A Comprehensive Review And Analysis On MRI Based Brain Tumor Segmentation

A.R.Deepa, W.R. Sam Emmanuel

Abstract: Brain tumor is a crucial brain disease that arises because of the group of irregular cells that grows inside and around the brain. Several imaging approaches are used to detect the brain tumor. Among all the imaging technique, a safe and non-invasive imaging technique called the MRI is mainly utilized for brain tumor detection. MRI is considered as a major-medical imaging technique for diagnosing and monitoring brain tumors, and their function for respective treatment. The MRI process of brain tumor identification takes place usually by experienced radiologists. Also for more effective treatment and greater accuracy, clinicians constantly strive in the computer vision based approaches to detect brain tissue from MRI images. In this paper, we presented a comparative study on existing MRI based brain tumor segmentation methods. In addition, we highlight the various algorithms used in different stages of brain tumor segmentation such as pre-processing, feature extraction and classification with its merits and demerits.

Index Terms: Brain tumor, Medical Resonance Imaging, Segmentation, Feature Extraction, Feature Selection, Classification.

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1 INTRODUCTION

In general, the tumor is defined as tissue cluster formed due to the aggregation of abnormal cells in the body. Typically, at an appropriate time, the old cells are being replaced by new ones [1]. Due to the advent of a cancerous tumor(s), this cycle is disrupted. The tumor cells grow exponentially and don't perish, unlike healthy cells. At present imaging technology is must for patient diagnosis [2]. The various medical images like MRI, Ultrasound, CT, X-ray etc play an important role in the field of process of disease, diagnosing and treating [3]. The recent revolution in medical imaging results from techniques such as CT and (MRI) can provide detailed information about disease. and can identify many pathologic conditions giving an accurate diagnosis. Furthermore, the new techniques are helping to advance fundamental biomedical research [4]. Medical imaging is one of the most common techniques used to improving the diagnoses, understanding and treatment of a large variety of diseases [5]. The brain imaging analysis is main objective in the field of medical image analysis [6]. Magnetic resonance (MR) imaging have many benefits over the medical imaging modalities such as a useful non-invasive technique for assisting in clinical diagnoses, the high level of contrast resolution, multispectral characteristics and ability to provide rich information about human soft tissue [7]. MRI provides useful information in the field of surgery, radiotherapy treatment planning, stereotactic neurosurgery [8] Computer Aided Diagnosis system has been developed for Automatic Detection of Brain Tumor through MRI. Improving the ability to identify early stage tumors is an important goal for physicians, because early detection of class of disease is a key factor in producing successful treatments [9]. There is different type of detection techniques which is used to develop the CAD [10].

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To create a CAD system, the integration of various image processing techniques such as segmentation, feature extraction and classification are essential [11] [12].

2 BRAIN TUMOR

Brain is the center of human central nervous system. The brain is a complex organ as it contains 50-100 billion neurons forming a gigantic network [13]. There are two types of brain tumors namely primary tumor and secondary or metastatic tumor [14]. Usually, the primary brain tumor outsets in the brain and tends to stay during its growth tenure [15]. Whereas, the secondary brain tumor commences elsewhere as cancer in the body and later spreads to the brain region. Further, the primary brain tumor has two sub-division namely, (i) Benign tumor and (ii) Malignant tumor [16]. In the diagnosis of brain tumor, determination of the exact location is an important task, using which helps to find out the shape & size of tumor [17]. In brain tumor detection techniques, image segmentation plays a vital role there are many image segmentation methods are used to extract tumor from magnetic resonance imaging images of brain [18]. Whereas segmentation provides the detailed information about the soft brain tissues such as gray matter (GM), white matter(WM), cerebral spinal fluid (CSF)etc. There are two types of segmentation involves a manual segmentation and automatic segmentation [19]. Manual segmentation technique depends on experience or expert knowledge of human and time consuming technique but reduces the computational efficiency. Whereas automatic segmentation deals with histogram. Which is only based on the intensity of pixels [20].

2.1 Automatic MRI Segmentation

To distinguish and find the anomalies present in the brain image, the radiologist need to physically observe the MRI pictures in the existing scenarios [21]. To find the variations from the norm expends time and need lot of endeavors. Along these lines, there requires an associate instrument which aides in distinguishing the presence of tumor in the MRI image of brain and stage precisely [22]. In this manner

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recognition of tumor in brain plays a curial and extreme occupation in the field of medical image processing. This brings the need of introducing automatic MRI segmentation techniques for brain tumor detection [23].

2.2 MRI Modalities

Tissue appearance can be influenced by variable behavior of protons appeared in various tissues. The speed at which versatile hydrogen protons are moving becomes helpful in deciding measure of sign created by explicit tissue [24]. Essentially, MRI images are of three modalities [25]:

- T1-Weighted
- T2-Weighted
- Fluid-Attenuated Inversion Recovery (FLAIR)images

In medical image processing T1-weighted and T2-weighted images are two MRI modalities most often used for visualizations [26]. These MR slice weightings refer to the important signal (whether it be the T1 time or the T2 time) measured to make the contrast in the image. The areas with high fat content have a short T1 time relative to water; T1-weighted images can be taken as visualizing locations of fat [27]. In contrast areas with high water content have a short T2 time related to areas of high fat content, T2-weighted images can be observed as visualizing locations of water [28]. An example T1, T2-weighted and FLAIR images are shown in figure 1. In finding out brain tumors, a second T1-weighted image is collected frequently after the injection of a contrast agent. These contrast agent components use to have elements whose composition makes a decrease in the T1 time of nearby tissue (gadolinium is one example) [29]. The image left: T1-weighted image (light regions visualize locations of fat). The Image Top right: T2-weighted image (light regions visualize locations of water) [30].
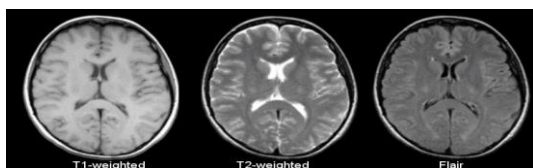

