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Techniques for Detection and Analysis of Tumours from Brain MRI Images: A Review

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ABSTRACT

Analysis of MRI images and extraction of brain tumours from MRI images are challenging tasks in medical image processing. Researchers have contributed in segmenting and analysing brain tumour by applying varieties of the techniques and different hybrid approaches, however, due to diversity in appearance of tumour from patient to patient and also due to different tumour types, it has still been a challenge to exactly and correctly identify tumours from brain MRI image. Analysing brain MR images manually for finding exact boundaries of tumour by physicians is very time consuming and challenging due to low contrast MRI image and similarities of intensities between brain tissues. Many semi-automated and automated approaches have been developed to analyse MRI images and to delineate desired regions, such as tissues and tumour, and analyse their properties. This paper presents a comprehensive review of the state of the art methods for analysis of MRI images and methods for detection tumour from it. The review focuses, specifically, on important phases of MRI image analysis like feature extraction, segmentation and classification techniques. The challenges while processing brain MRI images as well as merits and demerits of existing methods for tumour analysis have been discussed.

1 Introduction

Magnetic Resonance Imaging (MRI) has been widely used as one of popular imaging techniques to visualize tumour region by physicians as it gives high soft tissues contrast compared to other technique like Computed Tomography (CT), Positron Emission Tomography (PET) [1,**6**]. To study various properties of tumours, its presence and to correctly separate out tumour from other healthy tissues, multiple MRI sequences like T1-weighted, T1c-weighted, T2-weighted and FLAIR images are used where each sequence provides different information and helps to locate tumour, edema or necrotic regions [1].

Major tasks during analysis of brain MRI images are to study abnormalities in brain, to separate out healthy tissues of brain mainly into Grey Matter (GM), White Matter (WM) and Cerebro Spinal Fluid (CSF), to detect presence of tumour, necrotic region, edema or lesion and to study pathological area like

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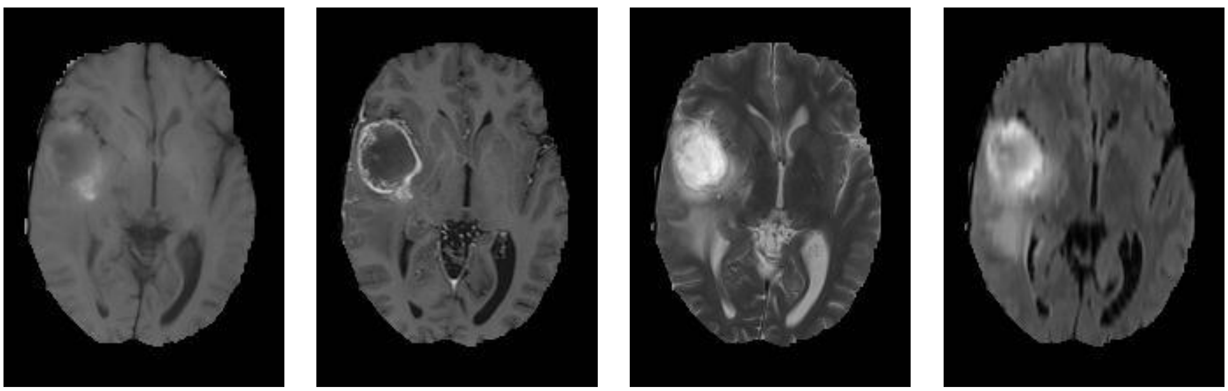
cancer for diagnostic purpose [2,3]. It also includes finding size of tumour, location of tumour and different categories of tumours.

Brain tumours are mainly classified based its degree of aggression and location of origin. Tumours which originate from brain are called primary brain tumours while tumours which originate from other part of body are called metastatic brain tumours. As per guidelines of WHO, grading of brain tumour ranges from I(lowest) to IV(highest) based on aggression of tumour. Grade III and IV tumours are malignant and chances of survival are very less while grade I and II are semi-malignant and better prognosis is possible [1]. Gliomas are most common primary brain tumour seen in human brain. Brain tumours are of different types which are (1) Lymphoma (2) Gliomas (3) Meningioma (4) Medulloblastoma (5) Pituitary adenoma and (6) Craniopharyngioma [2]. Based on analysis of healthy tissues also relation with specific disease can be predicted. The analysis also helps in surgical planning, predicting growth of tumour and aggression of tumour.



