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Detection and Severity Analysis of Brain Tumor in MR Image

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***Abstract*— Brain tumor segmentation is the important procedure to separate the abnormal brain tissues from the normal brain tissue for early tumor detection. As MRI is the non invasive technique, it is widely used for the segmentation. Although numerous brain tumor segmentation methods are available, segmenting the tumor tissues is still a challenging task because of high diversity in tumor appearance and boundaries. This paper aims to provide the review of various brain tumor segmentation methods for MR images. Brain tumor segmentation consist of four basic step as per the review: Preprocessing, Feature Extraction, Segmentation, Post processing. Challenges of the reviewed methods are mentioned in this paper. Moreover the parameters for the performance evaluation and validation of result also discussed.**

***Index terms — Brain Tumor; Magnetic Resonance Image(MRI); Regularization; Supervised Learning*.**

I. INTRODUCTION

Brain tumor is the uncontrolled growth of the abnormal tissue in brain or the central spin that can disrupt the normal brain function. Brain tumor can be classified into two types based on the origin of the tumor and whether they are cancerous or not. Two types of brain tumor are Benign(Primary) and Malignant(Secondary or Metastatic). Benign tumors are least aggressive that originate in the brain and do not consist of cancerous cells. This type of tumor grows slowly and are curable. Malignant tumors have cancerous cell that originate anywhere in the body and spread to the brain. This type of tumor has rapid growth and do not have the clear boundaries. The World Health Organization (WHO) issued the most widely used grading scheme that classifies the tumor in four grades. In that grading scheme grade I and grade II tumors are considered as benign brain tumor (low-grade) and grade III and grade IV are considered as malignant brain tumor (high-grade)[1].

Image modalities plays an important role in brain tumor detection. There are various imaging modalities available such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Magnetic Resonance Spectroscopy (MRS) which provides the exact characteristics about tumor metabolism and morphology[2].

Magnetic Resonance Imaging (MRI) is the standard and non-invasive technique that provides good information about tumor size, shape and localization. In clinics, various types of MRI sequences are used to diagnose the tumor. These image sequences incorporate five types i.e. T1-weighted MRI (T1w), T1-weighted MRI with contrast enhancement (T1wc), T2-weighted MRI (T2w), Proton Density-weighted MRI (PDw), Fluid Attenuated Inversion Recovery (FLAIR), Fig. 1 shows the four standard sequences of glioblastoma (a type of brain tumor) patient[1].

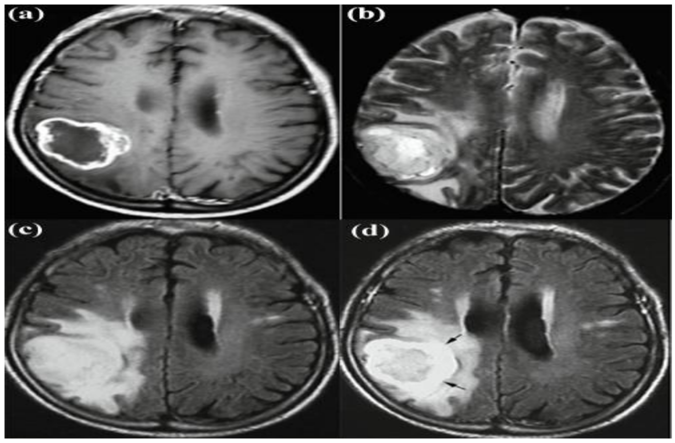

Figure 1. Four imaging modalities: (a) T1-weighted; (b) T2-weighted; (c) FLAIR; (d) FLAIR with contrast Enhancement[1].

The rest of this review is organized as follow: In Section II, the basic steps for brain tumor are explained. The existing methods for preprocessing are briefly discussed in Section III. Various methods for feature extraction in medical images are explained in Section IV. The most important and challenging step is segmentation and its various methods are explained in Section V. In Section VI some basic parameter defined for performance evaluation and validation. Finally, conclusion of the review is presented in Section VII.