Figure 1: Modalities of MRI Images

To diagnosis a brain tumor, Magnetic Resonance Imaging is commonly used, because of its advantages of high resolution to delicate tissues of brain and it is a non-ionizing, non-radioactive which will not damages human organs [31]. Combined with medical knowledge and clinical experience, the experienced diagnosist can locate the tumor sizes, shapes, anatomical structure and other pathological characteristics of brain tumors which help in suggesting the proper treatment to the patients [32]. Because there are several MRI examinations for every patient in the whole therapeutic treatment, each of which can give data in multiple sequences, it is a large amount of

data to be dealt with for the doctors [33]. Long time of hard work will inevitably lead to mistakes in the diagnosis of the tumor contours for the doctors. Moreover, it is subjective for the doctors to determine the state of the diseases per their medical knowledge and clinical experiences [34]. Therefore, developing an automatic or a semi-automatic computer-aided diagnosis system is meaningful in real medical treatments, which can release the workload of doctors and improve the accuracy by giving objective results [35].

3 BRAIN TUMOR SEGMENTATION

Identifying brain tumor is challenging and this process mainly comprises three stages such as pre-processing, feature extraction and classification [36] as shown in figure 2.

Figure 2: Stages of Brain Tumor Segmentation

Before feature extraction, the pre-processing phase performs image enhancement functions such as noise reduction, denoising, filtering, and skull removal [37]. The feature extraction refers to the previous function of measuring image segmentation values, such as energy, entropy, correlation, correction, and standard deviation. The second step is segmentation, and the final one is classification. The existing methods in segmentation of tumor imaging and its classification include Artificial Neural Network (ANN), Self-Organizing Mapping (SOM), Learning Vector Quantization (LVQ), segmentation of the hydrographic basin and clustering [38].

3.1 Pre-processing

The preprocessing phase is very important in MRI segmentation of an image. Using these techniques, they qualify the results of the segmentation. Normally, image segmentation requires preprocessed techniques to achieve segmentation. This pre-processing has different methods of image processing, such as the de-noising method, the inhomogeneity method, and the filtering method, etc. to obtain robust MRI tumor segmentation. Faisal *et al*. [39] have introduced an improved approach for 2-D tumor segmentation. In this method, a robust automated brain tumor detection method is presented with modified Partial Differential Equations (PDE) to denote cerebral MRI images. A new skull removal technique has also used, which successfully removes the skull. On testing the novel approach under multiple brain imaging, the results provided a good Peak Signal-to-Noise Ratio (PSNR) value and accuracy in detecting the tumor automatically. Sulaiman *et al*. [40] introduced a switching based grouping algorithm. This algorithm has employed on MRI brain images that are corrupted by an assured amount of noise and salt. Also, the effective realization of the projected

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method has demonstrated by quantitative measurements. Prima *et al*. [41] offered the popular NL algorithm to propose the alternation of the intensity of the MRI image. In this, each voxel of an image is weighted by the sum of the similar voxel intensities. In some images, there were certain redundancies. Voxel image has generally evaluated in the space quarter of a voxel. In traditional NL, the algorithm and the voxel cell must be processed. Aksam *et al*. [42] introduced the Enhanced Non-Local Means algorithm for applying magnetic resonance to the brain by providing several extensions of the Improved Adaptive Non Local Means (IANLM). Initially, IANLM is modified to Rician noise in magnetic resonance imaging by applying a Rican diagonal correction procedure. Secondly, a selective medial filtering procedure is used as a post-processing step to overcome the IANLM limits. Several varying parameters of the algorithm is proposed by Enhanced Non-Local Means (ENLM), to optimize the application of brain MRI. Finally, the impact of the ENLM algorithm on segmentation is studied, and improved segmentation results have been achieved compared to other segmentation techniques at the cutting edge. Bauer *et al*. [43] introduced automatic brain segmentation based on the atlas registration with a Markov Random Field (MRF). This method was based on the Atlas registration and was a combination of biological, medical treatment. Here, the brain tumor has specified as a random field without markers. MRF has performed with basic methods. The advantage of the method is that the image is evaluated qualitatively and compared to the existing method. Also, this method can be used to align the image and adjust the spatial noise for noise estimation. Nie *et al*. [44] have introduced the MRF space precision field for tumor identification in multi-channel sequences using various techniques such as MRF and Space Precision. This method has several techniques such as Hidden Markov Random Field (HMRF) and spatially weighted spatial accuracy vector based on the precision of the space. The multi-channel segmentation method can be employed to achieve alignment of low-resolution FLAIR, T1, and T2 images. The advantage of this method is that the correct images of inhomogeneity and the implementation of skull removal images are automatically displayed. A series of wavelets is a representation of an integrated square function through an orthonormal series determined by a wavelet which is proposed by Salwe *et al*. [45]. The wavelet transformation has applied over the grayscale image and all the diagonal, vertical, and horizontal coefficients and stored for later processing. Demirhan *et al*. [46] established the Wavelet transformation method for the segmentation process. It takes advantage of being adaptable to frequency, time, and discontinuities in the image. Joseph *et al*. [47] have established the morphology filtering method, which has been applied to detect the size and shape of the structure's image. In this method, the operation has

