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A Survey of MR Image Brain Tumour Segmentation Using Different Classification Techniques

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Abstract- **Brain tumour is a common dangerous diseases affecting human beings. The Magnetic Resonance Imaging (MRI) segmentation is one among the most important techniques for detecting the tumour from the brain MRI. The chances of survival are great when the tumour detection is done correct at its early stage. In brain MRI analysis, image segmentation is generally used for the measurement and visualization of the brain's anatomical structures, for the analysis of brain changes, for the delineation of regions of pathology, and for planning for surgery and image-guided treatments. In the last few years, different segmentation techniques with various degrees of accuracy and degree of complexity have been formulated and studied in the literature. This paper gives an overview of Brain MRI analysis techniques that can be helpful for the MRI brain tumour segmentation and classification. The characteristics of many methodologies are discussed, which may be useful in the selection of the most suitable one for solving a problem in hand. This survey details several MRI Brain Tumour analysis procedures such as inclusion of pre-processing methods, segmentation methods, feature extraction methods and classification methods of MRI images.**

Keywords-----Brain Tumour, Magnetic Resonance Imaging (MRI), pre-processing methods, MRI image segmentation, Feature Extraction, Classification methods.

1.INTRODUCTION

In the recent few years, the huge growth in non-invasive brain imaging technologies has paved the way for the analysis and study of the brain anatomy and function. Tremendous improvement in locating brain injury and studying the brain anatomy has been attained with the use of Magnetic Resonance Imaging (MRI) [1]. Also the progresses made in brain MR imaging have also helped in gaining large amount of data with an ever-growing high level of quality. The inspection of these huge and complicated MRI datasets has turned out to be a time-taking and complicated job for clinicians, who have to perform the extraction of important information without any automation. This manual analysis consumes a lot of time frequently and is prone to errors due to different inter- or intra operator variability studies. These hurdles in brain MRI data analysis needed inventions in computerized techniques for the improvement of disease diagnosis and testing. In the recent times, computerized methods for MR image tumour analysis process based on the segmentation with classification techniques have been widely used for assisting doctors in qualitative diagnosis. Chiefly the Brain MRI segmentation is an important task in many clinical applications because it impacts the result of the entire analysis. This is because various processing steps depend on segmentation of anatomic regions with accuracy. For instance, MRI segmentation is generally used for the measurement and visualization of different brain structures, for delineation of lesions, for the brain development analysis, and for image-guided interventions and planning of surgery. These diverse image processing applications has given rise to the development of multiple segmentation techniques with various degrees of accuracy and degree of complexity. Fundamental components of structural brain MRI analysis comprise of classifying the MRI data into particular tissue types and identifying and describing certain anatomical structures [2]. Classification refers to the association of each element in the image with a tissue class, the classes being specified earlier. The issues of segmentation and classification are closely related, segmentation means classification, while classifier inherently segments an Image.

The major problems [3] in segmentation of brain MRI are Noise, Intensity in homogeneity, Shading artifact, Partial volume. Still there are some issues like accurate and reproducible segmentation and characterization of abnormalities using intelligent algorithms because of the variety of shapes, locations and image intensities of different brain tumours. This paper provides a review of the methods and techniques utilized in MRI brain tumour segmentation

[4] and classification. This paper is mainly focused on the study of different brain tumour segmentation and classification system. There are various motivations for the development of techniques for medical image segmentation making use of the classification methods. Every year, new brain MRI automatic segmentation algorithms are brought out [5]. This study gives a description of different segmentation and classification techniques for brain MRI brain images. The Figure 1(a) and 1(b) depicts the sample dataset of Normal brain image and brain tumour images obtained using the segmentation process of brain image with different classification techniques.

