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A Review on Brain Tumor Classification Methodologies

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ABSTRACT

Brain tumor is one of the leading disease in the world. So automated identification and classification of tumors are important for diagnosis. Magnetic resonance imaging (MRI)is widely used modality for imaging brain. Brain tumor classification refers to classify the brain MR images as normal or abnormal, benign or malignant, low grade or high grade or types. This paper reviews various techniques used for the classification of brain tumors from MR images. Brain tumor classification can be divided into three phases as preprocessing, feature extraction and classification. As segmentation is not mandatory for classification, hence resides in the first phase. The feature extraction phase also contains feature reduction. DWT is efficient for both preprocessing and feature extraction. Texture analysis based on GLCM gives better features for classification where PCA reduces the feature vector maintaining the accuracy of classification of brain MRI. Shape features are important where segmentation has already been performed. The use of SVM along with appropriate kernel techniques can help in classifying the brain tumors from MRI. High accuracy has been achieved to classify brain MRI as normal or abnormal, benign or malignant and low grade or high grade. But classifying the tumors into more particular types is more challenging.

Keywords : Brain Tumor, DWT, Feature Extraction, Feature Reduction MRI, MRI Classification.

I. INTRODUCTION

A tumor is an unnecessary growth of cell which is no more required by the body. A brain tumor occurs when abnormal cells form within any part of the brain. Brain tumors are commonly affecting more people nowadays which can cause cancer. According to the national health portal of India, 5-10 among 1,00,000 suffers from brain tumors and is the 2nd greatest cause of cancer in India. A report from brain tumor organization shows that around 7,00,000 people of the US suffer from primary brain tumors where kids are more suffered. This serious problem raises a global warning for which 8th June is celebrated as the World Brain Tumor Day.

1. Brain Tumor and Types

A brain tumor may be cancerous (benign) or non-cancerous (malignant). A benign tumor is a non-cancerous tumor. The least aggressive type of brain tumor is often called a benign brain tumor. They originate from cells within or surrounding the brain, do not contain cancer cells, grow slowly, and typically have clear borders that do not spread large [44]. An example of a benign tumor is a meningioma., low-grade glioma, pituitary tumor. A malignant tumor is a cancerous tumor. Malignant brain tumors contain cancer that starts in cells of the brain is called cells and often do not have clear borders.[44]. The World Health Organization (WHO) has created a standard by which all tumors are classified as a grade. Tumors are classified as Grade I, Grade II. Grade III, and Grade IV [43]. Lower-grade tumors (grades I & II) are not very aggressive and are usually associated with long-term survival. Higher grade tumors (grade III & IV) grow more quickly, can cause more damage, and are often more difficult to treat. These are considered malignant or cancerous.1.2 Diagnosis of Brain Tumors.

2. Brain Tumor Diagnosis

Tumors vary in type and size, and the type of tissue they occur in often signifies their shape and how they grow. By the virtue of medical imaging techniques, it is possible to visually diagnosis the brain tumor. Imaging modalities like Magnetic resonance imaging(MRI), Computed Tomography(CT), PET, SPEC etc. Human experts identify the tumor position from the medical image along with its category. To automate the process of identifying tumor position from medical images, various segmentation techniques are evolved. By the application of image processing, we can find the percentage of affected area of the tumor along and classify their grade and types.. The selection of an appropriate segmentation technique largely depends on the type of images and application areas [48]. Classifying the images into can help in applying suitable segmentation technique.

3. Magnetic Resonance Imaging (MRI)

MRI is the widelyused modality analyze abnormality in the brain. It is the medical imaging technique that uses a magnetic field and radio frequency (RF) signals to produce images of anatomical structures, of the presence of disease and various biological functions within the human body. MRI produces images that are distinctly different from the images produced by other imaging modalities [45]. The present MRI systems can produce images equal to 65,535 gray levels which quite impossible for a human to visualize [40]. Brain region consists of different tissues like White Matter(WM), Gray Matter(GM), Cerebrospinal Fluid (CSF) along with brain tumor [42]. Each tissue is characterized by two relaxation times: Tl and T2. T1 images are used for distinguishing healthy tissues, whereas T2 images are used to highlight the edema region which produces a bright signal on the image. In T1 graded images, most tumors appear dark or give low signal and in T2 weighted images most tumors appear bright.