performed by structural elements such as the input image and the structural image. The input image elements are larger than the structural element, and the input element was used to probe the input image. The central pixel of the structural image has defined by the basis of the structural element, and the input image element defines around the structural image. Here, the input image was represented by the corresponding image when the image was adapted. This method contains two functions, such as expansion and erosion. Expansion has the highest value of all the pixels, but the erosion has a very low value for each pixel. The output of the erosion function is a very thin image, and on the other hand, expansion has a very thick image neighborhood. Askins [48] introduced the morphological filtering method. The method is efficient for pre-processing image segmentation. The morphological filter has two main functions, like dilatation and erosion, to identify the tumor cell in the brain. Ananda *et al*. [49] describe a new structure for primary tumors automatic segmentation and its limitation by the magnetic resonance of the brain using morphological filtering techniques. This method uses weighted T2 and FLAIR T1 images. This approach is very simple, precise, and consumes less time than existing methods. They took 50 patients for the testing process with different types of tumors, forms, image intensity, size, and have achieved better results. Dawngliana *et al*. [50] introduced the central filter method, which was used to achieve noise reduction in the brain image. Depending on the average value and the intensity of the image, they replaced the pixel value. The median filter has proved to be the best way to reject noise from the MRI image. The noise removal retains the edge of the image. The filter produces the image of the MRI brain with high contrast and high quality. Kavitha *et al*. [51] set the Gaussian filtering method mainly to remove unwanted passages from the entrance during fall and growth time. The change in the function of the Gaussian filter inputs is also known as the Weierstrass transformation. The Gaussian filtering method works both continuously and discreetly. Iscan *et al*. [52] use 2D-Complex Wavelet Transform (CWT), and Incremental Supervised Neural Network (ISNN) for the segmentation of brain images, which segments the images into seven classes. Several segmentation approaches might be applied to form binary images. The performance of the novel approach is directly related to the selected segmentation approach performance. After the segmentation, the tumor has extracted from the background simply by throwing back the pixels. The symmetry of the axis in the MR image determines the use of the properties of the moment. The analysis of asymmetry using the Zernike moments of each of the six segmented tissues of the head and two vectors are individually formed in the left and right sides of the symmetry axis on the sagittal plane using the Zernike moments of segmented tissues. The execution of the

method was further studied by moving the tumor site and modifying its size in the phantom image. Sikka *et al*. [53] have designed segmentation of imaging using k-means and optimized c-means.   Segmentation performs for all proposed tumor detection methods. Several methods such as hydrographic segmentation for clustering algorithm optimized clustering k -means with a genetic algorithm, and c-optimization means clustering with genetic algorithm has introduced. The comparison was also made regarding the tumor region and search time. From the comparison, the grouping of C-Means after optimization was found to be better than other methods.   However, the genetic algorithm improves the convergence, and the calculation time is low. Thus, the issue of segmentation has also been addressed. Park *et al*. [54] have established the skull stripping technique to address the issues in the segmentation of the brain tumor and the parameter of the MR scanner. The segmentation images obtained are usually in low contrast, and these poor-quality images are very difficult for segmenting precisely. When compared with the clustering methods, the Skull stripping method was difficult to perform. Pereira *et al*. [55] have established the intensity normalization of image segmentation. The standard deviation and the mean intensity values were computed in each sequence. After that, the sequence will be normalized to unit variance and mean value. The introduced method was used for the MRI image segmentation to increase the image quality, intensities of the image, and image contrast across the acquisition and patients.

3.2 Feature Extraction
The feature extraction method withdraws the features from outlier for detecting the tumor in the image segmentation. Feature extraction was used to detect the tumor and its exact position of the tumor. The feature extract method has classified into three types. Dubey *et al*. [56] describe the three semi-automated approaches presented for tumor imaging segmentation that exceeds the precision and sensitivity limits of current solutions. In the RoI method, the selected segmentation region has converted to a label matrix, and all the images are extracted to use in the image toolbox. The goal is to examine three techniques: level set, marker-controlled watershed and Modified Gradient Magnitude Region Growing Technique (MGMRGT) and then compared against expert's manual segmentations. Finally, the reliability of brain tumor area measurements quantitatively compared with manual tracking method and semi-automated segmentation methods. Zulpe *et al*. [57] introduced GLCM Textural Features for brain tumor identification. The second-order statistic quality feature extraction of image segmentation is known as GLC Matrix. Whereas the GLCM is a co-occurrence matrix, and the images are split into several rows and columns to specify

the grayscale intensity values that are determined between 0 to255. The GLCM textual features of each class have then applied to two layers of Feedforward Neural Network, which offers a 97.5% classification rate. Ghanavati *et al*. [58] introduced a multimodal frame for automatic tumor detection by combining different MRI modalities, including T1-weighted, T2-weighted, and T1 with gadolinium contrast agent. Initially, the intensity, shape deformation, symmetry, and texture characteristics have extracted from each image where the AdaBoost Classifier was used to select the most discriminating features and to segment the tumor region. MR images with simulated tumors have been used as real truth for training and validating the detection method. Parisot *et al*. [59] exploited previous knowledge in the form of a limited graph representing the expected spatial positions of the tumor class. Such information was coupled with image-based classification techniques, along with space-smoothing constraints to produce a reliable detection map in a unified graphical formula. Effective linear programming in terms of both performance and the computational load was considered to recover the lowest potential of the objective function.

3.3 Segmentation
It is critical to segment the tumor by protecting the healthy tissues as well as after applying any therapy. Almost in all medical image processing techniques, initially, the segmentation is processed. For understanding the structure and function of the brain using automatic segmentation, the brain organs are divided into white matter, gray matter, and Cerebrospinal fluid. Weglinski [60] introduced segmentation of brain cell division into the dominant part of medical processing. The purpose of the method is to find scrap and pomology inside the brain. This method is a growing approach to the sowing region that refines the area of the brain segment attacked by the tumor. The advantage of the method it can refine the real-world MRI data set to display clearly and separate pixels. Zabir *et al*. [61] established the new model of brain tumor segmentation, particularly in the glioma region. This type of brain tumor arising from the glial cell, which accounts for about 80% of the dangerous conditions. Here, they explained that the rate of growth of the disease by dividing into two types: high grade and low-grade glioma. The proposed techniques detect tumor cells by using automatic computer-assisted techniques. The proposed method could increase the overall detection of the tumor and recognize the various types of glioma (tumor). Sachdeva *et al*. [62] have designed a new approach to the active contour model. This method has different patterns such as Gradient Vector Flow (GVF), Magnetostatic Active Profile (MAC), and Vector Fluid Flow (VFF). The active modeling method has been used to analyze the performance of homogeneous brain tumor techniques. The main advantage of this method is the fact