(a) (b) (c) (d)

Figure 1: (a) T1-weighted (b) T1- weighted with contrast enhanced (T1c) (c) T2- weighted and (d) FLAIR MRI real image sequence of brain of single person with high grade tumour collected from BRATS 2012 dataset [4]

Different MRI sequences have capability to separate different tissues which are generally highlighted in specific sequence based on tissue properties, e.g. T1-weighted image is good at separating healthy tissues in brain, T1c (Contrast enhanced with gadolinium-DTPA) helps in separating tumour boundaries which appear brighter because of contrasting agent, edema surrounded by tumour is detected well in T2-weighted images, while FLAIR images are best specifically in differentiating edema region from CSF [1,5]. Different sequences of brain MRI images of single patient are shown in Fig. 1 where we can notice different appearance of tissues in different sequences.

Brain tumour segmentations techniques mainly fall into three categories namely manual, semi automated and fully automated depending upon the human interaction required with the system. Various soft computing techniques have contributed a lot in the field of research for semi automated and fully automated segmentation of brain MRI images and many techniques have given promising solutions for image segmentation [3].

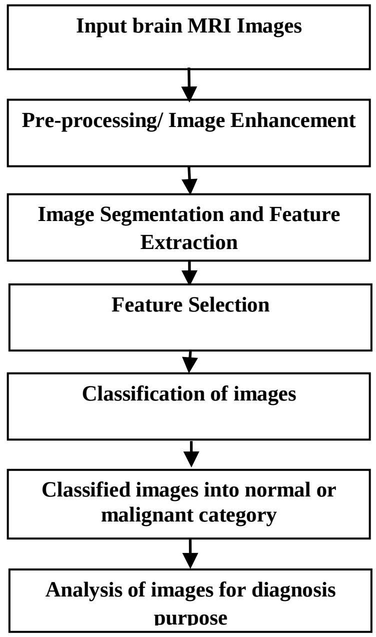


Figure 2: Block diagram of brain MRI image classification and analysis

Detection and correct segmentation of brain tumour is very difficult and challenging task due to low contrast image, unknown noise, unknown shape and size of tumour which varies from patient to patient, partial volume effect caused because of artefacts and uneven texture of tumours which appear differently for different patients [6].

Analysis of brain MRI images includes various phases as shown in Fig.2 where images are first pre-processed and enhanced mainly to remove noise, to normalize intensity values, to improve contrast and to extract brain from skull. Pre-processing helps in separating desired regions more accurately and also improves classification accuracy. After pre-processing, images are divided into homogeneous regions with similar properties called segmentation and features are extracted in feature extraction step. Most commonly seen Pattern Recognition problem in the domain of medical image analysis is finding discriminating features from a set of medical images and classifying them into set of classes. Feature extraction and feature selection plays very important role for detecting and classifying brain tumours [7]. Features are extracted mainly based on intensity values, texture properties, intensity gradients and edge detection.

Important features are selected in the feature selection phase by applying algorithms and based on these selected features, finally images are classified into various categories like normal or malignant by applying classifiers like SVM, ANN, kNN, Naïve Bayes and others which are discussed in subsequent sections.

This paper focuses on review of state of the art techniques from the literature which could be applied in each phase of brain MRI image analysis to achieve desired task. The paper is organized as follows. Section 2 presents review on pre-processing methods for enhancement of MRI images. Section 3 focuses on review of segmentation methods. Section 4 presents review of feature extraction and classification techniques. Section 5 concludes and summarizes the literature review.

2 Review of Pre-processing methods for enhancement of MRI images

MRI images are of poor quality [6, 8] for human visualization to understand finer details of tissue structures of brain. Also because of poor quality it is challenging to be processed by computational algorithms for further analysis. So, before algorithms are applied on images for further processing like segmentation or classification, images should be pre-processed and enhanced so as to improve segmentation and classification results. Researchers have proposed state of the art noise removal techniques which include linear and nonlinear filtering methods, wavelet based models, MRF (Markov Random Fields), NL-means (non-local means), anisotropic diffusion filtering and analytically correction schemes, and other advanced filters [2]. During noise removal it is very important to preserve edges and structure details without degrading image quality otherwise it degrades performance.