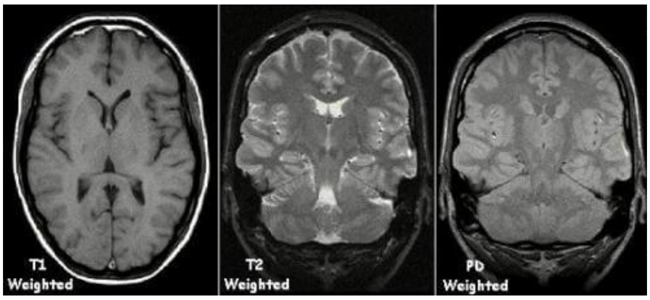

Figure 1 : T1, T2, pd weighted MRI

II. BRAIN TUMOR CLASSIFICATION

Brain MR images can be classified as normal or abnormal, benign or malignant, grade, or types. Various image classification techniques are used to categorize the MR images. The classification technique can also be used for the segmentation of brain tmor [39]. Although segmentation of brain tumor helps in classification MRI, classification of tumor can help to select appropriate segmentation technique for different types. For classification, segmentation is not always mandatory. So in the context of brain MRI classification segmentation can be considered as preprocessing task. Classification of Brain tumor from MRI can be divided into 3 phases as in fig 2. Feature reduction is a part of feature extraction.

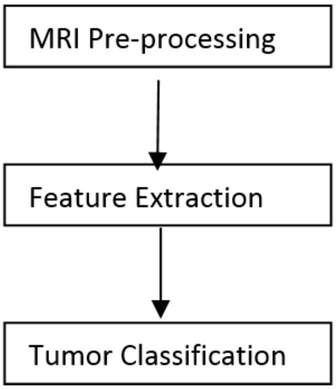

Figure 2. brain tumor classification methodology

2.1 Preprocessing

The preprocessing step is done before the feature extraction phase. Image pre-processing techniques like filtration and resolution enhancement are used to improve the quality of an image [41]. The preprocessing before feature extraction for the classification of brain MR images may or may not include the segmentation phase. Various preprocessing techniques used for brain MRI classification are given below.

2.1.1 Segmentation Based

Brain MRI segmentation refers to the process of dividing the brain region into segments. In this type of preprocessing, brain MR image segmentation is performed to extract the brain tumor region. Then features are extracted from the segmented part for the classification purpose. Thresholding, region growing, K-mean Algorithm, Fuzzy c-mean algorithm (FCM), Markov Random Model (MRF), K-Nearest Neighborhood, Self Organizing Map are mainly used for MR image segmentation [36]. Segmentation can be automatic, semi-automatic and manual [38]. ROI based segmentation can be performed to manually select the tumor region[9][18]. Unsupervised clustering techniques like K-mean [4] and TKFCM [19] are used in the preprocessing phase to augment the tumor portion. Complex segmentation methods that combine various techniques for segmentation can also be used for the segmentation of brain MR images [11]. SVM can also be used for segmentation to classify the pixel as normal or abnormal [10]. Evolutionary algorithms like GA can also be used for brain tumor segmentation [37]. Segmentation process helps in reducing the area of interest from which features will be extracted.

2.1.2 Without Segmentation

In this type, the MR image of the brain tumor goes under various preprocessing without performing segmentation. Then the preprocessed image is taken to extract various features and then classification is done. Techniques like denoising, wavelet transform, skull masking are used for preprocessing of brain tumor MR image before feature extraction. Brain MR images are very complex as it contains various matters and tissues along with the tumor. The smoothly varying intensity is also a problem for classification.

Most of the imaging techniques are degraded by noise. So to preserve the edges and contours of the medical image efficient denoising techniques are required [41]. Methods such as the use of an Anisotropic Diffusion filter helps in removing noise in brain MR images [10]. A hybrid technique that uses linear and non-linear filters for noise removal can also be used on brain MR images[4]. Discrete wavelet transform (DWT) is one of the best techniques used as preprocessing for feature extraction. DWT can represent an image more accurately in various resolutions. DWT can be decomposed into various levels by further decomposition of the approximation sub-band. The filtering technique through domain transform can also possible to remove noise from brain MRI [4]. The wavelet decomposition is done based on the mother wavelet. DB-4 and HAAR wavelets are widely used as mother wavelet*s.*

The skull masking technique is used to eliminate the skull present in the MR image to reduce the size of the interested area [25]. Other preprocessing techniques like morphological processing [26] and grayscale normalization [2] are also done for better appearance of the image that helps in classification.