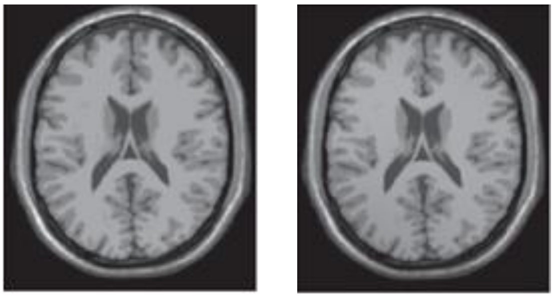

Figure 1(a). The sample dataset MRI brain image

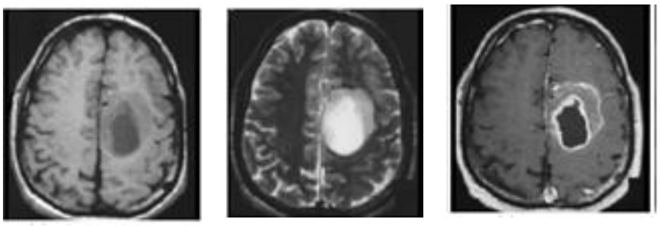

Figure 1(b). The sample dataset MRI brain Tumour images

2. SURVEY OF IMAGE PROCESSNG METHODS FOR MRI IMAGES

The images obtained with the help of MRI scanning is used in Machine intelligence for the detection of diseases like brain tumour using image processing techniques. For image segmentation, various types of algorithms are to be evolved, so that the normal & abnormal MRI Images can be classified either by machine or computer. The MRI Image goes through a series of steps for analysis using image processing techniques is illustrated in Figure.2,

2.1 IMAGE ACQUISITION

Antonie, et al [6] gave the introduction for the image acquisition module, which denotes the first step in an image processing system. In this step, chances for noise being introduced is more, leading to decrease in the quality of the image. The next step of the MRI brain tumour segmentation analysis deals with the enhancement of the image for improving the quality or performing a denoising. The denoising method is a wavelet-based method that will be described in the theoretical section. After the denoising has been conducted, the image enters the segmentation method, then the features are extracted from images using various types of feature extracting methods. Then the feature extracted images are entered into classifier module that will classify the feature images (T1-weighted, PD-weighted and T2- weighted) based on the statistical parameters describing the image. In this step the classifier should be capable of distinguishing between a normal and abnormal slice of brain. The thought of classifying the normal and abnormal images is useful, for the purpose of reducing the normal images and segmenting only those having the possibility of being affected with tumour with the help of the classification method. The last step is the representation of the segmentation with the classification of the image for detecting the tumour. This step avails some previous information from the classification step to make use of an adaptive histogram threshold for better tumor segmentation. After a MRI image has passed through the system, the outcome is the segmentation of the existing tumor.

2.2 PRE-PROCESSING

Pre-processing of MRI images is the primary step in image analysis that involves the use of image enhancement and noise reduction techniques utilized for boosting the image quality. Enhancement and noise reduction techniques are applied in brain tumour detection for obtaining best possible results. Most of the image segmentation methods mainly focus on the filtering methods for pre-processing input image samples for removing noises. This survey work chiefly studies these different filtering methods for noise removal.

