Computer-Aided Diagnosis Systems for Brain Pathology Identification Techniques in Magnetic Resonance Images - A Survey

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ABSTRACT

This paper reviews the recent researches of computer-aided diagnosis (CAD) systems for automatic detection of brain diseases. Automated detection of the abnormalities in medical images is an important and necessary procedure in medical diagnosis planning and treatment. In this review paper, it is intended to summarize and compare the methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI) used in different stages of Computer Aided Diagnosis System. In this review paper, an extensive comparative analysis is performed to provide the merits and demerits of various available techniques. This work also explores the applicability of the techniques in brain tumor diagnosis in MR images.

KEYWORDS: Brain tumor, Preprocessing, Segmentation, Feature Extraction, Feature Selection, Classification**,** Computer-aided diagnosis, Magnetic Resonance Image.

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1. INTRODUCTION

1.1 BRAIN TUMOR

Brain tumor is one of the major causes for the increase in Mortality among children and adults. A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth [1]. Most Research in developed countries Show that the number of people who develop brain tumors and die from them has increased perhaps as much as 300 over past three decades. The National Brain Tumor Foundation (NBTF) for research in United States estimates that 29,000 people in the U.S are diagnosed with primary brain tumors each year, and nearly 13,000 people die. In children, brain tumors are the cause of one quarter of all cancer deaths. The overall annual incidence of primary brain tumors in the U.S is 11 - 12 per 100,000 people for primary malignant brain tumors, that rate is 6 - 7 per 1,00,000. In the UK, over 4,200 people are diagnosed with a brain tumor every year (2007 estimates). There are about 200other types of tumors diagnosed in UK each year. In India, totally 80,271 people are affected by various types of tumor (2007 estimates).NBTF reported highest rate of primary malignant brain tumor occurred in Northern Europe, United States and Israel. Lowest rate arised in India and Philippines. Brain tumor pathologies are the most common fatality in the current scenario of health care society. Hence, accurate detection of the type of the brain abnormality is highly essential for treatment planning.

brain tumor is one of the most common brain diseases, so its diagnosis and treatment have a vital importance for more than 400000 persons per year in the world (based on the World Health Organization (WHO) estimates), so its diagnosis and treatment have a vital importance.

1.2 COMPUTER AIDED DIAGNOSIS OF BRAIN TUMOR

Computer Aided Diagnosis is gaining significant importance in the day-to-day life. Specifically, the usage of the computer aided systems for computational biomedical applications has been explored to a higher extent. Medical image analysis is an important biomedical application which is highly computational in nature and requires the aid of the automated systems. These image analysis techniques are often used to detect the abnormalities in the human bodies through scan images. In the recent past, the development of Computer Aided Diagnosis (CAD) systems for assisting the physicians for making better decisions have been the area of interest [2]. The CAD system includes two stages. First stage has preprocessing and segmentation. Second, feature extraction, feature selection and classification.Figure1 show the general CAD system.

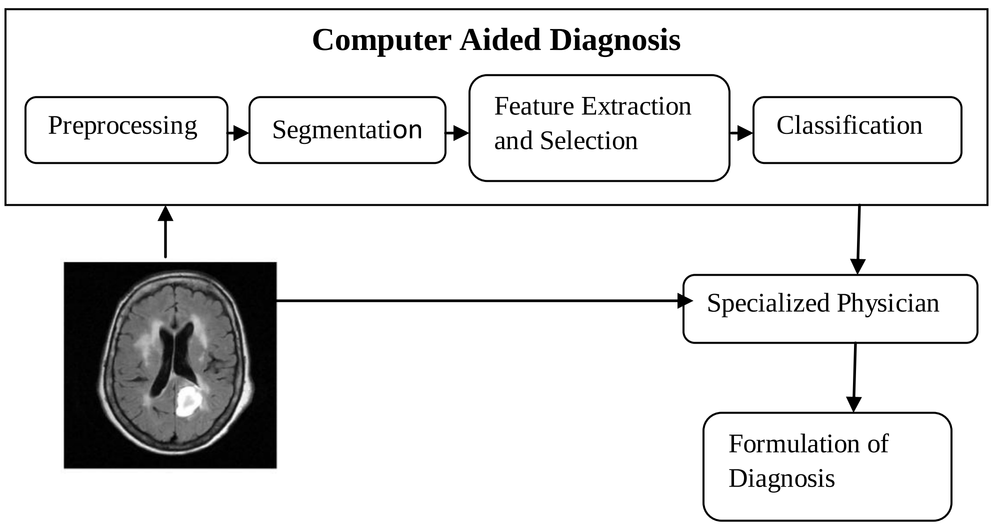

Fig1. Overview of the computer aided diagnosis system.