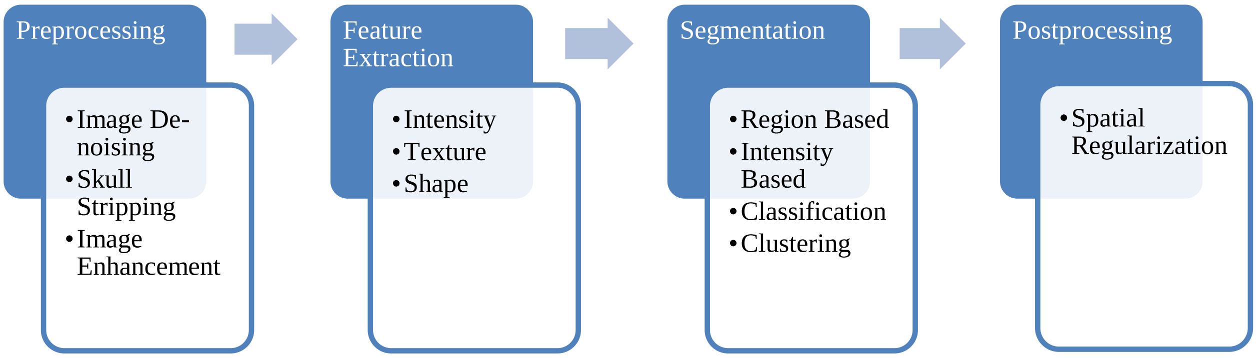

Figure 2. Steps for brain tumor detection

II. Steps for Brain Tumor Segmentation

There are mainly four steps in brain tumor detection as shown in Fig. 2.

A. Preprocessing

Preprocessing gives the finer image from raw MRI image. So preprocessing is directly related to the quality of segmentation result. These pre-processing operations include de-noising, skull-stripping, image enhancement etc.[1].

B. Feature Extraction

Feature extraction is a method to transform an image into its set of features[3]. To segment the brain tumor accurately, feature extraction is the fundamental task. For medical images, important features are texture , colour , shape, intensity etc.[2].

C. Segmentation

segmentation is the method to differentiate the abnormal brain tissues i.e. active cells, necrotic core, and edema (Fig. 3) from normal brain tissues[1]. Based on the requirement of human interaction brain tumor segmentation methods classified into three main types that includes manual , semi automatic and fully automatic segmentation[1].for tumor detection various segmentation methods available that includes intensity based methods, region based methods, asymmetry based methods and machine learning techniques[4].

D. Postprocessing

This includes various post processing technique for better result such as spatial regularization , shape constraints and local constraints[2].

III. Preprocessing

MRI acquisition process have the trade-offs between resolution, acquisition speed, and signal-to-noise ratio (SNR) which highly affect the image quality. One way to improve the SNR is to increase the acquisition time but it is not practical because of technical limitations and patient comfort. Hence, reduction in acquisition time degrades both the SNR and the contrast. It is difficult to segment the tumor from the noisy and low-contrast MRI data and most of the segmentation algorithms are very sensitive to noise, intensity in-homogeneities and low contrast. Hence preprocessing is required to reduce noise and to enhance contrast between regions[5].These pre-processing includes de-noising, skull-stripping, image enhancement, etc, that have direct impact on the results of brain tumor segmentation[1].

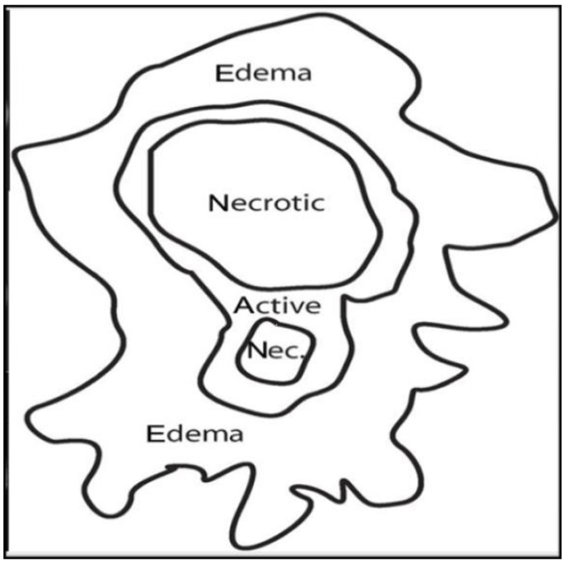

Figure 3. Three main components of abnormal brain tissue[1].