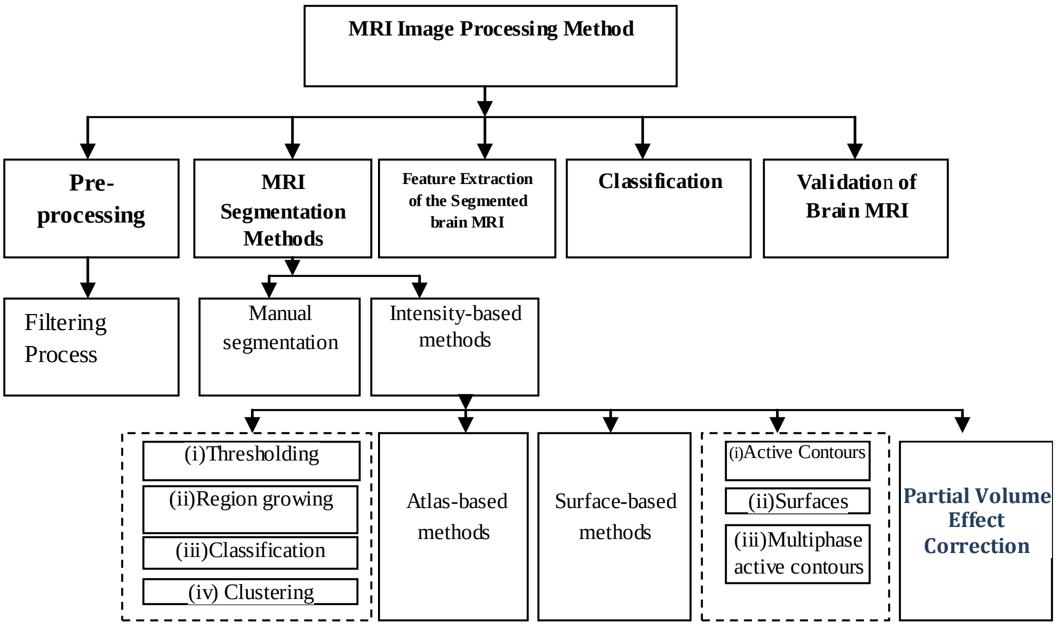

Figure 2.MRI Image Processing method

Ma, et al, [7] introduced Filtering as a very good example for pre-processing step for MRI brain image segmentation. In this work, MRI brain tumour image segmentation process is studied from various angles. As a first step, Filtering, that is one of the pre-processing methods used before image segmentation, is applied on the MR Brain images and its effect on MR brain tumour image segmentation is studied. There are various kinds of filtering algorithms which are used for the elimination of noises from MR brain tumour images.

2.2.1 Filtering methods for pre-processing of MRI images

Pre-processing algorithms enhance the quality of a visual data and coding efficiency by eliminating unnecessary data before encoding [8]. The aim of filtering is the reduction of the noise and improvement in the quality of the MRI image visually. Sometimes, smoothing is mentioned as filtering. The pre-processing algorithms play a crucial part in the pre-processing of MRI brain image segmentation. The usability of various spatial as well as temporal filters and filtering methods has been talked about in this section.

Roy, et al, [9] proposed a few of the de-noising methods. Despite of the presence of sufficient number of state of the art techniques of de-noising, accurate elimination of noise from MRI image poses a serious issue. Techniques such as deployment of standard filters to highly advanced filters, nonlinear filtering techniques, anisotropic nonlinear diffusion filtering, a Markov Random Field (MRF) models, wavelet models, non-local means models (NL-means) and analytical correction schemes are available. Non-Local (NL) method makes use of the information that is redundant in images. The replacement of pixel values is done by using the weighted average of locality which is similar to the vicinity surrounding of the image. Analytical correction method tries to differentiate between noise and noise-free signal from the obtained image.

A Markov Random Field method (MRF), spatial correlation information is used for preservation and noise estimation is performed [9]. Wavelet based methods are used for denoising and preservation of the original signal. Usage of wavelet based techniques on MRI images renders the wavelet and scaling coefficients not reliable [9]. These methods have close similarity with respect to cost of computation, de-noising, quality of de-noising and preservation of boundary. So, de-noising is yet an unresolved problem and de-noising techniques require enhancement. Linear filters eliminate noise by the updation of the pixel value by the weighted average of neighbour region though degrading the image quality considerably. Then again, non linear filters preserve edges but also lead to degradation of fine structures. There are several filtering technologies which can enhance the MRI image quality. This section shows that some other filtering techniques such as high pass filtering and Median Filtering effectively help in reducing the noises in the gray-level brain MR Images with filters, which is described as follows.

Patil, et al, [10] suggested that in the MRI Brain tumour extracting procedure, the MRI Brain tumour images are provided as the input to a High Pass Filter. A high pass filter is the fundamental element for many of the sharpening techniques. An image is sharpened during the contrast enhancement between adjacent areas with minute distinction in brightness or darkness. A high pass filter attempts to hold back the high frequency information in an image while decreasing the lower frequency information. The kernel of the high pass filter is developed to enhance the brightness of the centre pixel relative to neighbouring pixels. The kernel array generally consists of a single positive value at its centre, which is entirely surrounded by negative values.

Wang, et al, [11] discussed a new median-based filter, Progressive Switching Median (PSM) filter, which is useful for restoring images affected by salt–pepper impulse noise. The median filter provides results which is a more reliable average than the mean and so a single very unrepresentative pixel in a vicinity will not affect the median value considerably. As the median value must actually be the value of one of the neighbouring pixels, there is no creation of new unrealistic pixel values by the median filter when it straddles an edge. PSM Filtering is performed by two step process in which the first step is identification of noise pixel with fixed window size. In case of the test pixel not within the maximum or minimum value compared to the rest of the pixel then this pixel is considered as a corrupted pixel and in the next step these corrupted pixels are replaced by the median value intensity. The results obtained from this median filter is very good and the sensitivity of the median is much less than the mean to extreme values. Hence median filtering is very much capable to eliminate this deviation without reducing the sharpness of the image. Then based on the studies, this paper introduced the bilateral median filters for denoising the MR images.