that they have two different sets of data in five homogeneous, heterogeneous, different diffusion tumors, and the synthesis of the images. Bhat *et al*. [63] introduced an active contour model of the river basin algorithm. Here, the active modeling method was used in the tumor region of the cerebral tumor segmentation extract. This method has been used to reduce the complexity of image computation and to improve image segmentation without noise. The advantage of this method is the high quality of image acquisition interval, clear extraction of the concave tumor region, precise tumor segmentation, and low sensitivity noise. Maiti *et al*. [64] introduced the basin type of the tumor detection method. The river basin for the brain color NMR method in HSV color space techniques are used to detect the edges of the image. Using HSV image techniques, images are divided into hue, saturation, and intensity. The advantage of this method is that the segmentation images rounded using the edge detector improve the accuracy. Dhage *et al*. [65] introduced river basin segmentation with ICCL coding techniques of connected components to detect tumor segmentation. The paper proposes the potential of hydrographic segmentation, such as image acquisition, image preprocessing, and contrast parameter. The Watershed method divides the abnormal tissue from the usual closure tissue to obtain a real identification of the required area, which helps the surgeon to discriminate the complex area. The advantages are simplicity, consistency, and reduced noise. Moreover, the high-frequency MRI elements were extracted from the MR image and the exact position, shape, and variables like perimeter, eccentricity, entropy, and centroid are also calculated. Vriji [66] introduced medical image processing using river basin segmentation. The proposed segmentation techniques used Computer Assisted Diagnostic (CAD) segmentation. In the proposed section, there are two phases, such as the pre-processing and improvement phase. Initially, the medical image has been transformed into the standard formatted image. The segmentation method has several advantages since exploring the possible use of MR segmentation imaging accurately improves brain, 2D, and 3D brain tumor shape for surgical planning and gauge cancer. Cuadra *et al*. [67] have introduced the method of deformation of the Atlas for complex tumor areas. These explain the growth of the lesion and the condition of the lesion based on three stages. The first step is to bring the bluff record, and the next is to scatter. The last step is for the deformation of the seed, combined with the model of the lesion. The method based on the atlas has exceeded the limitation of the size of the seed per target. The disadvantage is that more time is required to set up the atlas for computational procedures. Gordillo *et al*. [68] proposed an automatic and unattended brain tumor method. This method covered the completely new approach explained the operation in two steps: 1. fully

automatic, 2. without surveillance. The method was completely accessible based on automatic and intensity objectives. The purpose of the fuzzy method used to measure the exact image of the brain tumor in qualitative comparison with the existing method. This performance was achieved in 2 dimensions. Khotanlou *et al*. [69] proposed 3D MR images. The fuzzy method can be applied to different types of brain tumors. Here, they mainly used a new type of fuzzy methods, such as the fuzzy classification method and the symmetry analysis method to identify tumor areas. This method had several steps applied to the tumor area. The steps are primarily to calculate the exact symmetry plane; secondly, it was used both in tumor segmentation and in the initial brain tumor detection, and the two methods are presented in the initial segmentation of the tumor. The method has several advantages such as automation in symmetry analysis, and the broad range of tumors was more general. It has also been used to find the type of tumor, such as edema. El-melegy *et al*. [70] introduced the new fuzzy c-medium approach to detect normal and abnormal brain tissues in the magnetic resonance data series. The unwanted information is modeled, this information is the legalized cluster was produced by the fuzzy algorithm. It was used to correct the noise signal and unwanted data. The advantage of this method is better segmentation of the correct value, detection of normal and irregular brain cells and can be used to find the large type of tumors and shapes, sizes, position, tissue homogeneity. Zarandi *et al*. [71] introduced the second fuzzy type to diagnose brain tumor in the human body using magnetic resonance imaging T1. The image processor of this method was executed in four modules. The first step applied Possibilistic C-Mean (PCM) in the fuzzy distance method II, Mahalanobis, and the Kwon validity index. In the next part, the threshold method was used. The last step was used to recognize the tumor's condition in the brain. This type of method has several advantages because it was used to test the brain and measure the exact brain value and recognized better brain tumor than the fuzzy type I method. Dou *et al*. [72] proposed a fuzzy method for the detection of brain tumor in multispectral, T1-weighted magnetic resonance, weighted T2 weights, and proton density for image segmentation. In this method, some algorithms are applied, such as the first multispectral MRI record. The second section collects information from the intensity of the image. Using this information, the fuzzy is automatically defined as a parameter. Finally, the fuzzy image segmentation was valid for the result of the image. This method has provided several main advantages, such as segmentation of the 3D image, this type of segmentation use complete automation to take complete pathological information Liu *et al*. [73] introduced a method for accurate and high-grade tumor segmentation. This method that uses multiple MRI

