imaging for a tumor detection. Now present the analysis of performance of existing techniques in Brain Magnetic resonance imaging for a tumor detection. Our study is presented on the basis of various techniques used in tumor detection and includes the strength and the scope of improvements for each technique. These observations will be highly useful to the researchers putting efforts in the domain of detection of tumor for improving the accuracy rate particularly. The main objective of this research is the automatic analysis detection and segmentation of multiple tumors from Magnetic Resonance Image (MRI).

## *Index Terms*- Brain tumor, artificial neural network, SVM, Fuzzy c-means, Segmentation, Feature Extraction.

### I.INRODUCTION

Brain has been an important part of our nervous system. A tumor is mass of unnecessary and abnormal cell growing in the brain. There are two types of tumors as Benign and Malignant. Benign tumors are non cancerous and malignant tumors are cancerous and they rapidly. Gliomas are the most frequent primary brain tumors in adults. Dice scores in the range 74-85% [1]. In medical field it is Priorty to detect tumor at an early stage. There are different method for tumor detection. Improved possibilistic fuzzy c-means(PFCM) method which is based on similarity measure. This method is based on identifiey the outliers in an image. This gives 85% accuracy [2]. level set method for image segmentation in the presence of intensity inhomogeneity [3]. Another method for detection of tumor is An automatic segmentation method based on CNN, exploring small 3×3kernels [4]. Random forest (RF) is one of the most successful supervised voxel-wise classifiers that enjoys sustained attentions in the medical image segmentation[5]. The Multi -atlas segmentation (MAR) describes register and fuse label information from multiple normal brains for segmentation. It aheives78% for recall, 91% for precision. [6]. It is evident that a lot of research efforts have been made on the recognition of various sign languages. However, there exists a wide scope to present the performance study of techniques applied in Brain tumor detection to recognize various tumor and its stage, comprehensively so as to provide ease for the research community.

Detection of brain tumor involves various Phases such as Preprocessing, segmentation, Feature extraction, and classification. Figure 1 shows different stages in brain tumor detection. Image Preprocessing techniques are applied to improve the quality of image.

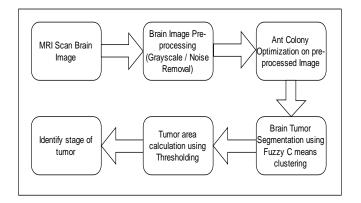


Fig. 1. Phases in brain tumor detection

Numerous brain tumor segmentation techniques play an important role in enhancing performance of Brain tumor detection of MRI images. Section 2 emphasizes on several existing techniques in Brain tumor detection in detail. In Section 3, we present the performance study of techniques in



HGRS for sign languages based on the performance of specific systems. Lastly, we conclude with the conclusion in Section 4.

## II. EXISTING TECHNIQUES IN BRAIN MRI SEGMENTATION AND TUMOR DETECTION

The purpose of this section is to give an overview of the different segmentation methods, which are used in the literature for improving the segmentation and for introducing maximum possible reliability. Segmentation methods are classified into different groups according to their own specific characteristics. The brain MRI image segmentation is classified as k-means, SVM, FCM, k-nearest neighbour, neural network, and others methods etc.

Maoguo Gong, Zhiqiang Zhou, and Jingjing Ma [7] proposed method for tumor detection which is based on an image fusion strategy and a novel fuzzy clustering algorithm. This proposed method based on image fusion to generate a new image. An average operator and minimum local area energy are used to fuse the wavelet coefficients for a low-frequency band and a high-frequency band. The proposed model achieves an accuracy of 95.86%.

Ayse Demirhan, Mustafa [8] Proposed new algorithm for segmentation that segments brain MRI images into tumor, matter (WM), gray matter (GM) and edema, white cerebrospinal fluid (CSF). For this T1, T2 and FLAIR MRI images of 20 subjects suffering from glial tumor are used. The self-organizing map (SOM) is used for segmentation that is trained with unsupervised learning algorithm. The detection of the healthy tissues is compared simultaneously with the diseased tissues because examining the change caused by the tumor and edema on healthy tissues is very important for next treatment planning. The results achived are that average Dice similarity indexes are 91% for WM, 87% for GM, 96% for CSF, 61% for tumor, and 77% for edema.

Andac Hamamci, Nadir Kucuk, Kutlay Karaman, Kayihan Engin, and Gozde Unal [9] Author proposed cellular automata (CA) based seeded tumor segmentation method which is based on contrast enhanced T1 weighted magnetic resonance (MR) images. The Cellular automata CA framework solves the shortest path problem. In that regard, modification in the state transition function of the CA to calculate the exact shortest path solution. Furthermore, a sensitivity parameter is introduced to adapt to the heterogeneous tumor segmentation problem. Studies are carried out on both clinical and synthetic brain tumor datasets demonstrate 80%-90% overlap performance of the proposed algorithm with an less sensitivity to seed initialization, robustness to different and heterogeneous tumor types, as well as its efficiency in terms of computation time.

Bjoern H. Menze, Andras Jakab [10] Proposed the BRATS brain tumor segmentation benchmark. The largest public dataset

used for this task and evaluated a large number of stateof the-art brain tumor segmentation methods. Results indicate that, while brain tumor segmentation is difficult even for human raters, Accuracy obtained is, Dice scores of over 80% for whole tumor segmentation. Segmenting the tumor core region, and 70% and 60% for the active core region in high-grade gliomas, proved more challenging.

Ghulam Gilanie, Usama Ijaz Bajwa [11] Proposed method, using Gabor filter and support vector machines, classifies brain MRI slices as normal or abnormal. Accuracy, sensitivity, specificity and ROC-curve have been used as standard quantitative measures to evaluate the proposed algorithm. It achieving an accuracy of 97.5%, sensitivity of 99%, specificity of 92% and ROC-curve as 0.99.