2.3 MRI SEGMENTATION METHODS

The brain tumour segmentation methods can be grouped into different categories based on many principles. In the clinic, brain tumour segmentation methods are generally classified into three main categories including manual, semi-automatic, and fully automatic segmentations according to the degree of needed human interaction. In this stage of processing, after the pre-processing is performed using effective filtering method, segmentation is initiated using the following methods in the brain MRI images:

Mustaqeem, et al [12] proposed segmentation methods such as threshold segmentation and watershed segmentation method. These segmentation techniques are the easiest segmentation methods. In threshold techniques, the input MRI brain- gray scale image is converted into a binary format. This method bases itself on a threshold value which will convert gray scale image into a binary image format. The important logic is the extraction of a threshold value. Another method is watershed segmentation. It is one among the best methods for grouping pixels of an image based on their intensities. Pixels which fall under similar intensities are categorized together. It is a good segmentation technique for division of an image for separating a tumour from the image.

Shakowat, et al [13] studied about a Morphological image processing (or morphology) technique, which describes a range of image processing techniques dealing with the shape (or morphology) of features in an image. Morphological operations are normally applied for removing imperfections which are introduced during segmentation, and hence they usually operate on bi-level images i.e. binary images [14]. It makes use of morphological operation in boundary extraction, Region filling, extraction of connected components, thinning/thickening, and skeletonisation. Any on pixel in the structuring element covers an on pixel in the image with structuring element. Structuring elements can be of any size and create any shape. However, for the sake of simplicity it utilizes rectangular structuring elements with their origin at the middle pixel. Basically, morphological image processing is very much like spatial filtering and the structuring element is moved across every pixel in the original image to give a pixel in the new processed image and the value of this new pixel relies on the operation performed.

Wong et al [15] gave the introduction for a new segmentation method which is Region-based. These segmentation methods examined pixels in an image and form disjoint regions by merging neighbourhood pixels with homogeneous properties according to a predefined similarity criterion. The region growing and the watershed segmentation methods are part of the region-based methods and in general are used in the process of brain tumour segmentation. The region growing is the one of the simplest and most prevalent region-based segmentation method and is useful for extracting a connected region of similar pixels from an image [16]. The main disadvantage of region growing method is the partial volume effect which restricts the accuracy of MR brain image segmentation.

Canny, et al, [17] proposed Edge-based segmentation techniques. In this technique an algorithm searches for pixels with high gradient values which are generally edge pixels and then attempts to connect them for producing a curve which denotes a boundary of the object. The user fixes an initial guess for the contour, which is then deformed by image driven forces to the boundaries of the desired objects. In these models, two types of forces are taken into consideration. The internal forces, defined within the curve, are designed to keep the model smooth during the deformation process. The external forces, that are computed from the image data, are defined to move the model towards an object boundary. The Canny edge detection algorithm is also called as the optimal edge detector.

Cuadra, et al, [18] conducted a study on Atlas-based segmentation approaches, which have widespread use in guiding brain tissue segmentation. Atlases can be useful in restricting the tumour location and also for generative classification models. Generally, atlas-based algorithm, which are used for the segmentation of brain tumour includes three steps: As a first step, an affine registration brings the atlas and the patient into global correspondence; In the second step, the seeding of a synthetic tumour into the brain atlas provides a template for the brain tumour. The third step involves the deformation of the seeded atlas by optical flow principles and brain tumour growth. Few researchers used atlases not only for imposing spatial constraints, but also for providing probabilistic information about the tissue model. A probabilistic tissue model is employed and an Expectation Maximization (EM) method for the segmentation of the brain tumour through modifying an atlas with patient-specific information about tumour location from different MRI modalities is used. The advantage of this category of methods is that domain knowledge can be merged for better consideration with atlas-based segmentation, whereas the disadvantage is that the variability of such previous information is hard for accountability in the case of image segmentation. For the purpose of comparing these different segmentation methods as described by Gonzalez et al [19], the merits and demerits of the most commonly used methods in brain tumours detection are clearly summarized in Table 1.

Practically, a mixture of two or more techniques i.e. the hybrid techniques has found widespread applications in image segmentation. Since the Hybrid techniques show a resemblance of human brain, the results are speedy, accurate and hence achieve tractability, robustness and economic. Also, Region based active contour model for segmentation with hybrid classifier are employed to MR brain image segmentation as discussed.