algorithms is FLAIR, T1 and T2 to combine improvement tissues and non-fatal tissues in the tumor area. This method has used several steps, such as recording the T1 and TIE scenes and subtracting by specifying the VIO and seed needed to segment the connectivity. This method can be used for automation and continuous image with accurate high-speed values and can also improve the efficiency of the MRI segmentation system. Solomon *et al*. [74] established the identification of the brain tumor using a hidden Markov model. Response to treatment responses is classified as complete response, the response in partial, stable disease and progressive disease. The proposed method for paper has several steps, such as 3D spatial segmentation, the hidden model, the trading model. Here they explained the automated approach using probabilistic intelligence both in space and time to segment tumors from RMD space-time RMR data. The advantages of the method are the 4D segmentation method being the improvement over the existing method, the inclusion of positive sentences from the normal intensive tissue was greatly reduced. Bauer *et al*. [75] presented an automatic method of segmenting the brain tumor. The approach was based on the atlas method, being the combination of biomedical treatment. Here, the cerebral tumor is specified as a random field marker without mesh, MRF was performed with the basic methods: the tumor would be the first in the displacement pattern, the tumor increased in the three dimensions. The advantage of the method by which the image is evaluated qualitatively and clearly has been compared with the existing method. Bauer *et al*. [76] have introduced the method based on the atlas using the random field Markov. The proposed techniques have been explained of the mesh-free method applied to compare healthy segmentation of the brain image and abnormal segmentation of brain tissues. The advantages are represented by the 2D image, this method is applied in five different sets of tumor data and visualize the conditions and dimensions of the tumor cell. Mori *et al*. [77] have established the Diffusion tensor imaging method to detect tumor status. The proposed methods are based on DTI, color code image, and 3D tract techniques. The proposed techniques utilized to identify the anatomy of white matter. The foremost advantage of the DTI provides new information on the special link between the tumor level and the adjacent white matter sections that may be useful for administrative planning. Zou *et al*. [78] presented systematic approaches to validate the accuracy of the results of automatic image segmentation, which led to the probabilistic interpretation of the tumor class by pixel. He then developed an EM algorithm to estimate the latent gold standard. In addition, they modeled the results of probability segmentation using a mix of two beta distributions with different form parameters. Therefore, precision measurements, including the ROC curve, mutual

information and the similarity of the nuts were estimated. Furthermore, an optimal threshold was obtained within each metric. Aslam *et al*. [79] presented an improved edge detection algorithm for brain tumor segmentation. It is based on the detection of Sobel edges which Combines the Sobel method with the dependent image threshold method and finds different regions using the boundary cycle algorithm. Eventually, the tumors are extracted from the image using the intensity information in the closed contours. The algorithm is implemented in C and its performance is measured. The results of the simulation show that the algorithm offers superior performance compared to conventional segmentation

3.4 Classification

The classification of the tumor region from normal tissue is an important criterion for a robust medical imaging application. There are numerous methods to classify the tumor part. Neural Network is a short-haired network connected to each neuron. Each neuron receives the weighted information and produces the weighted production. This method is based on the function of the biological neural network. It mainly classifies the image of the normal and abnormal brain. Lee *et al*. [80] investigates the performance of tumor segmentation of a recent variant of Discriminative Random Fields (DRF) models that exploit the SVM classification method. In combination with a powerful magnetic resonance pre-processing pipeline and a series of alignment features, we evaluate the use of SVM, MRF and two types of DRF as classifiers for three segmentation tasks related to the target planning of radiotherapy for brain tumors. SVM-based DRFs, therefore, offer a significant advantage over other approaches. Cai *et al*. [81] the parameter of the SVM method, the kernel's default, produces a good result. Sometimes the researcher wants to create the intensity of the voxel using a large number of MRI modes based on function vectors. Using this method, SVM was classified. This method was not only used for tissue segmentation, and also used for brain tumor segmentation. This method was used only for the segmentation of the lateral tumor regions developed based on the kernel class and to obtain a better result. Bauer *et al*. [82] module for multi-kernel SVM. This type of technique was used for multiple segmentation of brain tumor imaging, and this method consists of two steps. The tumor regions should be classified in multi-image format and will receive multi-distance results and the maximum probability. Tian *et al*. [83] introduced a Learning Vector Quantization algorithm and was a type of neural computation based on the supervised method. In LVQ, training data is based on the input space. The quantification of the learning vector defined by some classes, such as prototypes and the nearest neighbor's rule. LVQs have three types of levels, such as input level, exit level, and

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competitive level. In segmentation, there are more fabrics, which are separated by layers. Here the input data was a competitive layer, used to classify in the self-organizing method so that the output level will compete with the target classes. Using LVQ input data similar to Euclidean factors and distance are determined. Corso *et al*. [84] present a new method for automatically segmenting heterogeneous image data, which was a step towards overcoming the gap between bottom-up affinity segmentation methods and top-down generalized approaches. The main contribution of the document was a Bayesian formula incorporating the attributions of soft models in computational affinities, which are conventionally non-modular. Then integrate the affinities of the conscious multilevel segmentation model using the weighted aggregation algorithm and apply the technique for detecting and segmenting brain tumor cells and MR multi-channel edema. The efficient calculation method executes orders of magnitude faster than the latest cutting-edge techniques, providing comparable or better results. Patenaude *et al*. [85] a Bayesian layout model has been proposed that incorporates both form information and intensity from a training set. The idea is similar to the active aspect model, except that it uses a probabilistic structure to estimate the relationship between form and intensity and to a large extent, uses conditional probabilities. Furthermore, the method can be used to perform peak analysis to investigate differences in shape between groups of subjects. It provides a local and direct measurement of geometric changes that are not based on tissue classification or arbitrary extension of leveling. Logeswari and Karnan [86] proposed a cluster Self-Organizing Map (SOM) algorithm for the segmentation of the medical image. This document describes the two-step segmentation method. In the first phase, the image of the MRI brain was obtained from the patient's database. This film eliminates artifact and noise. In the second phase, the image segmentation allows to accurately identify the main tissue structures in these volumes of images. They present a new method of segmentation of unsupervised MR images based on the C-Means fuzzy clustering algorithm for segmentation. Dhanalakshmi and Kanimozhi [87] a K-mean clustering method for identifying MR brain images are mainly based on characteristics and attributes. The number of object groups was called K-means, which is a positive integer. When the Euclidian has minimized, it makes a distance between the cluster's centroid and the data. The K-mean clustering was the unattended method type. In the K-mean method training group, the cluster in random order calculates the values of each cluster and each pixel. Based on the distance value, the cluster center was detected. K indicates that the method was used to position the images in bounds and objects. The main purpose of group