2. LITERATURE SURVEY ON IMAGE PREPROCESSING

Since most of the real life data is noisy, inconsistent and incomplete, preprocessing becomes necessary. Image pre-processing is one of the Preliminary steps which are highly required to ensure the high accuracy of the subsequent steps. The raw MR images normally consist of many artifacts such as intensity in-homogeneities, cranial tissues, Patient motions duration imaging times, thermal noise and exist of any metal things in imaging environment and film artifacts or label on the MRI such as patient name, age and marks etc. which reduces the overall accuracy. So it is needed to be removed by pre-processing procedures before any analyzing. The enhancement activities also used to remove the film artifacts, labels and filtering the images. Several de-noising approaches have been surveyed and analyzed in this section.

Table1. Literature survey of image preprocessing

De-noising approach	**Remarks**
Gabor & QMF Filters[1]	These primitive methods along with reducing the noise blur the important and detailed structures necessary for subsequent steps.
Non-linear anisotropic Diffusion[2] ,Curvature anisotropic Diffusion[3]	These methods can preserve boundary sharpness and fine details while suppressing noise and enhancing contrast-to-noise ratio
Statistical Parametric Mapping Method[4]	It is used to align the image properly and it uses left-to right symmetry to confer Robustness to areas of abnormality.
Mixture Model and Wavelet Shrinkage[5]	The discrimination between edge- and noise-related coefficients is achieved by updating the shrinkage Function along consecutive scales and applying spatial constraints. This method increase signal to noise ratio.
Wavelets & Wavelet Packets[6],	It vanishes the noise coefficients by thresholding the detail components.
Weighted least squares estimation method [7].	It reduce the inter-slice intensity variations by applying a weighted least squares estimation method also reduces intensity in homogeneity and intensity differences among the various scans as some scans appear relatively brighter or darker than others.
Diffusion filtering combined with non-adaptive intensity thresholding [8]	It is used to enhance the region of interest. The main drawback of this technique is the non-adaptive nature of the threshold value.
Wavelets and curve lets [9]	The noise removal technique using wavelet and curvelet is implemented in [9]. Hybrid approaches involving Variance Stabilizing Transform are also used in this work. But this technique is applicable for images with Poisson noise
Tracking algorithm[10]	The film artifacts and unwanted skull portions of brain are removed using tracking algorithms. This technique is not much efficient.
Contrast agent accumulation model [11]	This improves only the contrast of the image and the unwanted tissues are not eliminated.

The wiener Filter[12]	Weiner filter is a type of linear filter and have been used extensively for the restoration of noisy and blurred image. Wiener-filters a grayscale image that has been degraded by constant power additive noise.
Median Filter [13]	It can remove the noise high frequency components from MRI without disturbing the edges and it is used to reduce salt and pepper noise.
Adaptive center filter[14]	It is developed for impulsive noise reduction of an image without the degradation of an original image. The image is processed using an adaptive filter. The shape of the filter basis is adapted to high contrasted edges of the image. In this way, the artifacts introduced by a circularly symmetric filter at the border of high contrasted areas are reduced.
morphological operations[[15]	Cranial tissues often interfere with the brain tissues which results in inferior classification accuracy. Hence, the skull tissue removal is a significant pre-processing step in the area of brain image analysis. In this work, a series of morphological operations are used to eliminate the skull tissues.
Weighted Median filter [16]	It can remove salt and pepper noise from MRI without disturbing of the edges and have the robustness and edge Preserving capability of the classical median filter. WM filters have noise attenuation capability. WM filters belong to the broad class of nonlinear filters
Histogram Equalization[17]	The procedure used in this report is Histogram equalization, using Median filter, using Un sharp mask, thresholding and using from Mean filter respectively for each image A single pass of this filter did not seem to provide sufficient noise reduction, the image was passed through the filter a second time