The active contour methods result in an efficient way for segmentation, in which the detection of the object boundaries are conducted by evolving curves. In this research work, hybrid techniques, which introduced a new region-based active contour with hybrid classifiers model, on the basis of the image global information for the halting process is introduced.

Techniques	**Advantages**	**Disadvantages**
Threshold based	• These threshold methods are very much useful for image linearization which is a very important task for any type of segmentation.	• These algorithms do not act properly for every type MRI of brain image, due to the large intensity variation in the foreground and background images.
Watershed	• The best methods for grouping pixels of an image based on their intensities.	• The main issue of watershed transform is its being sensitive to intensity variations, which results in over segmentation, occurring when the image is segmented into a large number of unwanted regions. The over segmentation problem still persists in this method.
Region growing	• Region growing methods can accurately isolate the regions that have similar properties that are defined. Its performance is good with regard to noise	• It requires a seed point that is selected manually by the user and thereby helps in elimination of all pixels connected to the Preliminary seed on the basis of some predefined condition, and is very much sensitive to noise.

Atlas based	• In the case of Atlas-guided approaches, the transfer of the labels is conducted along with the segmentation. They also render a standardized system for the study of morphometric properties.	• The disadvantage of atlas-based techniques can be the time required for atlas construction in any place iteration based procedure or a complex non-rigid registration is integrated in it. Since the atlas based segmentation is normally utilized when the information obtained from the gray level intensities are not adequate, there is difficulty in producing objective validation.
GA	• Genetic algorithms are population based process for finding exact or approximate solution for optimization of the search. The problem is influenced by the general procedure of using biological organism in computing.	• One of the drawbacks of the genetic algorithms is that it truly relies upon the fitness function.
Major issues from Existing Works		
The chief problems faced with the already available systems are more sensitivity to intensity variations, which results in this method over segmenting the input image. Over segmentation of the image creates unnecessary backgrounds, which is not eliminated in the existing tumour segmentation techniques and another issue is that these existing methods truly depends upon only the fitness function.		
Active Contour based segmentation	**Advantages**	
Active Contour based segmentation	To get over the issues posed by the available methods, the works utilize region based active contour model. The active contour techniques provide an efficient means for segmentation, in which the detection of the object boundaries are conducted by evolving curves.	

Table 1. The advantages and disadvantages of generally used segmentation methods for human brain tumours through MR images.

Consequently, the model provides robustness towards noise. Level set representation is employed for the mobile curves and thus the changes of topology during the evolution are dealt automatically. Moreover, an inherent energy term is introduced, and it drives the level set function to be near to a signed distance function, that eliminates the necessity of the expensive re-initialization for the developing level set function. Few tumour segmentation results obtained using the method presented in this work are shown in Table.2 which clearly shows the segmentation with Hybrid techniques are effective in MRI brain tumour segmentation. The correct rate of the segmentation accuracy is computed by using, false positive rate (FP). The segmentation result is positive in the presence of the clinical abnormality and false negative rate (FN). Similarly the segmentation result is negative in the presence of the clinical abnormality due to the abnormality the MRI brain image pixel size which is changed in segmentation process. These factors affect the accuracy rate of the segmentation process. The segmentation process accuracy correct rate is defined as below:

FP = False Positive Pixel's number / tumour Size ------------------ (1)

FN = False Negative Pixel's number / tumour Size ------------------ (2)

Correct rate = FP + FN------------------- (3)

Table.2 The segmentation accuracy correct rate of the different segmentation Methods

Segmentation Methods	Accuracy (%)
Active Contour based segmentation	97.3
GA	96.1
Region growing	92
Watershed threshold segmentation	90.5

2.4 FEATURE EXTRACTION METHODS FOR ANALYSIS OF MR BRAIN IMAGES

Feature extraction methodologies analyze images for the extraction of the most prominent features that provide a representation of the various classes of objects. Features are used as inputs to classifiers which assign them to the class that they represent. The intention of feature extraction is the reduction of the original data by measuring certain properties, or features, that distinguish one input pattern from another pattern. The selected feature should provide the characteristics of the input type to the classifier by taking into account the description of the relevant properties of the image into feature vectors. In this section different type of features are studied for feature extraction process as follows:

2.4.1 Shape Features

Xuan, et al [20] proposed symmetry-based extracting method, which is also known as shape based feature extracting method. This method extracts features such as circularity, irregularity, Area, Perimeter, and Shape Index. This method used a unique characteristic of brain MR images. A normal brain has symmetry, it has two cerebral hemispheres, and if it is with tumour, it will turn asymmetric because tumour generally occurs in one cerebral hemisphere and holds the normal structure's place. The simplest way for detection of the asymmetry is subtracting one hemisphere from the other pixel by pixel. Yet, the human brain is not exactly symmetric, and there are always some slight variances. The symmetry-based features are defined as the asymmetry map S value of the central pixel in each block. These features are helpful for shape features extraction in the MR brain image processing.

2.4.2 Intensity features

Xuan, et al [20] gave the introduction for another different type feature of the MR brain images for feature extraction prior to the classification. i.e. the Intensity-based features extraction. This type of extraction has the intensity-based statistical features, that are extracted from each block, including the mean intensity, maximum intensity, minimum intensity, range (maximum intensity minus minimum intensity), central pixel's intensity, variance, standard variance, median intensity, skewness, and kurtosis. The intensity values are a direct reflection of the physical characteristics of tissues in MRI. Eventhough, different tissues may have overlapping of intensity values. For achieving good classification performance, other information such as anatomic knowledge should also be taken into consideration.

2.4.3 Texture features

Texture features such as Contrast (CON), Correlation (CORR), Entropy (E), Energy (ENER), Homogeneity (H), Cluster shade, Sum of Square Variance (SSV). In the case of Texture-based features in normal MR brain images, the relative positions of different tissues are usually fixed, hence there are certain texture patterns within one tissue and among different tissues, such as the gyrus. This is crucial for the detection of white and gray matters. Homogeneous texture descriptor (HTD) in MPEG-7 is employed in this work for representing the block texture. Since HTD can capture the most important features of a texture pattern, different texture patterns differentiation in one image can be performed by it. HTD is extracted by Gabor filter banks which partitions the frequency space with equal angle of 30 degrees in angular direction and with octave division in radial direction. There are different techniques for feature extraction e.g. Haralick, et al, [21] proposed a new feature extraction technique based on textures, Liu, et al, [22] presented a Gabor features for feature extraction for MR brain images and Kociołek, et al [23] presented a feature based on wavelet transform. The other feature extracting techniques are based on features like texture, shape and intensity, which are defined by LU, et al [24], as Principal Component Analysis, minimum noise fraction transform, Discriminant Analysis, Decision Boundary Feature Extraction, Non-parametric Weighted Feature Extraction and Spectral Mixture Analysis.

Based on the study of the above mentioned various feature extraction techniques, three kinds of features are extracted in proposed work which are used as hybrid techniques. These describe the structure's information of intensity, symmetry and texture of the MR images. The modification of an image into its set of features is referred to as feature extraction. The features definitely have some redundance, but the aim of this step is the discovery of potentially useful features. The feature selection will be conducted for reducing the redundancy. Classification is performed only by selecting only those individual features which can best discriminate among classes. Moreover a final hybrid classifier as well as the feature selection strategy is also obtained. The extraction of the useful features pertaining to the image from the image is done for the purpose of classification. After feature extraction, these features as single entities are used for classification as mean and benign MR image. The following section discusses the different type of classification methods for the MR brain images.

2.5 MR BRAIN IMAGE CLASSIFICATION METHODS

The significant process in the system of brain tumour analysis procedure is the brain image classification. The chief goal of this step is the differentiation of the different abnormal brain images on the basis of the optimal feature set. Many different traditional classifiers are available for categorization but most of the previous works depend on Artificial Intelligence (AI) techniques which can give results with greater accuracy in comparison with the conventional classifiers. This work analyzes the different types of classifiers in the MR brain Image classification method. The application of various ANN for image classification is studied by Egmont et al [25]. The non-availability of rapid convergence rate of the conventional neural networks is also described in the report. This lays emphasis on the need of modified neural networks with superior convergence rate for image classification applications. Lukas, et al [26] has classified four different types of tumour using LDA technique. But the classification accuracy obtained in the report is in the order of 80% which is comparatively low. This work also proposed ideas for the various reasons responsible for wrong classifications. Classification based on Support Vector Machine of varied levels of MR glioma images is conducted by Guo-Zheng et al [27]. This method is considered to perform better than rule based systems but again, the accuracy reported in the paper is less. This work handles only glioma images and thus the deficiency of generalizing ability of this work is another setback of this system.