segmentation was the region exhausted in the photo and exclusive. Zhang *et al*. [88] The Fuzzy C-mean cluster method was introduced and was used to allow two or more data groups to identify brain tumor. This cluster will analyze the data and divide it into the collection of an object in the cluster. The C-mean method has two properties, such as homogeneity data within the cluster, and heterogeneity between cluster data, allowing different data from the different cluster. This method is not suitable for identifying the fuzzy model, but the cluster method will divide the data and create the membership function. Shokouhifar *et al*. [89] introduced the medium cluster algorithm to identify the brain tumor in the original images with a traditional method of MRI segmentation. The performance of this method has been simple and fast but does not identifies noise and abnormal images. Normally, MRI images present unwanted noises and inaccuracies. But this C-mean method will find the exact shape and size of the target. The neural network region associated with pulses of interest for images is very important for image segmentation, each image segment being a process and analysis for smoothing the image. The primary function of this method is used to identify the front of the image. Pulse-Coupled Neural Networks has managed to solve the image problem that identifies the model, image segmentation, and detects image margins. These define the RoI in segmenting the image. PCNN can find the image pixel neuron. In image segmentation, each neuron divides into three phases: pulse generation, section, and modulation. The output contains a few steps, such as segmenting image, plot, and edge information, which is a dynamic output. Chou *et al*. [90] presented an extended neural network algorithm coupled to pulses that work in 3-D over the entire image volume. They evaluated performance based on different Signal to Noise Ratio (SNR), resolution, and tested those methods against brain surface extractor algorithm in the brain. The results show that the method goes beyond existing methods and was robust with reduced SNR effects, partial volume at lower resolutions, and facilitate the automatic processing of large-scale studies on rodent brains.

4 PERFORMANCE ANALYSIS & COMPARISON

In this section the performance of the existing brain tumor segmentation algorithms are evaluated and compared using a brain tumor dataset which contain a total of 253 MRI brain images with 155 abnormal (cancerous) brain MRI images and 98 normal (non-cancerous) MRI brain images. The simulation is carried out on a personal computer (4.0 GHz CPU, 8GB RAM) using MATLAB (2016a). Table 2.1 Compares some existing works carried out for segmenting brain tumor from MRI images.

Table 2.1: Comparison of existing algorithms used for brain tumor segmentation

Study	Author Name	Title	Techniques used		
			Pre-Processing	Extracted Features	Segmentation/ Classification
[51]	Kavitha et al. 2012	An efficient approach for brain tumor detection based on modified region growing and neural network in MRI images	Gaussian filtering	Area, mean, correlation, orientation, covariance	Modified region growing & Feed Forward Neural network
[52]	Iscan et al. 2010	Tumor detection by using Zernike moments on segmented magnetic resonance brain images	2D continuous wavelet transform	Zernike moments	Incremental supervised neural network
[53]	Sikka et al. 2009	A fully automated algorithm under modified FCM framework for improved brain MR image segmentation	Homomorphic filtering	Contrast	Modified fuzzy c-mean (MFCM) technique Neighborhood-based membership ambiguity correction
[55]	Pereira et al. 2016	Brain tumor segmentation using convolutional neural networks in MRI images	Bias field correction	First-order and fractals-based texture gradients, brain symmetry, and physical properties	Convolutional Neural Networks
[56]	Dubey et al. 2011	Evaluation of three methods for MRI brain tumor segmentation	Image smoothing and contrast enhancement	Intensity, location, orientation	Modified gradient magnitude region growing technique, level set segmentation, Marker-Controlled Watershed Segmentation
[57]	Zulpe & Pawar 2012	GLCM textural features for brain tumor classification	Gaussian filtering	GLCM Texture Features	Feed Forward Neural network
[58]	Ghanavati et al. 2012	Automatic brain tumor detection in magnetic resonance images	Bias correction, image registration	Intensity, shape deformation, symmetry, and texture	AdaBoost classifier
[60]	Lahmiri & Boukadoum 2011	Brain MRI classification using an ensemble system and LH and HL wavelet sub-bands features	2D-DWT	Statistical Feature Extraction from LH and HL coefficients	SVM classifier
[61]	Zabir et al. 2015	Automatic brain tumor detection and segmentation from multi-modal MRI images based on region growing and level set evolution	Squared shape filter	Intensity features	Fully automatic Region growing level set estimation
[62]	Sachdeva et al. 2012	A novel content-based active contour model for brain tumor segmentation'	-	Intensity, Texture and GLCM Features	Content-based active contour
[63]	Bhat & kunte 2010	A mixed model based on Watershed and Active contour algorithms for brain tumor segmentation	Watershed segmentation	-	Active contour algorithm.
[64]	Maiti & Chakraborty 2012	A new method for brain tumor segmentation based on watershed and edge detection algorithms in HSV colour model	Contrast enhancement	-	watershed method with canny edge detection
[65]	Dhage et al. 2015	Watershed segmentation brain tumor detection	Median & Bilateral Filter	-	Watershed Segmentation & Connected Component Labeling (CCL)