2.2 Feature Extraction

Feature extraction is the process of reducing the size of data needed to represent the original data. Processing, processing the whole image data for classification can take more computational space and time. Hence feature extraction process is applied to extract the different types of meaningful information through which the original image can be correctly identified. The features are used to train the classification model. Images of the same class have some common patterns in their features set. Local features like geometric features and global features like topological features [49]. In this stage, primary features are extracted from the given image. Texture, shape, statistical, intensity-based features are primarily used for the classification of brain MRI.

2.2.1 Texture Analysis

Texture analysis refers to the characterization of regions in an image by their texture content. Textures are complex visual patterns composed of entities, or subpatterns, that have characteristic brightness, color, slope, size, etc.[47]. Texture analysis attempts to quantify the variations in intensity values and gray levels. Texture analysis can be used to find the texture boundaries called feature segmentation. Gray level co-occurrence matrix(GLCM) [21] and Gabor texture [25] are used for texture analysis for brain tumor classification. GLCM method is widely used for extracting statistical texture features which are also known as Harlick features [14].

2.2.2 Shape Analysis

It is the process of analyzing the geometric shape of the object. Statistical shape analysis refers to the analysis of a given set of shapes by statistical methods. A shape description method generates a shape descriptor vector (also called a feature vector) from a given shape [46]. Different types of tumor can have same shape and same type of tumors can differ in size. So shape analysis may not help in classifying brain tumor into different types. The shape descriptor is mainly useful where segmentation has already done [18][25] .

2.2.3 Wavelet Transform

DWT based feature extraction techniques are widely used for the classification of brain tumors from MR images. Increasing the level of DWT results in decreasing the size of the coefficients and it can also able to represent an image more precisely in lower resolutions. Hence the DWT coefficients can be used instead of the whole image for feature extraction [6] [7] [8]. As a brain MRI contains more valuable information, DWT helps in reducing resolution while preserving information. The DWT coefficients of an image can also be used as a feature vector [3][12]. We can say that DWT is the technique that can be used for preprocessing as well as feature extraction for brain MRI classification. DCT coefficients can also be used as a feature vector for classification [13]. Some researchers concluded the haar wavelet gives better performance than the db4 wavelet in reducing dimension [35].

2.2.4 Feature Selection

Determining a subset of initial features is called feature selection. It is also known as a dimension reduction technique. Although feature extraction reduces the dimensionality, sometimes extracted feature are too large to process. Feature selection is the step where the dimensionality of the primary feature vector is again reduced. Methods like LDA [2] and PCA [5] used in brain tumor classification and they use the statistical property of the feature vector for feature reduction. More advanced methods like GA [1][8], Simulated Annealing (SA) [22], Recursive feature extraction (SVM- RFE) [25] are used to reduce the feature vector with a positive impact on classification accuracy. GA is a special form of local search that models our understanding of evolution [37].

2.3 Classification

Classification is an important part of computer vision as it helps the computer to automate decisions. Image classification refers to categorize the image into one of the predefined classes. Classification of brain MRI means to predict the type and grade of tumor [18] and whether the image normal or abnormal [19]. The classification step is mostly accomplished by machine learning algorithms. As a brain tumor, MR image very complex, supervised machine learning techniques like SVM, NN, KNN, etc are preferred for classification of brain MR images. New machine learning boosting algorithm like Adaboost can also be used for brain tumor classification purposes [24]. Some commonly used classification techniques used on brain MRI are as follows:

2.3.1 Neural Networks

The mechanism behind the neural network is similar to the way human learns or percepts. According to Robert Hecht-Neilson (inventor of one of the first neurocomputer),"Neural Network is a computing system made up of some simple highly interconnected processing elements which process information by their dynamic state response to external inputs." Artificial Neural Networks (ANN) are widely used for achieving better accuracy. Neural networks play an important role in classifications by using supervised and unsupervised techniques [50]. NNs like Probabilistic Neural Network (PNN) [13][15], FF-NN [9], BP-NN [11] are supervised, while SOM-NN [3] is an unsupervised classification method based on clustering. ANN also used for the classification of a brain tumor in MRS images [17]. Advance methods like ACPSO are also used to optimize the parameters for neural networks.