Willem et al [28] have made use of the Kohonen neural networks for image classification. Some modifications of the traditional Kohonen neural network are also realised in this work which establishes to be much superior to the traditional neural networks. Rajalakshmi, et al [29] introduced a hybrid approach for classifying brain magnetic resonance images (MRI) according to color transformed hybrid clustering segmentation algorithm and wrapper based feature extraction with multi-class support vector machine (SVM). The color, texture and shape features have been selected and these features are used for classifying MR brain images into three types namely normal, benign and malignant. The classification of MR images by wrapper approach with Multi class Support Vector Machine classifier (MC-SVM) are done on the basis of the colour, texture and shape features. The MC-SVM classifier performance is then compared with different kernel functions. The analysis and performance parameters like accuracy of classification show that the brain MRI classification is best performed by making use of MC- SVM with Gaussian RBF kernel function rather than linear and polynomial kernel functions.

Table 3 The advantages and disadvantages of widely used classification techniques for human brain tumours through MR images

Methods	**Advantages**	**Disadvantages**
K-NN	• It provides accurate results about distance, weighted average about pixels and it can be utilized for large number of training sets • The large degree of local sensitivity renders closest neighbour classifiers highly vulnerable to noise present in the training data. • The algorithm is simple and powerful.	• The drawback of this algorithm is the selection of k impacts the performance of the k-NN algorithm. It takes immense amount of memory; therefore its classification/estimation takes time. • The accuracy of the k-NN algorithm can be seriously degraded by the presence of noisy or unnecessary artifacts, or in the case of the feature scales not uniform with their significance
ANN	• A neural network can be utilized to perform tasks that a linear program cannot do. • A neural network learns and hence does not require reprogramming. Neural networks are self-adaptive data driven techniques which can adapt themselves to the data without any specification explicit about the functional or distributional form for the base model.	• The neural network requires training for operation. A high processing time is a necessity for large neural networks. • Minimization required for fitting involves a good deal of computational effort.
SVM	• It lowers the number of wrong classifications in any set of samples possible • Most realizations of SVM algorithm require computing and memory storage of the complete kernel matrix of the entire input sample. • The chief advantage of SVM is that has the capability for training practical, nonlinear classifiers in high dimensional spaces making use of a small training set.	• Many of the realizations of SVM algorithm require computing and memory storage of the entire kernel matrix of every input sample. • The optimality of the solution got has the dependency on the kernel used, and there is no technique available for knowing a priori which will be selected as the best kernel for a solid task. The best value for the parameter C is an unknown priori.

FCM	• This technique has two main merits: it decides a membership degree of data to each class, thus making soft clustering possible, and it is an automated algorithm.	• The main drawback is that the requirement of prior knowledge of the clusters number. The need for initiation of many initial parameters inclusive of the seed pixel is one among the drawbacks of this system
EM	• The main advantages of this algorithm are its speed and simplicity which helps it possible to be run on large datasets.	• A common drawback of EM algorithm is that the distribution of intensity of brain images is realized as a normal distribution. • The disadvantage of EM is, it does not directly include spatial modelling and hence yields insensitivity to noise and intensity non-uniformities.
Important issues from Existing Works		
• The important issue in the existing method is over fitting problem and performance accuracy.		
Hybrid classification method for MRI brain	**Advantages**	
Levenberg-Marquardt Training algorithm with BAT algorithm in Neural Network (LMBAT-NN)	For overcoming these issues, a hybrid classification method with swarm intelligence based algorithm LMBAT-NN can be used. It is more robust, flexible and self adaptive. The hybrid classifiers are helpful in increasing the performance of the MR brain Image process.	

The System proposed can be used for obtaining the best classification performance with good accuracy and lower error rate. The important goal of the above described works is the improvement of the classification efficiency. In this work, study of different types of tumour segmentation and classification techniques is carried out. It shows that this work achieves high accuracy within a shorter time period. A comparative analysis between the various techniques is described in detail in Table.3 to be presented in this work.