MRI images are of low contrast and many techniques are available that improve the contrast of the image and enhance the image that finally helps in improving visual appearance. Kharrat et. al. [8] presented mathematic morphology method for image enhancement which outperformed other well known methods like Contrast Limited Adaptive Histogram Equalization (CLAHE) and Beghdadi one. Anisotropic Wiener filter has shown good results in [9] for denoising as well as pre-processing of MRI images where it does not only reduce noise but also enhances image by preserving edges compared to other versions of wiener like isotropic and orientation where performance is measured not only in terms of MSE but also in terms of memory used, computational cost and performance. Basic wiener approach was similar to other popular wavelet based approaches as reported in literature but anisotropic property in wiener filter improved performance [9].

Gabor filters have been used for edge detection and texture based feature extraction but Veni et. al. [10] proposed Gabor filter based approach on Hexagonal Sampled Grids of x-ray images for image enhancement and obtained results of high quality in terms of the visualization of images and edges which were also well preserved. Best results obtained for texture images and approach found to be ideal for generating medical atlas from MRI images. Brain atlas reflects common anatomical map and structure of a brain which is prepared from different subjects before segmentation process is carried out. Atlas is used as prior knowledge and found to be useful when contrast between brain tissues is poor. So, to take advantage of atlas in segmentation, image is first registered with an atlas in a process called image registration [6].

Mainly for analysis of brain tissues from MRI images, non-brain region like skull is removed in pre-processing step. Chan-Vese algorithm of active contour used in [11] is known approach to separate brain region from skull by applying thresholding where threshold value is calculated based on intensity of skull region (non tissue) which is nearly zero and appears as black.

Techniques for segmentation of medical images are reviewed in the following section.

3 Review of Segmentation Methods for Brain MRI Images

Segmentation divides an image into set of segments or regions based on similar properties like similar intensity values, texture properties or based on given threshold values. Researchers have proposed many segmentation approaches which are generally classified as threshold-based, pixel classification based, region-based and model based techniques [3].

Many methods are proposed for segmentation of brain tumour which can be classified as (1) Machine learning and computational intelligent techniques like Artificial Neural Network (ANN), Fuzzy c-means (FCM), Support Vector Machine (SVM), k-Nearest Neighbour (kNN), Self-organizing map (SOM), k-means (2) Statistical models like Maximum Likelihood (ML), Gaussian Mixture Model (GMM), Expectation Maximization (EM) (3) Contour based techniques like active contours, deformable models, level set and (4) Thresholding, edge detection and region based techniques. Each category of methods has their own strength and weaknesses, hence proper selection of a method depends on background knowledge and suitable conditions to get best results from that method.

3.1 Machine learning and Computational intelligence based methods

From decades many methods are proposed by researchers for medical image analysis but with emergence of computational intelligence and machine learning methods in medical image processing, promising results have been obtained.

Gliomas tumour on the scale of grade IV are also referred as Glioblastoma Multiforme (GBM) [1]. Jason Corso et al. proposed Bayesian model based segmentation approach which is faster compared to other state of the art segmentation approaches to segment GBM brain tumour and edema. It is a novel approach of extending Segmentation by Weighted Aggregation (SWA) algorithm and incorporating model based affinities calculation which was model free conventionally. The Proposed approach was fully automated, faster in execution and achieved comparatively good segmentation accuracy than few existing techniques. Nearly 70% segmentation accuracy was achieved and a few failure cases were also reported with scope of improvement [12].

Fuzzy c-means (FCM) clustering method has been widely used for segmenting medical images [13,14,15]. Bing, et al. presented fuzzy level set based automated approach of segmenting medical images. After initial segmentations by FCM, controlling parameters of level sets are estimated and it further evolves to find object boundaries and results into robust segmentation. It achieved good segmentation results to separate WM, GM tissues in brain MRI and tumour in CT scan images [13].

Bidirectional Associative Memory (BAM)-type Artificial Neural Network (ANN) based method for segmentation and classification of medical images, proposed by Sharma, et al. [16] performed good even in presence of noise and achieved 100% classification rate. In this method, only for selecting texture features, supervision is required, but no training is required then after. The larger size object may increase computational time for segmentation.

Khotanlou, et al. [14] proposed and compared two methods for 3D brain tumour segmentation from MRI, one based on Fuzzy and deformable models, and other based on symmetry analysis and deformable models. Also, both methods were compared with manual segmentation and found comparable results. The first method based on symmetry analysis showed improved results in segmentation quality, while the other fuzzy based method was faster and unsupervised. Deformable models refined segmentation by imposing spatial constraints.