2.3.2 K-Nearest Neighbourhood (KNN)

KNN algorithm is a simple supervised machine learning algorithm. No underlying assumption on the dataset required in this method and it can be used for classification as well as regression. It is based on an approach that similar things are nearer to each other. KNN used for brain MRI classification in [6] and [20].

2.3.3 Support Vector Machine (SVM)

SVM is a supervised machine learning technique that is used for classification and regression problems. Normally SVM used for binary classification. SVM classifies the dataset into two categories by drawing a hyperplane. A hyperplane is a line that divides the plane into two parts. We can also be called a decision boundary. For a more complex dataset where a straight line can't be drawn, kernel techniques also used to draw circular hyperplane. There are different types of SVM kernel such as gaussian or radial basis function kernel, linear kernel, polynomial kernel, etc and the Gaussian kernel is better than other kernels [3][5]. SVM outperforms NN [3] and gave a better performance than KNN, Adaboost [2]. SVM is a systematic and effective method for two-class problems and better than rule-based systems [51]. Parameter optimization of SVM can be done using advanced algorithms [22]. Ensemble classifiers based on SVM can also be used for brain tumor classification [27].

III. LITERATURE REVIEW

In 2006 [3], Chaplot et al performed classification on 52 T2 weighted brain MR images. The second level wavelet coefficients were directly used as features for classification through both supervised and unsupervised machine learning techniques. SVM with RBF kernel gave 98% accuracy while SOM based neural network produced an accuracy of 94%.

Yao et al in 2009 [18], proposed a classification method to find out type as well as a grade of the tumor from 102 T1 weighted MR images. Manual segmentation performed to find out a region of interest and shape, intensity and rotation invariant texture features were extracted from the segmented tumor region. The feature selection was accomplished in a recursive manner using the SVM-RFE method. Then the classification made by SVM gave an accuracy of 85% for type prediction and 88% for grade prediction. The leave-one-out cross-validation technique was used in SVM.

Zacharki et al in 2009 [25] proposed a similar method like [18]. Features were extracted from the manually segmented MR image. Shape, statistical, intensity features were extracted with the Gabor texture feature. Feature selection was done by the SVM-RFE algorithm. The GRB kernel binary SVM with leave-one-out cross-validation gave 87% accuracy for both type and grade classification. 102 MR images of different types like T1, T2 and FLAIR were used.

In 2010 [6], Ahmed et al proposed a technique based on MR image for classification of normal and abnormal brain tumor images. In this paper, 70 T2 weighted MR images were used. PCA is applied to the extracted level-3 DWT coefficients to reduce the dimensionality of the feature vector. In this paper, KNN outperformed feed-forward backpropagation ANN. The classification accuracy for ANN was 97% where KNN gave 98.6% accuracy.

A hybrid approach for brain MR image classification was proposed by Zhang et al, in 2010 [7]. Level-3 Haar wavelet decomposed coefficient was used as a primary feature vector. PCA was used for feature selection. Forward neural network classified the MR images as normal and abnormal. This resulting accuracy of the hybrid technique FNN-ACPSO was 98.75%. K-fold cross-validation was also used. The total number of 160 T2 weighted brain MR images were taken as a dataset.

Ahmed et al, in 2010 [1] proposed a brain MR image classification technique to classify the image as normal, benign, malignant. in this paper, GLCM features were extracted from 2-level DWT coefficients of brain MR image and genetic algorithm(GA) was used for optimal feature selection. The classification was done by SVM accomplished with 5-fold cross-validation to avoid data overfitting. This method shows 97.59% accuracy for the RBF kernel. 83 T2 weighted images were used in this research. The same approach was applied by the author in [8] and the DWT based feature extraction and GA based feature selection with SVM RBF kernel was 100% for 83 images. K-fold is applied to obtain training and testing sets.

In 2011 [12], Othman et al, implemented a multiclass SVM with RBF kernel to classify normal and abnormal brain MR images. DWT based feature extraction technique was used where level-2 coefficients of MR image were taken as features. SVM gave 65% classification accuracy on 60 T2 FLAIR weighted MR images. In the same year, Othman and Basri proposed another method on brain MRI classification using a probabilistic neural network(PNN) [15]. PCA was used for feature selection. The accuracy of the proposed scheme varies from 73-100% according to spread value which was used as the smoothing factor for RBF kernel-based PNN.

