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## Review of Brain Tumour Segmentation Approaches

Nagampreet Kaur<sup>1</sup>

Natasha Sharma<sup>2</sup>

[nagampreet.brar@gmail.com](mailto:nagampreet.brar@gmail.com)

[Ernatasha8587@gmail.com](mailto:Ernatasha8587@gmail.com)

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**Abstract**— Brain image segmentation is one of the most important parts of clinical diagnostic tools. Brain images mostly contain noise, in homogeneity and sometimes deviation. Therefore, accurate segmentation of brain images is a very difficult task. However, the process of accurate segmentation of these images is very important and crucial for a correct diagnosis by clinical tools. We presented a review of the methods used in brain segmentation. Reproducible segmentation and characterization of abnormalities are not straightforward. In the past, many researchers in the field of medical imaging and soft computing have made significant survey in the field of brain tumour segmentation.

**Keywords**—*medical image, segmentation, brain, MRI*

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### I. INTRODUCTION

The brain is the most significant part of the central nervous system. The framework and operation of the brain required to be studied noninvasively by doctors and researchers using MRI imaging methods. The body is composed of various types of cells. Individual type of cell has extraordinary operations. When cells lose the capability to control their growth, they split too often and without any order. The extra cells form a mass of tissue called a tumor. MRI acts as an assistant diagnostic tool for the doctors at the time of disease diagnosis and treatment. This imaging modality generates images of soft tissues. The accomplished medical images proves the internal structure, but the doctors want to know more than peer images, such as emphasizing the abnormal tissue, quantifying its size, depicting its shape, and so on [3]. If such tasks are covered by the doctors themselves, it may be inaccurate, time consuming and burden them heavily.

In the field of medical science an abnormal cell growth inside the brain is known as tumor. Human brain is considered to be the most sensitive part of the body. It control muscle movements and interpretation of sensory information like sight, sound, touch, taste, pain etc. A tumor can affect such sensory information and muscle movements or even results in more dangerous situation which includes loss of life as well. Since the position of the tumor is not fixed thus it can be formed in any part of the brain or human body. Depending upon the place of origination tumor can be categorized into primary tumors and secondary tumors. If the tumor is originated inside the skull then the tumor is known as primary brain tumor otherwise if the tumour's origination place is somewhere else in the body and moved towards brain then such tumors are called secondary tumors.

The exact cause of cancer is unknown. Brain cancer that originates in the brain is called a primary brain tumor. It can spread and destroy nearby parts of the brain. Cancers of the lung, skin, or blood cells (leukemia or lymphoma) can also spread (metastasize) to the brain, causing metastatic brain cancer. These groups of cancer cells can then single area or in different parts of the brain [13].

#### A. Types of tumors

1) Based on the location of the origin of tumors, they are classified as following:

- a) Primary brain tumors: Tumors which originates in the brain cells are called as primary brain tumors. In the case of primary brain tumors, sometimes they spread to other parts of the brain or to the spine. But spreading to other organs occurs only rarely.
- b) Metastatic brain tumors: Metastatic or secondary brain tumors are those which originate in other parts of the body and then spread to the brain. These tumors are named according to the location which they originate.

2) Based on the malignancy of tumors originated, they are classified as accordingly:

a) Benign brain tumors: From the name itself, it can be understood that the benign tumors are the least aggressive ones. They originate from cells within the brain or from associated parts of the brain and they will not contain cancer cells. They only grow slowly and also they have clear borders i.e. their growth are self-limited and they will not spread into other tissues.

b) Malignant brain tumors: These tumors contain cancerous cells and their growth is not self-limited. Often their borders are not clear. Also they grow rapidly and invade surrounding brain tissue. Hence they will become life threatening if proper treatment is not taken at the correct time.