Nanthagopal, et al. [17] presented texture feature extraction method based on Wavelet, segmentation and classification by SVM and Probabilistic Neural Network (PNN). The SVM reported highest classification and segmentation accuracy, better than PNN, and was comparable with the ground truth. The texture features based on co-occurrence and dominant run length improved segmentation accuracy. The limitation of the method was that it was applicable to CT scan images only, and needed new training during new dataset [17].

K-Nearest Neighbour (kNN) classifier was used to segment white matter lesion (WML) from brain MRI images in [18]. The performance of kNN was improved by incorporating spatial tissue type priors (TTPs), and by normalizing intensities. The proposed method reported good results with reference segmentation. TTPs helped to segment WML more accurately.

Demirhan, et al. [19] presented Self-Organizing Map (SOM) and Learning Vector Quantization (LVQ) based method for segmenting brain MRI images into grey matter, white matter and other background regions. LVQ was used to optimize and fine tune weights of SOM. Method reported good results for gray matter, while reported average results to segment white mater.

3.2 Statistical Methods

The applications of Gaussian Mixture Model (GMM) have been reported in [20, 21, 22] to estimate the distribution of intensities for the target classes. A comprehensive review of Gaussian mixture model based methods was presented by Balafar et al. for segmenting brain MRI images. They presented comparative analysis of methods as per reported results in [20]. The proposed segmentation methods were used to separate WM, GM and CSF from brain MRI where Markov Random Field (MRF) based methods have been reported in comparison with other approaches.

Hybrid approach of Markov Random Field and social algorithms comprising of ant colony optimization (ACO) and a Gossiping algorithm proposed by Yousefi, et al. was used to separate WM, GM and CSF regions of brain MRI. Their method improved computational time compared to classical MRF and hybrid method of MRF and ACO. Nearly equal or slightly improved Dice coefficient achieved by hybrid approach compared to two existing approaches. No significant improvement was found in the dice coefficient [23].

Multiple Gaussian components when used to represent multiple brain tissues, helped to produce smooth segmentation [21]. Greenspan, et al. proposed constrained Gaussian Mixture Model with multiple Gaussian components for segmenting brain MRI images. Expectation Maximization (EM) was used to learn parameters of GMM. The results were better and comparable with the state of the art algorithms like KVL algorithm, Marroquin algorithm and other reported results. Their method was completely automated and unsupervised approach where registration and atlas are not required. The results were compared based on Dice metric, Tanimoto metric and the mean absolute surface distance metric. It can be used as an alternative to the MRF model [21].

Saurabh et al. presented a novel approach of brain tumour segmentation from brain MRI using GMM based HRMF and Expectation Maximization method. Their hybrid approach of GMM and HRMF ensured smooth segmentation by incorporating spatial constraints. Their approach reported better results than FCM in terms of the smoothness of the segmentation. Multiple Gaussian components approximated brain tissues better than single Gaussian component [22].

A generative probabilistic model for segmenting brain tumour has been used in [24]. The proposed automated approach segmented tumour based on prior-atlas to study characteristics of healthy tissues and tumours from multimodal images. The method performed better than multivariate EM method for segmentation. The use of MRF to incorporate spatial prior helped in identifying tumour with similar characteristics.

3.3 Contour based methods

Active contour models such as Fluid Vector Flow (FVF), Gradient Vector Flow (GVF) and Magneto Static Active Contour (MAC) which are intensity-based have been proposed by Sachdeva et al. to segment tumours from medical images [25]. To incorporate texture features along with intensity values, content-based active contour (CBAC) has been proposed. Volume segmentation is achieved which is termed as 2.5-D, extension of 2D. CBAC has given better results compared to GVF, MAC, FVF for segmenting homogeneous, heterogeneous tumours with varying background conditions [25].

Rajendran et al. [15] proposed fuzzy clustering and deformable models based brain tumour segmentation. Initial segmentation is performed using fuzzy clustering which gives initial contour and final contours are determined using deformable model using GVF which gives exact tumour boundary. Proposed method is found to be accurate and robust for segmenting brain tumours [15].

Li et al. presented hybrid method of Watershed and level set for segmenting MRI images [26]. Initial segmentation is done based on watershed method and then level set method is applied to detect boundaries of objects from initial segments. Proposed method is fast and efficient. Region boundaries are easily identified by level set method as their edges are already detected by watershed method. Obtained results are better than C-V model which is important region based segmentation technique [26].