[68]	Gordillo et al. 2010	A new fuzzy approach to brain tumor segmentation	Filtering	Intensity	Fuzzy approach
[71]	Zarandi et al . 2007	Systematic image processing for diagnosing brain tumors	Fuzzy based image filtering	Mahalanobis distance, and Kwon validity index	Type-II Approximate Reasoning method
[73]	Liu et al. 2012	Classification of MR tumor images based on Gabor wavelet analysis	Wavelet analysis	Texture Features	Gabor wavelet analysis, SVM & LDA labelling
[74]	Solomon et al. 2006	Segmentation of brain tumors in 4D MR images using the hidden Markov model	-	-	3D-spatial segmentation & Hidden Markov model
[75]	Bauer et al. 2011	Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization	Edge-preserving smoothing filter	Intensity Features & mean, variance, skewness, kurtosis, energy, entropy	SVM combined with subsequent hierarchical regularization based on Conditional Random Fields
[79]	Aslam et al. 2015	Improved edge detection algorithm for brain tumor segmentation	-	Intensity features	Improved Edge Detection algorithm based on Sobel method and thresholding
[80]	Kharrat et al. 2010	A hybrid approach for automatic classification of brain MRI using genetic algorithm and support vector machine	Gabor filter	Texture features	Genetic algorithm (GA) and SVM

In most of the existing works, preprocessing is done before segmenting the original images. Preprocessing is performed in many ways mainly for removing the unwanted noise in the original image or to enhance the quality or intensity of the original image. In addition, some preprocessing techniques are performed for ROI extraction, skull stripping and outline removal of original image. To remove the unwanted noise from the original image filtering techniques such as Gaussian filter, Median filter, Gabor filter, Bilateral Filter, Smoothing filter, Homomorphic filter, Mean filter, Square shape filter etc are used often. Figure 3 shows the comparison results of different preprocessing techniques.
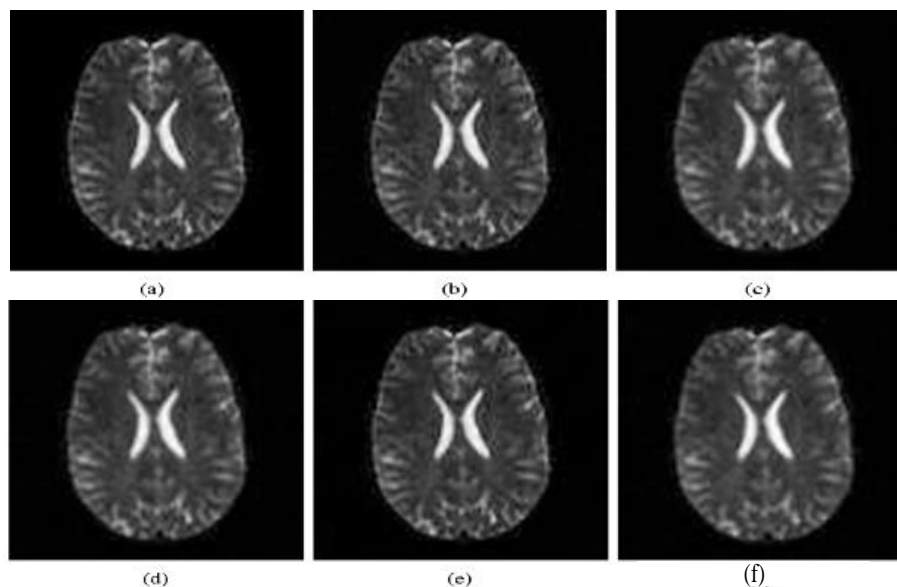

Figure 3: Comparison results of different preprocessing techniques (a) original image (b) Gaussian filter (c) Gabor filter (d) Median filter (e) Smoothing Filter (f) Homomorphic Filter

Figure 3 compares the results of different preprocessing techniques such as Gaussian filter [51], Homomorphic filter [53], Median filter [65], Smoothing Filter [75] and Gabor filter [80]. The intensity values of preprocessed images are higher than the original image and from figure 3 it is visible that Gaussian filter proposed in [51] serves its purpose

better than the other compared filters. From the literature works we identified that intensity based features, shape based features and texture features are most commonly used for feature extraction. We have randomly selected 10 brain images from the input dataset and the features values extracted from each image which are presented in table 2.2. The performance of classification algorithms is evaluated in terms of accuracy, sensitivity and specificity using the following expressions.

$$Accuracy = \frac{TP + TN}{FP + FN + TP + TN} \qquad (1)$$
$$Sensitivity = \frac{TP}{TP + FN} \qquad (2)$$
$$Specificity = \frac{TN}{TN + FP} \qquad (3)$$

Where TN=True Negative (correctly rejected), TP=True Positive (correctly identified), FN=False Negative (incorrectly rejected), FP=False Positive (incorrectly identified). From figure 4 to 6 we have compared the performance interms of accuracy, sensitivty and specificity of classifiers such as feed forward neural network (FNN) [51], increamental supervised neural network (ISNN) [52], Modified fuzzy c-means (MFCM) [53], convolutional neural network (CNN) [54], Adaboost [58], SVM [60], Fuzzy [68], Typr II Fuzzy [71], Hidden Markov Model (HMM) [74] and Genetic algorithm based SVM [80].
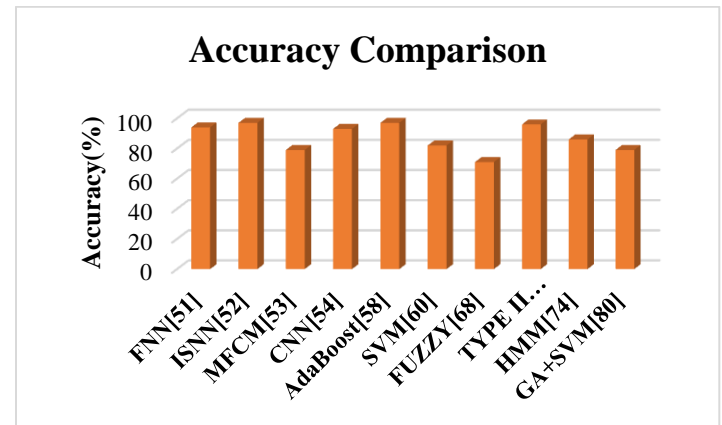

Figure 4: Accuracy Comparison

From figure 4 it is visible that the ISNN classifier proposed in [52] and the Adaboost classifier proposed in [88] attains a maximum accuracy of 96% with the proposed dataset. Similarly the FNN classifier proposed in [51], CNN classifier proposed in [54] and type II fuzzy classifier proposed in [68] attains the second maximum accuracy of 95%. The other classifiers proposed in [53], [60], [68], [78] and [80] also attains significant accuracies within the range from 80% to 90%.