3. LITERATURE SURVEY ON MR BRAIN IMAGE SEGMENTATION

Image segmentation is one of most important task in image processing .It is used to analyze images in different fields; such as medical, science, agriculture and industry fields. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures. During the past many researchers in the field of medical Segments the tumor from the brain is an important for to visualization the situation before do the surgery to achieve the desire result, it is important to raise the medical field to achieve the best result by using all the new techniques and by utilization all the computer features to enhance the segmentation purpose. Also it is used the computer to speed up the procedure got doing the segmentation. In recent literatures on medical image segmentation, several common approaches have been arrived. The available segmentation methods in literature for MR brain images can be broadly classified into eight categories shown in fig 2.

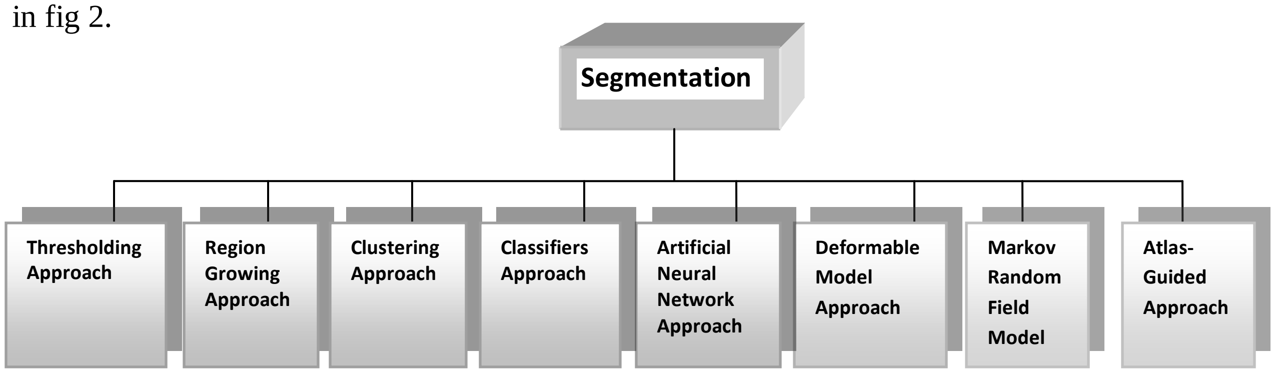

Fig 2 Category of MR brain image Segmentation

Table2. Literature survey of Segmentation

Segmentation Method	Remarks
Fast Marching Method[18]	It can be used as a fast initialization algorithm for image segmentation. Despite the fact that it requires low computational cost, in particular that the speed in this method is always positive or always negative. Automatic detection of the crossing of the interesting edges is difficult to implement.
GA with Deformable contour Method[19]	This report use genetic algorithm (GA) as a searching method applied with deformable contour to segment brain MR images. Multiscale approach has been used in order to help accelerating brain area identification at coarse scales and localizing more accurate brain contours at finer scales.

The maximum likelihood Approach [20	This approach segment the pathological tissue from the normal tissues .The drawback of this approach is that the proposed system is dependent class probabilities and threshold values.
Hidden Markov random field-Expectation Maximization[21]	HMRF model is a stochastic process generated by a MRF whose state sequence cannot be observed directly but can be indirectly estimated through observations. HMRF-EM framework, an accurate and robust segmentation can be achieved.
Modified Expectation Maximization (EM) algorithm [22]	This approach differentiate the healthy and the tumorous tissues. A set of tumor characteristics are presented in this paper which is highly essential for accurate segmentation. But the drawback of this work is the lack of quantitative analysis on the extracted tumor region.
Thresholding method [23]	This is simple and effective segmentation method for images with different intensities. The technique basically attempts for finding a threshold value, which enables the classification of pixels into different categories.
Radial basis function neural network (RBF) and contour model[24]	A combined radial basis function neural network and contour model based MR image segmentation technique is dealt in this paper. The contour model is used as a pre-segmentation step by developing the clear boundaries between the different tissues. RBF neural network is then used to segment the various brain tissues into different groups.
Atlas-based segmentation[25]	The atlas-based approach is able to segment several structures simultaneously, while preserving the anatomy topology. The method, provides a good trade-off between accuracy and robustness, and leads to reproducible segmentation and labeling.
Modified suppressed fuzzy c-means (MS-FCM) segmentation[26]	MS-FCM performs clustering and parameter selection, for the suppressed fuzzy c means algorithm simultaneously. It can easily select the parameter in Suppressed-FCM with a prototype-driven learning and also this algorithm seems to be simple in its computation. The parameter selection is on the basis of exponential separation strength among clusters.