AMRUTA HEBLI, Dr. SUDHA GUPTA [12] Presented support vector machine (SVM). In the work author classify tumor as benign and malignant. This work which help to detect the tumor and classify them into benign and malignant in quick time. In this work step by step procedure for image preprocessing, segmenting brain tumor using morphological operations, extracting tumor feature and classification of the tumor using SVM is accomplished with the actual clinical data. The segmentation of brain tumors from MR Images in a quick, accurate, authentic and reproductive way is still a challenging issue. To solve this issue K-means algorithm is used.

Samir Kumar Bandhyopadhyay and Tuhin Utsab Paul [13] Proposed K-means algorithm. Author Describes system of image registration and data fusion theory adapted for the segmentation of MR images. Propose a system of image registration and data fusion theory adapted for the segmentation of MR images. This system provides an efficient and fast way for diagnosis of the brain tumor.

P.Mohamed Shakeel, Tarek E. El. Tobel, Haytham Al-Feel, Gunasekaran Manogaran, S.Baskar [14] Proposed an algorithm which is Machine learning based back propagation neural networks (MLBPNN). It is used to enhance the exactness and proficiency in location of threat and to limit the entomb onlooker variety. In this work MLBPNN is analyzed with the help of infra-red sensor imaging technology. The features are extracted by using Fractal Dimension Algorithm (FDA) and then the most significant features are selected using Multi fractal detection(MFD) technique to reduce the complexity. Thus achieve 95.10% accuracy.

III.PERFORMANCE STUDY OF TECHNIQUES USED IN BRAIN MRI SEGMENTATION AND TUMOR DETECTION



Comparative performance study of different brain tumor Detection and Segmentation techniques are summarized in compare table (Table I) with advantages and limitations. In Table I. Most of the key features of methods are mentioned with limitations and advantages that make our work unique. We have studied various techniques in Brain tumor segmentation and detection and now present the analysis of performance of existing techniques in Brain tumor detection. This analysis has been performed on the basis of some vital factors such as accuracy, advantages, limitations and is depicted in Table 1.

#### TABLE I

### PERFORMANCE STUDY OF TECHNIQUES USED IN BRAIN MRI SEGMENTATION AND TUMOR DETECTION

| Title   | Proposed<br>Technique   | Accuracy       | Advantages  | Limitations   |
|---|---|----------------|---|---|
| Similarity Measure Based<br>Possibilistic FCM With Label<br>Information for Brain MRI<br>Segmentation                   | Possibilistic<br>fuzzy c-means<br>(PFCM)                                      | 95%            | Identify outlier of the image.<br>Useful for salt and paper<br>noise images     | Noise resistance, image detail preserve   |
| Image Segmentation using k-means<br>clustering, EM and Normalized Cuts  | K- means and<br>Expectation<br>Maximization(<br>EM)                           | 82%            | Increase the efficiency of the image retrieval process                          | Sensitive to initial seeds,<br>more time  |
| Brain tumor segmentation using using<br>convolutional neural networks in MRI<br>images                                  | Convolutional<br>neural<br>networks   | 88%            | Increased Accuracy by using<br>Kernel   | Time consuming process and<br>hard to select optimal<br>features                                  |
| Multi-Atlas Segmentation of MR<br>Tumor Brain Images Using Low-<br>Rank Based Image Recovery                            | Low-rank<br>based method  | 91%            | Improve the segmentation accuracy   | More Iterations have to performed   |
| Segmentation of tumor and edema<br>along with healthy tissues of the brain<br>using wavelets and neural network         | Neural<br>network   | 91% and<br>87% | Simple and flexible to<br>Implement   | Difficulty in selecting<br>optimal features to<br>distinguish different classes                   |
| Tumor-Cut: Segmentation of Brain<br>Tumors on Contrast Enhanced MR<br>Images for Radiosurgery Applications              | cellular<br>automata (CA)<br>based seeded<br>tumour<br>segmentation<br>method | 80%            | Solve the tumor delineation problem   | Difficult to handle Large<br>heterogeneous dataset  |
| Improved Implementation of Brain<br>MRI image Segmentation using Ant<br>Colony System                                   | Ant Colony<br>algorithm   | 92.91%         | Fast and accurate results<br>For segmentation of image                          | More time consumption   |
| Detection of brain tumor in MRI<br>images, using combination of<br>FCM and SVM  | Fuzzy c-<br>meansa and<br>Support vector<br>machine                           | 91.96%         | clustering and classification<br>algorithm are combined,<br>Efficient<br>method | Hard to choose SVM kernel<br>Function   |
| MRI Image classification using<br>Adaboost for brain tumor type   | Neural<br>network and<br>adaboost<br>algorithm                                | 89.90%         | Less time required Minimize<br>the error  | It can maximize the margin<br>with respect to features that<br>already selected                   |
| Classification of Tumors and It<br>Stages in Brain MRI Using Support<br>Vector Machine and Artificial Neural<br>Network | SVM<br>Classification<br>and ANN<br>classification                            | 97.44%.        | Increased Accuracy Classify<br>brain tumor with brain tumor<br>affected stages  | Difficulty in selecting<br>optimal features to<br>distinguish different classes<br>Time Consuming |



#### IV. CONCLUSION

We have studied many techniques used to recognize brain tumor detection techniques in detail. Our study is presented on the basis of fragmentation used in Brain tumor detection and includes the strength and the scope of improvements for each technique. A comprehensive comparison of performances of various brain tumor detection techniques has been presented and some important observations have been drawn. These observations will be highly useful to the researchers putting efforts in the domain of accuracy of detection of tumor from MRI images for improving the accuracy rate particularly.

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