Table 2.2: Feature Values Extracted for 10 brain images

| Study	Features Extracted		Input Images									
			Im1	Im2	Im3	Im4	Im5	Im6	Im7	Im8	Im9	Im10
[56],[58],[61],[62],[68],[75],[79]	Intensity based features	Mean	0.0003	0.00025	-9.2E-05	-0.047	-0.016	-0.014	-0.029	0.268	0.037	0.038
		Variance	0.0006	0.0008	-0.0012	-0.05	-0.011	-0.014	-0.03	0.076	0.0963	0.602
		STD	-2.6E-05	0.0005	-2.7E-05	-0.043	-0.025	-0.014	-0.025	0.056	0.197	-2.6E-05
		Skewnes	-0.0005	0.0001	0.0198	-0.037	-0.044	-9E-05	-0.029	0.005	0.066	-0.035
		Kurtosis	-0.0004	0.0009	0.044	-0.031	-0.059	-5E-05	-0.42	0.003	0.049	-0.44
[57],[62],[73],[80]	Texture features	Energy	-0.0041	0.0008	0.0601	-0.027	-0.061	-6E-05	-0.042	0.077	0.015	-0.041
		Entropy	-0.0046	0.0078	0.0825	-0.024	-0.05	-0.001	-0.035	0.258	-0.03	-0.46
		Contrast	-0.0063	0.0057	0.1392	-0.018	-0.034	-6E-05	-0.036	0.0191	-0.052	-0.63
		Correlati	-0.0082	8.2E-05	0.2325	-0.011	-0.028	5E-07	-0.043	7.7E-5	-0.058	-0.002
		Inertia	-0.0097	6.6E-06	0.3319	-2.3E-05	-0.028	7E-06	-0.052	-9E-05	-0.031	-0.097
[51],[56],[58]	Shape features	Area	-1.0E-03	-2.4E-05	3.9E-03	5.7E-05	-1.8E-04	-2E-05	-5.6E-04	-2.7E-04	3.3E-04	-1E-03
		Perimete	-1.0E-03	-6.1E-05	3.7E-03	9.6E-05	-8.7E-05	-6E-05	-4.7E-04	-3.5E-04	7.5E-04	-1E-03
		Orientat	-0.0008	-0.0011	0.3074	0.0123	-0.024	-0.11	-0.02	-0.32	0.059	-0.082
		Circulari	-0.0006	-0.0016	0.2038	0.0178	-0.057	-0.019	0.016	-0.26	0.687	-0.63
		Irregular	-0.0005	-0.0017	0.0035	0.223	-0.087	-0.025	0.712	-0.26	0.043	-0.054
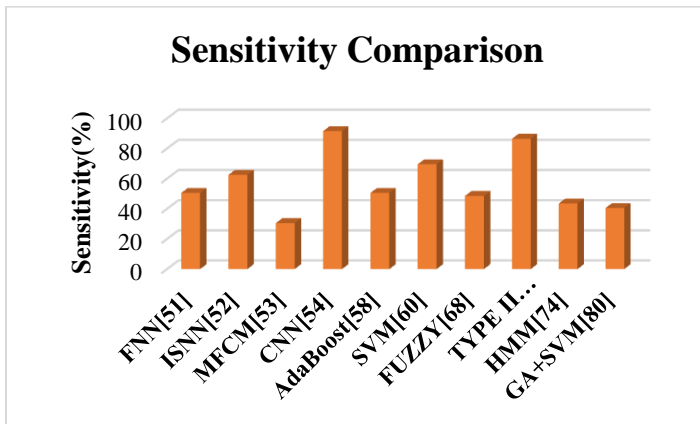
Figure 5: Sensitivity Comparison

From figure 5 it is visible that the sensitivity of CNN [54] and type II fuzzy classifier [68] is maximum than the other classifiers and the other classifiers also shows significant results. From figure 6 it is observed that the specificity of Adaboost classifier [58] is maximum when compared to other classifiers.
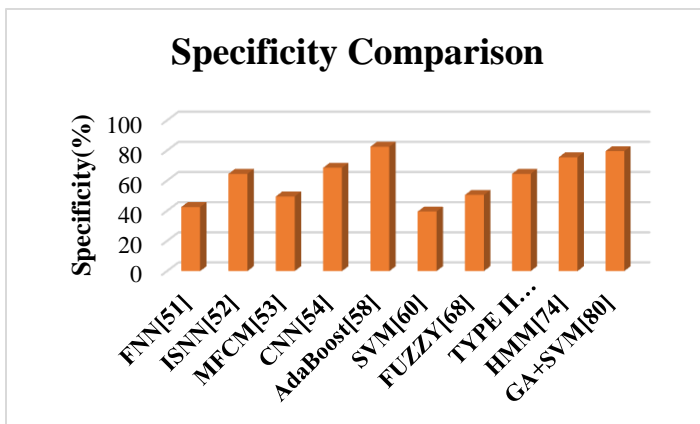

Figure 6: Specificity Comparison

5 CONCLUSION

A comparative analysis of MRI based brain tumor segmentation and classification techniques are presented in this paper. The goal of segmentation process is to detect brain tumor initially. For this purpose, various automated segmentation techniques are proposed which are highlighted in this paper. In addition, the different stages of brain tumor segmentation techniques such as pre-processing, feature extraction and classification is also explained in this paper. From the comparative analysis, it is observed that each technique has its own advantage and disadvantages and produce significant results in terms of accuracy, sensitivity and specificity. The determination of segmentation techniques is found to be very successful and reliable.

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