High speed parallel fuzzy C means algorithm[27]	The high speed parallel fuzzy C means algorithm is more advantageous both in the sequential FCM and parallel FCM which employs the clustering process in the segmentation techniques. When the image size is so large, the proposed algorithm works very fast and it requires minimum execution time.
Back propagation neural network [28]	In this paper comparative analysis is done with the Inverse Laplace Transform based technique. The report concluded that BPN is superior in terms of processing time and accuracy over the conventional algorithm.
Fast neural network[29]	An iterative-free training approach is followed in this network using the Huang's neural network. The convergence time period is considerably reduced since the weights are determined analytically rather than through conventional weight adjustment procedure.
Watershed transform and level set method[30]	It combines the watershed transform and region-based level set method. The watershed transform is first used to presegment the image. The region-based level set method is then applied for extracting the boundaries of objects on the basis of the presegmentation. The consumed time does not depend on the size of the image but the number of presegmented regions. This method is computationally efficient.
Bayes-based region growing algorithm[31]	Bayes-based region growing algorithm that estimates parameters by studying characteristics in local regions and constructs the bayes factor as a classifying criterion. The technique is not fully automatic and this method fails in producing acceptable results in a natural image. It only works inhomogeneous areas. Since this technique is noise sensitive, therefore, the extracted regions might have holes or even some discontinuities.
Marker controlled watershed Segmentation[32]	This method is quite versatile, fast and simple to use. This can be applied to all type of 2D MR images representing all tumors irrespective of their location in human body and their size.
Deformable models[33]	The segmentation efficiencies reported in this approach is very low and the report also concluded that the proposed approach is a failure in case of symmetrical tumor across the

	mid-sagittal plane.
Color based segmentation method[34]	This paper proposes a color-based segmentation method that uses the K-means clustering technique to track tumor objects in magnetic resonance (MR) brain images. Experiments demonstrate that the method can successfully achieve segmentation for MR brain images to help pathologists distinguish exactly lesion size and region.
LVQ neural network [35]	The concept of GA is incorporated in this technique to improve the performance of conventional LVQ. An analysis in terms of segmentation efficiency and convergence time Period is provided in the report.
Support Vector machine[36]	Support vector machine is a promising technique in image segmentation because of its good generalization performance, especially when the number of training samples is very small and the dimension of feature space is very high
A fuzzy kohonen neural network [37]	This technique is completely dependent on the input features which are the drawback of this system. The qualitative and quantitative analysis results are inadequate when compared with the other techniques.
Marker controlled watershed Segmentation[38]	This method is quite versatile, fast and simple to use. This can be applied to all type of 2D MR images representing all tumors irrespective of their location in human body and their size.
Modified-FCM segmentation[39]	An improved segmentation technique has been proposed in this paper on the basis of FCM clustering algorithm. The neighbor pixels of targets are varied by applying the Sigma filter principle. The proposed algorithm **is** compared with FCM algorithm in visual evaluation and quantitative evaluation thereby the efficacy of the proposed method was demonstrated.
The improved FCM algorithm [40]	It is based on the concept of data compression where the dimensionality of the input is highly reduced. Since the modified FCM algorithm uses a reduced dataset, the convergence rate is highly improved when compared with the conventional FCM.
Vector quantization[41]	This paper presents a vector quantization segmentation method to detect cancerous mass from MRI images. It is a very effective model