On the basis of the performance evaluation of classification methods, hybrid classifiers can be utilized in overcoming the limitations of the available approaches. This study infers that all classification results could have an error rate and on few situations they will either fail in identifying an abnormality, or identify an abnormality which is not present. It is usual to define this error rate by the terms true and false positive and true and false negative as follows:

True Positive (TP): the classification result is positive in the presence of the clinical abnormality. *True Negative (TN):* the classification result is negative in the absence of the clinical abnormality. *False Positive (FP):* the classification result is positive in the absence of the clinical abnormality. *False Negative (FN):* the classification result is negative in the presence of the clinical abnormality.

Table 4 is the contingency table which defines various terms used to describe the clinical efficiency of a classification based on the terms above and defined as follows:

$$\text{Sensitivity (SEN)} = TP/\,(TP+FN) *100\% \quad (4)$$

$$\text{Specificity(SPE)} = TN/\,(TN+FP) *100\% \quad (5)$$

$$\text{Accuracy (A)} = (TP+TN)/\,(TP+TN+FP+FN)*100\ \% \quad (6)$$

The terms which are used for the measurement of the performance of the classifiers as shown in Table 5.

Table 4: Contingency table

Actual Group	**Predicted Group**	
	Normal	**Abnormal**
Normal	TN	FP
Abnormal	FN	TP

In this survey work, many experiments have been conducted on certain number of MR brain images of different patient. First, the images are divided into different blocks and features are extracted from each block. Different types of classification techniques are then employed on each block of the images. Results of different type's classification of techniques are as shown in Table 5. The results of different types of classifiers is illustrated in Figure 3.

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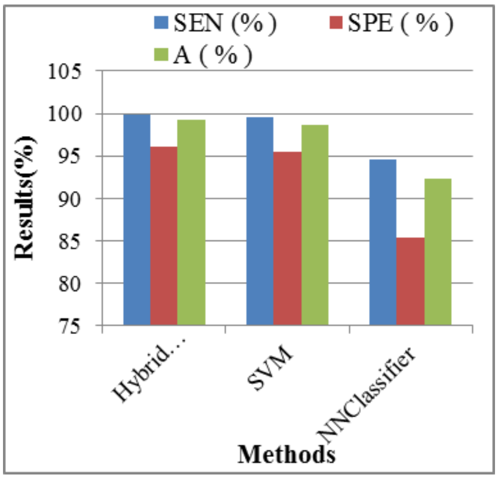

Figure 3.Classification results comparison for various methods

Table 5. Classification results of various types of classification methods

Methods	SEN (%)	SPE (%)	A (%)
Hybrid Classifiers	99.89	96.04	99.26
SVM	99.64	95.5	98.64
NN	94.60	85.39	92.37

The classification performances of this study depict the advantages of this technique: it is fast, easy in operation, non-invasive and economic. The limitation of this work is that the requirement of fresh training every time whenever there is an increase in image in image database. Further investigation will be conducted with large set of data and attempting to integrate between other machine learning techniques to overcome the weakness of the generalization for any datasets in determining the generalization of these results.

3. INFERENCE FROM EXISTING WORK

Many researchers have presented investigations for dealing with these issues of segmentation of MRI images through a hybrid classifier approach that will give fruitful results in diagnosing the diseases and it may be useful in medical field for various purposes. Hybrid classifiers have been a topic of interest for analysis for quite a few years. Even then, these powerful classifiers have their own disadvantages and limitations. Knowing that, the fusion of the Hybrid classifiers approaches will typically provide superior performances over using them one after another. Hence, a hybrid classification approach is proposed to coping up with such complex problems in MRI brain image analysis.

4. CONCLUSION AND FUTURE WORK

In this study, current studies of the different segmentation, feature extraction and classification algorithms have been reviewed. Especially, this paper studies different types of methodologies of Brain MRI segmentation with classification technique. Many image segmentation methods have been formulated in the past few decades for segmenting MRI brain images, but still it remains a challenge. A segmentation method may perform well for one MRI brain image but not for every other similar image. Thus it is very difficult to propose a generic segmentation method that can be used widely for all MRI brain images. In this technical work, the merits and demerits of various automated techniques for brain tumour identification are analyzed in detail. Many new hybrid approaches may be developed through the ideas expressed in this paper. The survey concludes that the hybrid classifier will provide fast and classification that can be efficiently used for segmenting MRI brain images with high degree of precision. Considering all these facts as an inspiration, hybrid classifier is considered with a futuristic perspective for research of MRI Images.

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