3.4 Threshold based methods and other methods

Threshold based methods mainly selects intensity values as threshold from given image and then it divides image into set of classes or segments based on this threshold value. Many methods are presented by researchers for automated selection of threshold value and Otsu method of global thresholding is a known method but it is not suitable for brain tumour segmentation [2, 27]. Also, only thresholding method generally fails to segment the tumour and researchers have suggested hybrid approach with thresholding to improve results [22].

Brain symmetry and Bhattacharya coefficient based fully automated approach proposed by Dvorak, et al. [28]. could separate edema of different size, shape and at different location from FLAIR MRI images. Edema was identified based on comparison of histogram of blocks from left and right hemispheres. Asymmetry between histogram of blocks is compared based on Bhattacharya coefficient and most asymmetric block is expected to contain edema [28]. With same principle of brain symmetry, Baidya Nath Saha et al. presented fast bounding box approach to detect tumour or edema. Average dice coefficient achieved are 0.57 and 0.52. To find out exact boundaries of tumour, other algorithms need to be applied [29].

4 Review of Feature Extraction and Classification Methods for Brain MRI Image Analysis

Tumour tissues from other tissues of brain as well as different categories of tumours can be separated from MRI images based on specific characteristics of tumour which are represented by their features. Hence feature extraction techniques play key role in extracting tumour as well as for classifying medical images into various categories based on extracted features. Most commonly used features for brain tumours are based on intensity values, texture properties, edge detection and intensity gradient [1]. Different tumours have different texture properties which represent different local image patterns, so texture based features can help in separating tumours. Also, texture based feature extraction methods have shown promising and reliable results than working with only intensity values of an image [30].

Many unsupervised and supervised techniques have been proposed by researchers using clustering as well as classification methods which are used for segmentation as well as for classification of medical images. Performance of classification algorithms are measured in terms of accuracy, specificity and sensitivity but their performance highly depends on initial pre-processing, segmentation and feature extraction techniques used. So, it is very important to optimize all phases of image analysis to achieve desired results.

Liu, et al. proposed hybrid approach of Gabor wavelet used for feature extraction, SVM used for tumour segmentation and LDA used for classification. Major goal was to separate different categories of tumour like PCNSL and GBM from T1c brain MRI images based on texture features and tumour shape. Proposed method achieved 100% sensitivity, 98% specificity and 98.9% accuracy in 3-fold cross-validation experiments. It was manual approach. Tumour-area and non-tumour selected to train the SVM [30].

Hybrid method of Gabor Wavelet and SVM was compared with other hybrid method of different DWT-Discrete Wavelet Transform (Daubechies-4) and SVM in [31] to classify MRI brain images. Gabor Wavelet was used for feature extraction and SVM was used for classification. Combination of different scales and orientations of Gabor filters and Linear, Sigmoid and RBF kernels of SVM were experimented. To reduce dimension, all Gabor filtered images were combined into one. They achieved 100% classification accuracy with proposed method with 3 scales, 8 orientations of Gabor and Sigmoid kernel of SVM [31].

Performance of Daubechies, Haar and Gabor wavelets was compared by Joohyun, et al. for extracting scale-invariant features. Salient image features were extracted with all the three wavelets, but Gabor wavelets outperformed other two. Haar had bad localization, Daubechies was not symmetric. Gabor wavelet performed well, but dimension of feature vector was very high [32].

Texture features from Lung CT scan images and other datasets extracted using Segmentation-based Fractal Texture Analysis (SFTA) in [33]. Performance compared with widely used methods like Haralick and Gabor filter banks and found better in case of SFTA. SFTA achieved higher precision and accuracy for both CBIR and image classification. Based on execution time, SFTA was faster than Gabor and Haralick with respect to feature extraction time. Gabor had equal accuracy for one dataset and less but nearly equal accuracy for other two datasets [33].

Feature extraction techniques like Scale Normalized Laplacian (SNL), Speeded-Up Robust Features (SURF), Shift Invariant Feature Transform (SIFT) were compared in [34] with newly introduced Brain Blob Detector and Descriptor (BBDD). All the techniques were applied on brain MRI images, where proposed BBDD method performed better than other mentioned algorithms like SNL, SURF and SIFT to discriminate sulcal blobs and gyral blobs [34].