Exact measurements in brain diagnosis are difficult because of various shapes, sizes and appearances of tumours. Tumours also cause abrupt defects in nearby tissues. Tumour is an abnormal growth of body tissue, it can be cancerous (malignant) or non-cancerous (Benign). In medical imaging technique, MRI Magnetic resonance imaging technique is used in radiology to visualize the internal structures of the body in detail. This produces a rotating magnetic field detectable by the scanner and this information gets recorded and constructs an image of the scanned area of the body. MRI has excellent contrast within soft tissues.

The goal of brain tumor segmentation is to extract the tumor parts that indicate clinical information for medical analysis and diagnosis which pathological property is varied on the individual patients. Magnetic Resonance Image (MRI) is a medical imaging that is appropriate for diagnosing brain lesions and non-invasive approach for therapy and treatment processes [3]. MRI used for the segmentation comprise of T1-weighted (T1), T2-weighted (T2), contrast- enhanced T1- weighted (CE- T1) and FLAIR images. On these images, brain tumor with differentiated image signals, such as T1 with hypointense or isointense, T2 and FLAIR with hyperintense, etc. [4]. Moreover, brain tumor may appear patterns either homogeneous or heterogeneous.

Magnetic resonance imaging (MRI) plays an important role in the medical imaging and delivers qualitative, quantitative and accurate information for medical diagnosis. It has various advantages over other medical imaging modalities with many applications, namely, cardiovascular, neurological, musculoskeletal, and in particular brain imaging. However, most issues of MR images processing arise from variations in intensity due to B1 and B0 field in homogeneity. This latter appears because of the non-uniformity even for a single tissue which may mislead many image analysis algorithms, especially the segmentation step [1]. In last decade, the power of MR imaging has focused on the malignant brain tumors.

Segmentation is a significant process to extract suspicious region from complex medical images. Primarily, Genetics is carried out on complete tumor. image, because of this the initial population set is quite large but now the size of the population set for the genetics is minimized [4-5]. The main aim of the present work is an effective segmentation technique is to identify and extract the tumor region in MRI Images.

The main aim of the segmentation process is partitioning image regions - also called classes – homogeneous with respect to a numerous of features or criteria. In medical imaging, segmentation is very significant, either for the extraction of parameters or measurements for the visualization and representation. The segmentation methods can be splitted into multiple classes ways: the most general is to separate the techniques of segmentation regions seeking uniformity within an area criterion and techniques edge detection, which focus on the interface among these regions. The arrival of mathematical tools and diversity of issues, however, often broke this dichotomy.

## II. LITERATURE REVIEW

**R.Preetha and G.R.Suresh [1]:** In brain MR images, the boundary of tumor tissue is extremely asymmetrical. Deformable models and Region based techniques are broadly used for medical image segmentation, to locate the boundary of the tumor. Issues related with non-linear distribution of real data, User interaction and poor convergence to the boundary region limited their usefulness. Clustering of brain tumor images, with the use of Fuzzy C means is strong and efficient for tumor localization. Still though the planned technique has high computational confusing, it proves superior outcomes in segmentation effectiveness and junction rate. The Fuzzy C means clustering with the addition of Feature extraction and classification shows potential in the field of brain tumor detection.

**Amitava Halder, Chandan Giri and Amiya Halder[2]:** proposed a well-organized brain tumor detection technique, which can identify tumor and establish it in the brain MRI images. This technique extracts the tumor with the use of K-means algorithm developed by Object labeling algorithm. It has also been found that some preprocessing steps (median filtering and morphological operation) are used for the purpose of tumor detection. It is pragmatic that the experimental outcomes of the suggested technique gives better outcomes in comparison to other methods

**Ankit Vidarthi and Namita Mittal[3]:** a new bi-clustering algorithm has been recommended to cluster out the maximum abnormality area from the brain MR image without any predefined threshold. For tumor segmentation, algorithm is on the basis of CLAP i.e. closely link associated pixel mechanism. Long ago, several types of techniques had useful on brain MR (Magnetic Resonance) imaging to find out the exact abnormality region from on the whole volume of the brain. The literature helps to detect that

several bi-clustering algorithms had cluster out the region on the basis of some predefined threshold value which results in generation of cluster which was dependent on particular threshold value only.