A. Image de-noising

It is a standard preprocessing task for MRI. There are several algorithms available for de-noising MRI data, some adapted from general image processing methods like Filtering methods i.e. Median filter[6] and Weiner filter[7].Some authors in [8],[9] argue that noise in MRI should be treated as Rician distribution which is more complex than standard Gaussian distribution. Various methods for image de-noising are shown in Fig. 4

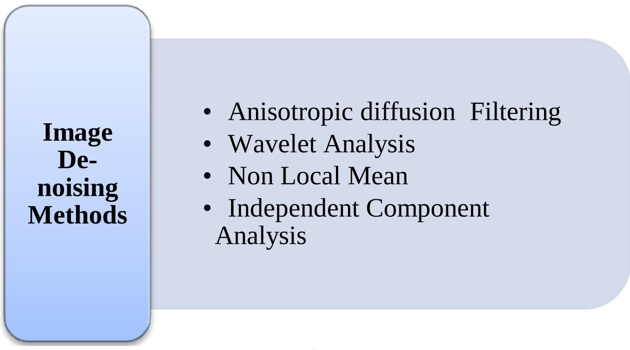

Figure 4. Reviewed Methods for Image De-noising

1) Anisotropic Diffusion Filtering: Anisotropic Diffusion is a multi-scale technique to detect edges. This method apply smoothing within continuous regions and avoids smoothing across boundaries[5]. This mechanism of smoothing and edge enhancement is obtain with the use of two orthogonal diffusion operator. One operator diffuses tangentially to the edges thus acts as an anisotropic smoothing operator, and the other diffuses normally to the edges and thus acts as an enhancement operator[10]. So, ADF is the current most popular method for the de-noising of brain tumor MRI images.

2) Wavelets Analysis: Wavelets analysis is intrinsically connected with the multi-resolution analysis which contain two basic operations: dyadic dilations and integer translation. This method can adapt discontinuities in both time and frequency which is the major advantage of this method. In this technique signal energy distributed along the scale-space. De-noising is achieved by applying thresholding to the wavelet mixing coefficient at different scales and discarding the non significant energy that do not change the signal characteristics[5].

3) Non-Local Means (NLM): The NL-means compares the geometrical configuration in neighborhood in addition with the comparison of gray level of single point[11]. It replaces the intensity of each voxel of given image by applying weighted average of the intensities of the other voxels of the image. These weights are the measure of similarity between neighboring voxels and the voxel to be reset, and the similarity is being evaluated using patches[12].

4) Independent Component Analysis (ICA): Independent component analysis (ICA) is a method to represents the set of multidimensional data vectors in the form of independent basis components. ICA de-noising methods rely on the fact that the transformed image have super Gaussian(sparse) distributions, so this method reduces the Gaussian noise by applying soft thresholding(shrinkage) to sparse components. The choice of a shrinkage function depends on how the sparse components are distributed[13].

ICA de-noising is best suitable de-noising in digitized MRI. But there is an issue that limits the performance of ICA is that, we cannot determine the variances (energies) and the order of independent components[14].

B. Skull stripping

It is the method for removing the non-cerebral tissue region such as skull, scalp, and meninges from the brain soft tissues. Fig. 5 shows a result of skull stripping of brain MRI[1]. Double thresholding and morphological operations can be used for skull striping and that gives the acceptable result[15]. The accuracy of skull striping directly affect the efficiency of tumor detection and hence it has been considered as an essential step for brain tumor segmentation. It has advantage that it reduces the chances of misclassification of abnormal tissues in brain[1].

C. Intensity normalization

It is the essential step for the preprocessing of MRI, especially when machine learning techniques are used for the segmentation. Contrast enhancement and mid range stretching will give brighter image which improves the quality of image[15]. Power law transformation and sharpening filter also give the noticeable enhancement in digitized MRI[6],[16]. Bias-field correction also applied to compensate the magnetic field in-homogeneities before the segmentation [2].