Aminul, et al. proposed Multi-fractral feature extraction method from MRI images and modified AdaBoost to improve classification [35]. Multi-fractral feature extraction helped to extract important texture features, while modified AdaBoost algorithm changed weights of classifier based on different parameters which improved performance. It was used to segment low grade glioma tumour. No atlas registration was required. The method performed better to segment low grade glioma tumour compared to other state of the art methods reported in literature performed on BRATS dataset [35].

El-Dahshan, et al. [7] presented hybrid approach of Artificial Neural Network (ANN) for segmentation and classification, Discrete Wavelet Transform (DWT) for feature extraction and Principal Component Analysis (PCA) for dimensionality reduction. Also presented state of the art brain tumour segmentation and classification methods applied on MRI images. Achieved good results compared to recent machine learning techniques. The proposed hybrid approach reported 99% accuracy, 92% specificity and 100% sensitivity, which is comparable with other approaches and found better in some cases.

Manually segmented white matter lesion features were given to SVM classifier for training in [36] and AdaBoost was used to further improve the performance by focusing and learning from misclassified results. The AdaBoost method reduced false positive rate by focusing more on similar samples. The segmentation was challenging, because of smaller size of lesion compared to other region [36].

5 Summary and Discussion

This paper presents a comprehensive review of state of the art methods reported in literature for brain tumour detection and analysis. The literature contains methods for brain MRI image analysis to achieve different objectives like segmentation of GM, WM and CSF, detection of tumours, analysis of tumours like its type, location and size, segmenting necrotic area, edema alongwith tumour, etc. A major problem observed is that the quantification of results reported by different authors in their proposed methods are tested on different datasets and testing on common single standard dataset is missing. Also, standard parameters to measure and compare accuracy of algorithms are also missing. Different authors have tried to prove their algorithms based on their own parameters. However, some authors have tried to validate their results based on some known performance parameters like Dice metric, mean absolute surface distance metric and Tanimoto metric for measuring accuracy of segmentation but they are not gold standard for comparing performance of segmentation algorithms. It has been studied and can be summarized that different methods have been demonstrated with their performances for different cases, different performance measures and on different database. As feature extraction methods, literature review of Gabor, Wavelet transform, Discrete Wavelet Transform (Daubechies-4), Haar, Bhattacharya coefficient based approach, SFTA, Haralick, SURF, SIFT, SNL, GMM, multi fractal techniques has been presented in this paper. Out of many diverse features, the Gabor filters and Wavelet transform based methods have been widely used and reported in literature. Texture based features have also shown good applications for identification of tumour and its categories. In this paper, the methods of segmentation grouped and reviewed in four categories: machine learning and computational intelligence methods, statistical methods, contour based methods, threshold based, and other methods. As segmentation methods, a review of Neural network based methods (like BAM, PNN, SOM, LVQ), MRF based methods, fuzzy classification, deformable models, GMM, GMM with EM, GMM with HMRF and EM, watershed with level set, SVM, Active contour model, and kNN based methods have been presented. It is observed during the review that SVM, ANN and kNN have been widely used as classifiers, while sometimes the Adaboost has been used to improve classification accuracy. Because of large intensity variations in MRI images, only thresholding based approaches do not provide desired results. Hence, in many works, the hybrid approach is suggested with thresholding method. However, it is also observed that the thresholding based methods are computationally fast and easy to implement. FCM has advantage of soft clustering, where it assigns membership values to each class. However, methods like FCM, Thresholding, deformable models and region growing are sensitive to noise. Hence, proper noise removal techniques should be applied in order to get desired results otherwise methods giving best results may also fail when noise levels present in different images vary. Sometimes, noise removal algorithms even though remove noise, but do not preserve edges of objects in an image which result into poor segmentation at later stage. On the other hands, methods exists which are robust and not influenced by noise like MRF which imposes strong spatial constraint, ANN and brain symmetry based on bhattacharya coefficient which compares histogram of block between left and right hemispheres based on assumption of brain symmetry. GMM based methods are computationally efficient and have capability to model complex problem. MRF imposes strong spatial constraint and has ability to represent complex dependency of data based on neighbourhood property. Because of this characteristic of MRF, it has been widely used for segmentation of tumour. In case of ANN, even though it performs well in learning and segmenting brain tumour, however trained network gives good results for patient specific dataset used for training and may not give expected results on different datasets because of different appearance and properties of tumour for different patient. On the other hand, SVM has got good generalization capability to produce good results even for previously unseen data of different patients. So, hybrid approach by combing strength of each individual method may give better results.

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