**Kailash Sinha and G.R.Sinha [4]:** presents a relative research of three segmentation technique carried out for tumor identification. The technique involves k-means clustering with watershed segmentation algorithm, optimized k-means clustering with genetic algorithm and optimized c- means clustering with genetic algorithm. Traditional k-means algorithm is sensitive to the initial cluster centers. Genetic c-means and k-means clustering methods are used to identify tumor in MRI of brain images. At the end of process the tumor is extracted from the MR image and its exact position and the shape are strong-minded. The experimental outcomes specify that genetic c-means not only terminate the over-segmentation issues, but also supply fast and effective clustering outcomes.

**Ahmad Chaddad et al[5]:** paper involve new features type of Glioblastoma (GEM) detection on the basis of Gaussian Mixture Model (GMM). The GMM features established the best performance largely. For the T1 and T2 weighted images, the accuracy performance was 100 % with 0% missed detection and 0% false alarm consequently. In FLAIR mode the accuracy decrease to 94.11 % with 2.95 % missed detection and 2.95 % false alarm. All the experimental outcome is very encouraging to progress the precocious GEM diagnosis.

**Koushik Pal and Subhajit Koley[6]:** A new type of brain tumor identification system is suggested and investigated in this paper by detecting Infected Region with the arrangement of Region Growing Algorithm, Cryptography and Digital Watermarking. The information associated to patients enclosed in the Electronic Patient Record (EPR), Region of Infection (ROI), doctor's name and diagnosis from symptoms are encrypted and embedded in the tomographic image itself using the recommended methodology – a combination of the Rivest-Shamir-Adelman (RSA) encryption and bit plane slicing watermarking methods. The infected region is detected through region growing and contour detection algorithm which requires to be perfect for accurate ROI identification resulting in a better treatment.

**Kimmi Verma and Rituvijay[7]:** The main goal of this work is to authenticate a quantitative method to extract various attributes from MR images. A technique known as hybrid segmentation that associate threshold segmentation, watershed segmentation, edge detection and morphological operators is considered jointly. This joined method is experimented with MR scanned images of human brains to detect tumour. Exact size and location of tumour is identified with the use of present hybrid segmentation method

**Chaiyanan Sompong, Sartra Wongthanavas [8]:** presents a unique segmentation technique for iso-intense signal tumor appeared in T1-weighted or T2- weighted magnetic resonance (MR) images. The suggested technique advanced the well-known Grow-cut algorithm with the use of the advanced local transition rule. The well-known grow-cut and tumor-cut algorithms are correlated with the use of dice similarity coefficient (DSC). In this regard, the recommended technique delivers better outcomes by reporting DSC of 84.17 % higher than Grow-cut and Tumor-cut with 80.81% and 80.14%, respectively.

**Deepthi Murthy T.S. and G.Sadashivappa [9]:** Various methods were developed to identified and segment the brain tumor. With the use of thresholding and morphological functions effective brain tumor segmentation is implemented. This is the efficient algorithm where segmentation of tumor is carried out and its features such as centroid, perimeter and area are calculated from the segmented tumor. To identified the brain tumor, scanned MRI images are given as the input. The work included here helps in medical field to detect tumor and its characteristics helps in giving the treatment plan to the patient. The whole paper is splitted into seven sections which are described in detailed in the following sections.

**Heena Hooda et al[10]:** discuss the performance analysis of image segmentation methods, viz., K-Means Clustering, Fuzzy C-Means Clustering and Region Growing for detection of brain tumor from sample MRI images of brain. The performance estimate of the above mentioned methods is done on the basis of error percentage associated to ground truth. The significant task in the diagnosis of brain tumor is regulated the exact location, orientation and area of the abnormal tissues.