	for image segmentation process. Vector quantization is a classical quantization technique from signal processing which allows the modeling of probability density functions by the distribution of prototype vectors.
Gaussian smoothing based FCM algorithm[42]	This approach has incorporated a feature selection algorithm for improved accuracy. Experimental analysis has revealed the suitability of this approach for noisy MR images. But the computational complexity of this approach is significantly high due to the bootstrap based feature selection techniques
Spatial Information with Fuzzy C-Means Clustering[43]	This approach utilizes histogram based Fuzzy C-Means clustering algorithm for the segmentation of medical images. The spatial probability of the neighboring pixels is incorporated in the objective function of FCM to increase the robustness against noise.
Hierarchical Self Organizing Map with FCM[44]	This paper, proposed a hybrid technique combining the advantages of Hierarchical self organizing map with FCM. This paper is used to give more information about brain tumor detection and segmentation of HSOM with FCM is the performance of the MRI image in terms of weight vector, execution time and tumor pixels are detected. The hybrid approach is accurately identifying the principal tissue structures in the image volumes.

4. LITERATURE SURVEY ON FEATURE EXTRACTION

Feature extraction refers to various quantitative measurements of medical images typically used for decision making regarding the pathology of a structure or tissue. Feature extraction can be carried out in the spectral or the spatial domain. Once the features have been extracted, selection of a subset of the most robust features is essential, aiming at improving classification accuracy and reducing the overall complexity. The purpose of feature extraction is to reduce the original data set by measuring certain properties or features that distinguish one input pattern from another pattern. The extracted feature should provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into a feature space. Related research work in feature extraction techniques are Gabor wavelet basede features for classification is used by [45] in this paper both DWT and Gabor wavelet transform is used to extract image features, and found that Gabor features are more effective than biorthogonal wavelet features, it also leads to more accurate classification results. Wavelet transform has received much attention as a promising tool for texture analysis , wavelet based optimal texture feature set for classification of brain tumor is implemented by [46] with lower computational effort.. The wavelet packets decomposition [47] technique is more efficient than the DWT technique. Apart from extracting the features from the whole image, features are also extracted from local regions which are used for image segmentation applications. The advantage of is that it gives richest analysis when compared with the wavelet transforms there by adding advantages to the performance of the system. [48]Adaptive Wavelet Packet Transform (ADWPT) and Local Binary Patterns (LBPs), textural features are combined together and used for classification .Although LBP features do not provide higher overall classification accuracies than ADWPT, it manages to provide higher accuracy for a meningioma subtype that is difficult to classify otherwise. In [49], four different dual-tree complex wavelet (DT-CWT) based texture feature extraction methods are developed and compared to segment and classify tissues. Methods that are proposed in this study are based on local energy calculations of sub-bands. Two of the methods use rotation variant texture features and the other two use rotation invariant features.. Results show that all DT-CWT based feature extraction methods are competitive with other filtering approaches. A novel feature set which comprises the features such as short run emphasis, run length non-uniformity, etc. which are based on run length matrices are described by [50]. The drawback of this work is the low classification accuracy which shows that these features do not guarantee superior results. First and second order statistical features are also extracted from each training points and used for segmentation applications. These types of features are used by [51]. This report suggested that the combination of histogram based statistical features is more effective than the intensity based features. Though many texture features have been used in the medical image classification, Spatial Gray Level Dependent Features (SGLDF) can be used to calculate the inter sample distance for better diagnosis is reported by[52]. Texture features extracted by gray level Co-occurrence matrix [53] .extracted features used in the knowledgebase which helps to distinguish between normal and abnormal brain tumors. Extracted texture features used in training of the artificial neural network. [54]. Feature extraction technique using Discrete Cosine Transform is implemented by [55] This report suggested that features extracted using Discrete cosine transform and down sample the extracted features by alternate pixel sampling. Results using DCT for feature extraction is pretty promising. Feature extraction based on block processing technique is reported by [56].