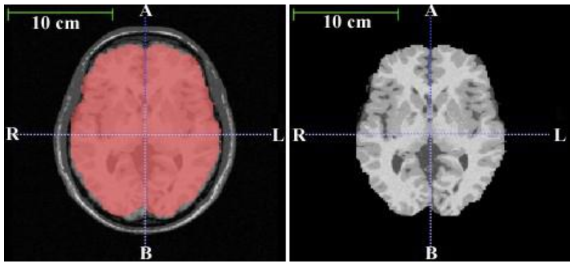

Figure 5. Brain tissues after skull-stripping [1].

IV. FEATURE EXTRACTION

Feature extraction gives the features on the basis of which brain MRI images can be easily classified as normal or abnormal. The features which are used for the segmentation of brain tumors largely depend on the type of tumor and its grade because different tumor types and grades have a lot of variability in appearance (e.g. intensity, shape, regularity, location, etc.)[2]. Different methods to detect the various features like Intensity, shape, texture from the brain MR images are discussed below. Various methods for feature extraction in medical images are shown in Fig. 6

A. Gray Level Histogram (intensity)

Colour histogram is the most common method to describe the low-level colour features of images. Medical images are only available in grayscale so a simpler histogram method called gray level histogram (GLH) is used to extract intensity of gray level colour map[17]. Moments of the gray-level histogram (MGH) also use to extract statistical properties of intensity distribution in local structure of the image that also give the satisfactory results.

MGH gives nine statistical properties (e.g. mean, variance, smoothness, uniformity, entropy, etc)[18].

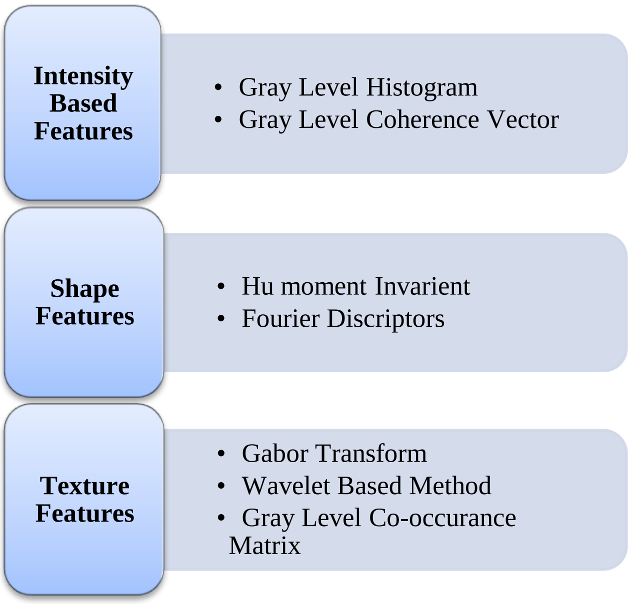

Figure 6. Reviewed Feature Extraction Technique

Mean gives the average value of intensity of the image. Variance is the intensity variation around the mean value. Skewness measures the symmetricity of histogram around the mean. Kurtosis provides the information regarding the flatness of histogram. Uniformity is represented by energy of the histogram. These properties are calculated and considered as the image features which are listed below[3],[18].

$$Mean: \ \mu = \sum_{l=0}^{G-1} ip(i) \tag{1}$$

$$Variance: \ \sigma^2 = \sum_{l=0}^{G-1} (i-\mu)^2 p(i) \tag{2}$$

$$Skewness: \ \mu_3 = \sigma^{-3} \sum_{l=0}^{G-1} (i-\mu)^3 p(i) \tag{3}$$

$$Kurtosis: \ \mu_4 = \sigma^{-4} \sum_{l=0}^{G-1} (i-\mu)^4 p(i) - 3 \tag{4}$$

$$Energy: \ E = \sum_{l=0}^{G-1} [p(i)]^2 \tag{5}$$

$$Entropy: \ H = -\sum_{l=0}^{G-1} p(i) \log_2 p(i) \tag{6}$$

B. Gray Level Coherence Vector (intensity)

Gray Level Coherence Vector (GLCV) is the technique for extracting intensity which uses the idea similar to Colour Coherence Vector (CCV)[19]. This method gives some spatial information about image. In this technique each pixel is classified as either coherent pixel or incoherent pixel. Pixels which belongs to a large connected group of similar pixels, are known as coherent pixels; otherwise it is known as incoherent pixels. The first procedure is to discretize the gray colourspace, which contains n distinct gray colours(or bins) that are used in the image. The next procedure is to classify the pixels within a bin as per its spatial information i.e. coherent or incoherent, by comparing the bin size with a predefined threshold value τ[17].