**G. Kharmega Sundararaj and Dr. V. Balamurugan[11]:** a tumor classification system has been considered and developed for MRI systems. The suggested technique composed of three stages namely pre-processing, feature extraction and classification. In their profound system classification has two divisions: i) training stage and ii) testing stage. Thus, the suggested system has been evaluated on a dataset of 40 patients. The proposed system was found effective in classification with a success of more than 95% of accuracy.

**Naouel Boughattas et al [12]:** suggested a brain tumor segmentation technique from multi-spectral MRI images. The segmentation task is then viewed as a learning issue where only the most important features from the feature base should be preferred and then a classifier can be used. The new concept is to use Multiple Kernel Learning (MKL) by comparing one or more kernels to individual feature in order to solve together the two problems: selection of the features and their corresponding kernels and training of the

classifier. Their algorithm was tested on the real data supplied by the challenge of Brats 2012 and was compared to the resulting top techniques. The outcome proves good performance of their technique.

**Saif Dawood Salman Al-Shaikhli et al[13]:** a unique approach for multi-class brain tumor classification on the basis of sparse coding and dictionary learning is suggested. They recommended an individual (per-class) dictionary learning and sparse coding classification using K-SVD algorithm. This perspective correlate topological and texture features to build and learn a dictionary. Experimental outcomes exhibits that the sparse coding based classification surpass other state-of-the-art techniques.

**Tomas Martinez-Cortes[14]:** handles the problem of automatic brain tumor classification from Magnetic Resonance Imaging (MRI) where, usually, general-purpose texture and shape features extracted from the Region of Interest (tumor) have become the usual parameterization of the problem. Their experimental outcomes shows that the use of clinical-based feature leads to an important increment of performance in terms of Area Under the Curve (AUC) when associated to a state-of-the art reference. Moreover, the suggested Bayesian fusion model clearly surpass other fusion mechanism, particularly when few diagnostic tests are accessible.

**Solmaz Abbasi and Farshad TajeriPour[15]:** a technique for 3D medical image segmentation is presented. This technique is used to identify brain tumor in MRI images by correlating Clustering and Classification techniques to reduce the difficulty of time and memory. This technique has obtained a fast speed for segmentation of MRI 3D images and has been classified with criteria of Dice's and Jacquard's coefficient on the brain tumor from magnetic resonance image retrieved from the Brats2013 database.

### III. CONCLUSIONS

DETECTING THE EXISTENCE OF BRAIN TUMORS FROM MRI IN A FAST, ACCURATE, AND REPRODUCIBLE WAY IS A CHALLENGING PROBLEM. MEDICAL IMAGE PROCESSING IS A VERY ACTIVE AND FAST-GROWING FIELD THAT HAS EVOLVED INTO AN ESTABLISHED DISCIPLINE. BRAIN TUMOR SEGMENTATION TECHNIQUES HAVE ALREADY SHOWN GREAT POTENTIAL IN DETECTING AND ANALYZING TUMORS IN CLINICAL IMAGES AND THIS TREND WILL UNDOUBTEDLY CONTINUE INTO THE FUTURE. MEDICAL IMAGE ANALYSIS NEEDS TO ADDRESS REAL-WORLD ISSUES THAT HAVE BEEN OUTSIDE THE REALM OF COMPUTER VISION [103]. THESE ISSUES COME LARGELY FROM THE FACT THAT THE END SYSTEMS ARE MOSTLY USED BY THE PHYSICIAN. THE HUMAN FACTOR IS ESSENTIAL, SINCE ANY SUCCESSFUL SOLUTION WILL HAVE TO BE ACCEPTED BY A PHYSICIAN AND INTEGRATED INTO THE MEDICAL PROCEDURAL WORK FLOW. THIS PUTS STRONG CONSTRAINTS ON THE TYPE OF APPLICABLE METHODS. DUE TO IT, THERE HAS BEEN A DISCREPANCY BETWEEN THE ADVANCED FRAMEWORKS PRESENTED IN COMPUTER VISION AND THE LOW-LEVEL METHODS USED BY RESEARCHERS WORKING ON REAL MEDICAL APPLICATION SOLUTIONS

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