5. LITERATURE SURVEY ON FEATURE SELECTION

Feature selection refers to the problem of dimensionality reduction of data, which initially consists of large number of features. The objective is to choose optimal subsets of the original features which still contain the information essential for the classification task while reducing the computational burden imposed by using many features. Once the features have been extracted, selection of a subset of the most robust features is essential, aiming at improving classification accuracy and reducing the overall complexity. Many earlier works reported the usage of feature selection techniques to enhance the quality of the output. In [57] GA was implemented along with neural network for pattern recognition and to determine the object orientation. The result showed good optimization by reducing the number of hidden nodes and the time required to train the neural network. Optimal fuzzy rule selection for classification is implemented by [58]. A hybrid neuro fuzzy approach is used in this work with the architecture performing the selection procedure. But this technique is highly sensitive to change in the parameters of the membership functions. Maximum output information based optimal feature set selection is performed by [59].This feature selection is performed for improving the performance of Multi layer Perceptron (MLP) classifiers. The features for which the classified outputs are high are selected as the optimal feature set. The output of the classifiers is estimated with mutual information and entropy. This paper [60] compares the performance of classical sequential methods, a floating search method, and the "globally optimal" branch and bound algorithm when applied to functional MRI and intracranial EEG to classify pathological events. This paper suggested that the sequential floating forward technique outperforms the other methodologies for these particular data. In terms of classification accuracy, the SFFS algorithm proves to be the best option for the automatic selection of features. A quantization based feature reduction technique for MR image classification techniques is used by [61]. This technique is quite faster but the major drawback is the loss of information which leads to inferior accuracy results. A Support Vector Machine (SVM) based feature selection technique is implemented by [62]. This technique is based on backward sequential algorithm which removes one feature at a time. The main disadvantages of this technique is that the time period required for convergence is more besides suffering from local optima. An enhancement of the PSO known as chaotic PSO is used for image classification in [63]. The results showed a considerable increase in the image classification accuracy with the proposed algorithm. A modified GA is proposed by [64]. This approach is based on graph based Cartesian approach. A comparative analysis is also performed with conventional GA to show the superior nature of the proposed approach. The performance measures used in this work are minimizing the redundancy and improving the computational efficiency. A hybrid algorithm of Genetic Algorithm (GA) and Tabu Search (TS) for feature selection in the Fuzzy ARTMAP NN classifier is presented by [65]. The capabilities of GA-TS is identifying and removing noisy features that can degrade classification accuracy. Results demonstrate that proposed GA-TS performs better in terms of feature compactness and classification accuracy than the ordinary GA. An extensive analysis on comparison of GA and PSO algorithms for feature selection is performed by [66]. The results concluded that PSO is better than GA in terms of accurate results. Classical sequential methods are compared against the genetic approach in [67]. In this work wrapper approach [68] with sequential forward selection, sequential backward selection, sequential floating backward selection, and GA is used to search for an optimal feature subset. Principal component analysis and classical sequential methods are compared against the genetic approach in terms of the best recognition rate achieved and the optimal number of features GA finds better solution than SFFS .Among the sequential search algorithms, Sequential floating forward selection (SFFS) produces best classification accuracy. Principal component analysis based feature reduction technique for magnetic resonance images is used by[69] The main idea behind using PCA in this approach is to reduce the dimensionality of the wavelet coefficients. This leads to more efficient and accurate classifier. To reduce the large number of features to a smaller set of features [70] applies GA-based global search method. GA is an adaptive method of global-optimization searching and simulates the behavior of the evolution process in nature and minimizes the dimensionality of the transformed patterns and maximizing classification accuracy. The approach is limited by the fact that it necessitates fresh training each time whenever there is a change in image database. PSO based optimal feature set selection is performed by [71].This optimization technique not only improves the convergence rate but also enhances the classification accuracy results to a higher\extent. Feature selection based on the correlation coefficient between features is performed by [72]. The correlation matrix was calculated for the set of 9 texture features for both normal and abnormal spaces. Any two features with correlation coefficient that exceeds 0.9 in both spaces can be combined together and thought as one feature reducing the dimensionality of the feature space by one. Therefore the maximum probability and contrast can be removed and the numbers of features are reduced to seven features. This Paper [73] uses ant colony optimization (ACO) as the technique for feature selection. In ACO, a colony of ants cooperates to look for solutions for the problem. Artificial ants incrementally build a solution by adding components to a partial solution under construction. With ACO, the image features are selected and images are retrieved from databases with high accuracy. In [74] the proposed feature selection method is kernel F-score feature selection method is provided both to transform from nonlinearly separable dataset to linearly separable dataset and to decrease the computation cost of classification algorithm, But a disadvantage of F-score method does not take the mutual information between features into account. Thus, this survey Provide many optimization techniques used for feature selection. Hence, the applicability of various algorithms for feature selection will be explored in this work for accurate classification