C. Hu Moment Invarient (shape)

Hu derived the invariant moments for shape representation. Hu has defined seven moments that are invariant to translation, scale and rotation. It is also skew invariant which can identify mirror images of an image or the identical images. This seven moments are used 7-dimensional feature vector[17].

D. Fourier Descriptor (shape)

Boundary and object representation can be easily done by Fourier Descriptors (FDs). Consider an image having N-point digital boundary which starts from an arbitrary point (x_0, y_0) and follows a steady counterclockwise direction. So, a set of coordinate pairs $(x_0, y_0), (x_1, y_1), \dots, (x_{N-1}, y_{N-1})$ can be generated which can be considered as a boundary points. These coordinates can be represented in a complex form such as

$$z(n) = x(n) + jy(n) \ ; \ n = 1,2,\dots,N-1 \tag{7}$$

The discrete Fourier transform (DFT) of *z(n)* given as below

$$a(k) = \sum_{n=0}^{N-1} z(n) exp\left[\frac{-j2\pi kn}{N}\right] \ ; \ 0 \le k \le N-1 \tag{8}$$

This complex coefficients *a(k)* are known as the Fourier Descriptors of the boundary points of an image[17].

E. Gabor Transform (texture)

Gabor filter is the texture descriptors introduced by Gabor in 1946. It is used to extract texture features by analyzing image in frequency domain. Basically, Gabor filter is a Gaussian function modulated by complex sinusoidal of frequency and orientation. It has the ability to perform both in spatial and frequency domain. It can be work in any number of dimensions[20]. A two dimensional Gabor function $g(x,y)$ and its Fourier transform $G(u,v)$ can be written as[21]:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right] \tag{9}$$

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\left(\frac{u-W^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right)\right]\right\} \tag{10}$$

Gabor wavelet forms a complete but non-orthogonal basis set that expands signal and provides the localized frequency descriptors which are referred as Gabor Wavelets

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. The non-orthogonality implies that there will be redundant information in the output data.

For a given image $I(x,y)$ Gabor wavelet transform is define as

$$W_{mn}(x,y) = \int I(x_1,y_1) g_{mn}^{*}(x-x_1, y-y_1) dx_1 dy_1 \quad (11)$$

Where * indicates the complex conjugate. Feature vector can be constructed using mean μ_{mn} and standard deviation σ_{mn} which can be define as

$$\mu_{mn} = \iint |W_{mn}(xy)|\, dxdy \quad (12)$$

$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(xy)| - \mu_{mn})^2\, dxdy} \quad (13)$$

F. Wavelet based Feature Detection(texture)

Wavelet transform is a series expansion technique that represent the signal at different levels of resolution[22]. Discrete Wavelet Transform decompose the image in the four sub band images and they are low-low (LL), low-high (LH), high-low (HL) and high-high (HH) channels. The energy within each sub band image is used as feature[17].The major problem in traditional wavelet transform, i.e. DWT and CWT, is they are not invariant to translation. To overcome this problem Demirhan et al.[23] used the Stationary Wavelet Transform (SWT) which is invariant to translation. Translation-invariance is achieved by removing the downsamplers and upsamplers in the DWT and upsampling the filter coefficients by a factor of 2^{j-1} in the j^{th} level of the algorithm. The complexity of SWT is directly proportional to number of samples. We can obtain statistical parameters such as energy, entropy, mean absolute deviation and standard deviation as a textural feature[23].

G. Gray Level Co-occurrence Matrix (GLCM)(texture)

For brain tumor segmentation, only intensity distribution-based features are not sufficient as they do not contain spatial information. Features extracted from the Gray Level Co-occurrence Matrix(GLCM) are based on the joint probability distribution of pairs of pixels. The dimension of the co-occurrence matrix is equal to the number of gray levels of the brain MRI[18]. It is defined as the occurrence of intensity levels i and j at a point and another point that is shifted by an offset d in θ direction[24]. Fourteen well-known coefficients were used as the GLCM-based features but only six of these features are the most relevant which are listed below[18].

$$Angular\ second\ moment\ (energy) : \sum_{l=0}^{G-1} \sum_{l=0}^{G-1} [p(i,j)]^2 \quad (14)$$

$$Correlation : \sum_{l=0}^{G-1} \sum_{l=0}^{G-1} \frac{ij\, p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (15)$$

$$Inertia : \sum_{l=0}^{G-1} \sum_{l=0}^{G-1} (i-j)^2 p(i,j) \quad (16)$$

$$Absolute\ value : \sum_{l=0}^{G-1} \sum_{l=0}^{G-1} |i-j| p(i,j) \quad (17)$$

$$Inverse\ difference : \sum_{l=0}^{G-1} \sum_{l=0}^{G-1} \frac{p(i,j)}{1+(i-j)^2} \quad (18)$$

$$Entropy : -\sum_{l=0}^{G-1} \sum_{l=0}^{G-1} p(i,j) \log_2[p(i)] \quad (19)$$

$$Maximum\ probability : \max_{i,j} p(i,j) \quad (20)$$

V. SEGMENTATION

Segmentation methods are mainly classified into three categories based on the degree of required human interaction that includes manual, semi-automatic, and fully automatic. Manual segmentation is very time consuming task and very much prone to error that yields to poor results. To address this issue, more advanced segmentation methods such as semi-automatic and fully automatic segmentation methods are introduced[1]. Various segmentation methods reviewed are shown in fig.7

A. Intensity Based Method

Intensity based methods are very simple and effective segmentation method which compares the intensity of image with one or more threshold. Low level operations like thresholding, edge detection and morphological techniques are the most popular techniques which lies under intensity based method. Thresholding technique mainly classified into global and local thresholding. If an image contains the objects having homogeneous intensity or the intensity difference between the objects, and the background is high then global thresholding is the best method for segmenting the object and background. Local thresholding can be determined by estimating the local statistical properties like mean intensity value for the different regions from the intensity histogram of an image[1]. The major issue in this method is extraction of tumor when the contrast of image is very low[1],[25],[26]. Morphological techniques are also intensity dependent. Moreover it cannot differentiate the tissues within the tumor[27].

Figure 7. Reviewed Segmentation Methods

B. Region Based Method

Region-based segmentation methods examine pixels as per predefine similarity criterion and generate the disjoint regions by merging neighborhood pixels. Watershed segmentation[7] and the region growing[27],[28] method are classified under the region based method. Region growing is the simplest method used to extract the connected region of similar pixels. It starts with at least one pixel that belongs to the Region of Interest (ROI) and Neighboring pixels are checked and those who satisfies the similarity criteria are added to that region[1]. It will correctly segment the regions that satisfy the similarity criterion. But partial volume effect limits the accuracy of this method. Another region based method, Watershed segmentation, is also the simplest method that consistently produces the complete boundaries[7]. But the problem of oversegmentation limits the performance of watershed technique due to weak and diffused edges generated by the edema[24].

Hence, It is hard to achieve a good result with the help of intensity based and region based methods. So these methods are sometime used in preprocessing[1].

C. Asymmetry Based Method

The healthy human brain is symmetrical about the mid-sagittal plane of brain. The tumor which appears in one of the cerebral hemisphere will generate the asymmetry between two, right and left, hemispheres that can be detected using asymmetry analysis[29]–[32]. Asymmetry based methods quite faster because segmentation is implemented only in one of the cerebral hemispheres. However, accurate detection of the mid-sagittal plane is a quite challenging and time consuming procedure [29]. Moreover , this method may not give accurate detection of tumor when a it is located across the mid-sagittal plane [31].

D. Machine Learning Methods

Machine learning techniques provide the effective way to segment and analyse the medical image data. Machine learning techniques are mainly classified into three types based on the use of labels of training data i.e. supervised learning, semi-supervised learning and unsupervised learning[1].