6. LITERATURE SURVEY ON MR BRAIN IMAGE CLASSIFICATION TECHNIQUES

Image classification is the technique of categorizing the abnormal input images into different tumor groups based on some similarity measures. The accuracy of this abnormality detection technique must be significantly high since the treatment planning is based on this identification. Automated image classification systems with high accuracy are highly essential for the real-time applications. Selection of a suitable classifier requires consideration of many factors:

- Classification accuracy
- Algorithm performance
- Computational resources

There are basically two types of classification. One is known as unsupervised classification and other is known as supervised classification. Unsupervised classification is the identification of natural groups, or structures, within multi-spectral data. The following characteristics apply to an unsupervised classification

- No extensive prior knowledge of the region is required
- Many of the detailed decisions required for supervised classification are not required for unsupervised classification creating less opportunity for the operator to make errors.
- Unsupervised classification allows unique classes to be recognized as distinct units.

Whereas supervised classification is the process of using samples of known identity to classify samples of unknown identity. The following characteristics apply to a supervised classification:

- Requires detailed knowledge of the area.
- Input patterns are provided with the labels
- Able to detect serious errors by examining training data to determine whether they have been correctly classified.

Table3. Literature survey of Classification

Classification Techniques	**remarks**
EM (Expectation-Maximization)algorithm[75]	This paper applied the EM algorithm in the detection of abnormalities. These algorithms proved to be capable of distinguishing large tumors from the surrounding brain tissues by training exclusively on normal brain images in healthy people in order to recognize deviation from normality. This requires high computational effort.
A neural network approach[76]	A neural network approach for melanoma detection is reported by this paper .Multivariate discriminant analysis is compared with this approach, diagnostic scores and model stability, are worse for MDA and the approach used in this system is computationally heavy.
Linear discriminant analysis (LDA), support vector machines (SVM) and least squares SVM (LS-SVM)[77]	This paper shows a comparative study of brain tumor classification based on long echo proton MRS signals .Linear discriminant analysis), support vector machines (SVM) and least squares SVM (LS-SVM) with a linear kernel and LS-SVM with a radial basis function (RBF) kernel are compared in this report. Kernel-based methods can perform well in processing high dimensional data. The major limitation is the limited number of available spectra for the tumor types which results in inferior classification accuracy
Linear Discriminant Analysis[78] .	The four different types of tumor is classified using LDA technique by this report . But the classification accuracy reported in the paper is in the order of 80% which is relatively low. This work also suggested the various reasons for misclassifications
Neural network self-organizing maps and support vector machine[79]	This paper, proposed a novel method using wavelets as input to neural network self-organizing maps and support vector machine for classification of magnetic resonance (MR) images of the brain. Classification rate is high for a support vector machine classifier compared to self-organizing map-based approach. But the major drawback is the low convergence rate.
Kohonen neural networks[80]	The application of Kohonen neural networks for image classification is explored in this

	paper. Some modifications of the conventional Kohonen neural network are also implemented in this work which proved to be much superior to the conventional neural networks.
Support Vector Machines (SVM) with kernel functions[81]	This paper utilizes Support Vector Machines (SVM) with linear, sigmoid, RBF kernel functions to classify the images into normal and abnormal groups. SVMs are trained using wavelet features and Gabor wavelet features for linear, RBF and sigmoid kernels. Gabor wavelets perform better than Daubechies wavelets in classification.
Least Squares Support Vector Machine (LS-SVM)with Linear and Non-Linear Kernals.[82]	In this report Least Squares Support Vector Machines classifier using linear as well as nonlinear Radial Basis Function (RBF) kernels are compared with other classifiers like SVM Multi Layer Perceptron and K-NN classifier. The proposed method using LS-SVM classifier outperformed all the other classifiers tested. LS-SVM has a higher accuracy of classification over other classifiers. The number of false negative in LS-SVM is very low compared to others. The LS – SVM classifier results show a high degree of sensitivity of the classifier to abnormal images.
Kohenon Network SOM(Self Organization map) and LVQ(Learning vector quantization) [83]	In this paper comparative studies of SOM, LVQ, combination of SOM and LVQ are conducted. The combined approach gives more reduced quantification error and higher rate of recognition classification rate. The execution time of the combined approach is shorter compared to that of LVQ
Modified Probabilistic Neural Network[84]	The modified Probabilistic Neural Network for tumor image classification is used in this paper. Abnormal images such as metastase, glioma and meningioma are differentiated using the least square feature transformation based PNN. A comparative analysis is also performed with SVM. This work inferred that the transform based PNN is superior to the SVM in terms of classification accuracy.
Probabilistic Neural Network[85]	A time efficient neural network such as PNN is used by for pattern classification problems. Emphasis was given for convergence time than the classification accuracy. The results concluded that the PNN is superior over