In unsupervised learning technique, only one set of observations is available. Usually these observations i.e. features are generated by a set of unobserved variables. This technique derive the relationships between samples or reveal the unobserved variables. Clustering methods are lies under the unsupervised learning[33]. For brain tumor segmentation k-mean clustering and fuzzy clustering are very popular unsupervised learning method[28],[34]-[37]. Clustering technique divides the one group of data into two or more cluster as per the membership score assigned to each data point. Membership score is derived from the Euclidian distance between the cluster center and the particular data point[1]. Unlike k-mean algorithm, Fuzzy C-Mean(FCM) assigns membership score to each data points for more than one cluster. Hence FCM give better result comparative to k-mean[38]. FCM is the iterative method so it is very time consuming. So for faster performance we can use Genetic Algorithm(GA)[39]. However these methods work well only for tumor having hyper intensity. It gives poor result for the non enhanced tumor. Moreover partial volume effect also limits the performance of clustering method[40].

In supervised learning technique, each sample have two sets of observation: One is input observations i.e. features and the other is output observations i.e. labels. This technique derive the functional relationship from the training data that will used to estimate the label of each pixel in testing data[4]. Classification algorithms are popular method of the supervised learning. In this method well trained classifiers like Support Vector Machine(SVM),Artificial Neural Network(ANN) ,extract the important features from the training data and then segment the testing data as per provided feature space. However these methods classify each pixel without considering the spatial correlation between the neighborhood pixel [6],[15],[41]-[43]. So these method will not give globally optimized result. To overcome this issue regularization step added as post-processing. Regularization can be achieved by the variants of random fields i.e. Markov Random Field(MRF), Conditional Random Field(CRF) [41]-[43].

For some application labeling of data is very expensive so combination of supervised and unsupervised learning is developed, known as semi-supervised learning which uses both labeled and unlabeled data to train the data[1].

VI. PERFORMANCE EVALUATION AND VALIDATION

Validation of any brain tumor segmentation method is must required due to its direct impact on surgical planning. Few years ago, due to lack of standard brain tumor database with ground truth data, researchers evaluate their proposed method on limited cases from their own data. Hence difficulty arises in comparing the performance of different methods. So, for quantitative performance evaluation several matrix are introduced which can be define as follow[6].

True Positive (TP): Tumor region is correctly identified as tumor.

True Negative (TN): Non tumor region is correctly identified as normal brain.

False Positive (FP): Non tumor region incorrectly identified as Tumor.

False Negative (FN): Tumor region incorrectly identified as normal brain.

The most common quantitative evaluation method is to calculate the overlap with the ground truth data. Most commonly used evaluation standards are Jaccard Similarity and Dice Similarity Coefficient(DSC). Value this coefficient ranges from 0 to s1 where 0 indicates no overlap and 1 indicates perfect overlap[1],[44]. These coefficients can be define as follow.

$$Jaccard\ Similarity = \frac{TP}{FP + TP + FN} \quad (21)$$

$$DSC = \frac{2 * TP}{(FP + TP) + (TP + FN)} \quad (22)$$

Other various parameters i.e. correspondence ratio, perfect match, accuracy, precision, sensitivity, specificity are also used to evaluate performance of the tumor segmentation method which can be define as follow[26],[28],[29],[40],[44],[6],[45]:

$$Perfect\ Match = \frac{TP}{GT} * 100 \quad (23)$$

$$Correspondence\ Ratio = [(TP - 0.5 * FP)/GT] * 100 \quad (24)$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) * 100 \quad (25)$$

$$Precision = TP/(TP + FP) * 100 \quad (26)$$

$$Sensitivity = TP/(TP + FN) * 100 \quad (27)$$

$$Specificity = TN/(TN + FP) * 100 \quad (28)$$

VII. CONCLUSION

This method provides the overview of state of art methods for brain tumor detection for MRI. As MRI is the non invasive technique, it is widely accepted as the standard technique. Manual segmentation of tumor is very time consuming and prone to error. Hence semi automatic and fully automatic methods can be used for tumor detection. For fully automatic proper preprocessing is required. For efficient preprocessing, Anisotropic Diffusion Filter and min-max stretching algorithm is widely used technique for image de-noising and image enhancement respectively. Segmentation of tumor is carried out on the basis of features of the brain image. Gabor filter and Gray Level Co-occurrence Matrix provides sufficient features required for segmentation. In segmentation, supervised learning process, Support Vector Machine (SVM) is popular technique which gives accurate and acceptable result.

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