	conventional neural networks in terms of training time period.
Forward back-propagation artificial neural network –(FP-ANN) and k-nearest neighbor (k-NN).[86]	This paper compares feed forward back-propagation artificial neural network and k-nearest neighbor (k-NN).The experimental results show that classification accuracy, sensitivity and specificity is high for k-NN. ANN method gained the worst classification accuracy, sensitivity and specificity rate. The limitation of this work is that it requires fresh training each time whenever there is an increase in image database. This method required less computation time due to the feature reduction based on the PCA.
Fuzzy ARTMAP[87]	An enhanced ART neural network for classification applications is implemented in this report. This employed the GA approach to select the order of training patterns to enhance the classification performance. This experiment is conducted on various datasets. But the classification accuracy results are different for different datasets which is one of the drawbacks of this approach.
Pruned association rule with MARI algorithm based classifier[88]	Brain tumor classification using pruned association rule with MARI algorithm is presented in this paper. This approach has been compared with naive Bayesian classifier and associative classifier. The experimental results have shown that the proposed method achieves high sensitivity (up to 96%), accuracy (up to 93%) and less execution time and standard error in the task of support decision making system.
Particle Swarm Optimization (PSO) based Counter Propagation Neural Network (CPN) classifier [89]	In this paper, Particle Swarm Optimization is used as the optimization algorithm and it is used along with the modified Counter Propagation Neural Network classifier. Conventional CPN, Modified CPN, PSO based CPN are analyzed in terms of classification accuracy and convergence time period. Experimental results show promising results for the PSO based modified CPN classifier in terms of the performance measures.
Neuro-Fuzzy Classifier[90]	The proposed work will be very useful under medicines for predicting early brain cancer cells using texture features and neuro

	classification.ANeuro-fuzzy classifier provides better classification during the recognition process. The considerable iteration time and the accuracy level is found to be about 50-60% improved in recognition compared to the existing neuro classifier.
Adaptive neuro fuzzy inference system (ANFIS) [91]	In this work, first order Sugeno model based ANFIS system is used for brain tumor image classification. The performance measures of ANFIS are compared with the results of the back propagation neural network and fuzzy nearest center classifier respectively. The error rate of fuzzy classifier and the neural classifier are high as they suffer from the drawbacks of random initial cluster center selection and requirement of large training data set. The classification accuracy of ANFIS is comparatively higher than the fuzzy and neural classifiers. The convergence time period of ANFIS is ten times better than the neural and the fuzzy classifier.
Hybrid technique (Wavelet Transform, Genetic Algorithm and Support vector machine)[92] .	This paper discussed a hybrid technique is designed by the wavelet transform (WT), genetic algorithm (GA) and supervised learning methods (SVM). The result of classification of this approach is better than the other one lacking the decomposition stage for classification of the MRI brain, benign or malignant tumor. The proposed approach gives high sensitivity, specificity and accuracy rates but less computation due to the feature extraction based on Wavelet Transform.The approach is limited by the fact that it necessitates fresh training each time Whenever there is a change in image database.

7. CONCLUSION

In this work, the merits and demerits of various automated techniques for brain tumor identification is analyzed in detail. This paper is used to give more information about brain tumor detection techniques. The suitability of the techniques for various applications is also illustrated in this survey. This report also aid in highlighting the significant contributions of engineering theory to the medical field.

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