In 2011 [16], Salim et al, proposed a classification scheme for brain MRI using a hybrid wavelet technique based feature extraction.Leval-2 DWT was applied to the MR image and then the statistical features of LL and HL sub-band calculated separately. The final feature set prepared from the PCA of features of both sub-bands. Binary SVM classifier using polynomial kernel used for classification purposes. The proposed methods result in high specificity and low specificity.

Abdulla et al, in 2011 [30], proposed a classification model for normal and abnormal brain MR images using SVM. In this proposed methodology coefficients of both haar and db4 wavelets were used as a feature vector. A total of 30 images of T2 FLAIR weighted images were taken under consideration. The system showed a low accuracy of 65% using the RBF kernel.
In 2012, a kernel-based SVM classifier for brain MR image classification was presented by Zhang et al, [5]. In this proposed work, Level-3 DWT coefficients were taken as primary features and reduced using PCA. The reduced features then used as a feature vector for classification through SVM. K-fold stratified cross-validation techniques were used to avoid overfitting. The experiment was performed on 160 T2 weighted MR images. The system performed 99.38 % accuracy using GRB kernel and 95% using a linear kernel.

Nitish et al, in 2012 [21], proposed a brain tumor classification method using GLCM textural features. T2 weighted 80 MR images were taken and textural features of the image were calculated from the gray level co-occurrence matrix of the image. 11 features of each class were extracted and an FF-NN used for classification showing 97.5% accuracy using the extracted features. All images used for training were also used for testing.

In 2013 [29], Jainy et al, proposed a method for multiclass brain tumor classification using segmentation before feature extraction. A content-based active contour model was used for the segmentation of the tumor region. The segmented part was taken as a region of interest(SROI) for feature extraction. LoG, GLCM, intensity-based, Gabor based features were extracted from SROIs. An MLP based ANN gave 91% overall accuracy after feature selection through PCA and 65% individual class accuracy.

Ahmed et al proposed a hybrid brain tumor classification method in 2015 [22]. In this research, GLCM based features were extracted from the level-1 DWT of T2 weighted MR images. Simulated Annealing(SA) used for feature selection and to obtain trainset and testset K-fold cross-validation was used. The genetic Algorithm used to get the optimized parameter for RBF kernel SVM. Then the SVM showed 95.65% accuracy for classifying the images as normal and abnormal. A total of 73 images were used in this paper.

Ketan et al, proposed another hybrid classifier method for brain cancer classification in MR images, in 2015 [23]. The hybrid classifier used RBF kernel SVM for classification where KNN was used to find the support vectors (SVM-KNN). The system gave 98% accuracy when out of 50 images, 46 images were used for training and all images were used for testing. Preprocessing like filtering, skull masking was performed to remove noise and non-brain area. Then grayscale, symmetrical and textural features were extracted for training purposes.

In 2015 [33], Chang et al proposed a method for brain tumor classification from MR images. In this methodology, T1 weighted contrast-enhanced MR images were used and ROI found out by performing two phases dilation operation called tumor augmentation and tumor region partition. Intensity histogram, GLCM, and Bag of words features were extracted and feature selection is done through LDA and the SVM classification gave 91.14% accuracy.

Vani et al, in 2016 [32], presented an automatic classification method for MR brain images. Level-2 DWT coefficient of original images was used for GLCM based textural feature extraction. This method gave 88.59% accuracy for classification using KNN. For MR images, the author used Brat 2012 dataset.

In 2017 [20], Vijay et al proposed a classification model for brain MR images. GLCM features were extracted from the preprocessed MR image. This method gave 96 % accuracy using SVM for a clinical dataset of 251 images and 86% accuracy using KNN for the same dataset to classify the image as benign or malignant. For Brat 2012 dataset, the system gave 85% and 72.5% accuracy using SVM and KNN respectively to classify the images as low-grade glioma or high-grade glioma.

In 2017 [24], Minz et al proposed a scheme for classification of brain tumor types from MR images. Threshold-based image segmentation was performed along with processing like RGB to gray color space conversion and filtering for noise removal. Then GLCM based textural features were extracted from the segmented images. An adaptive boosting technique called AdaBoost outperformed neural network with 89.90% accuracy.

Avirup et al presented a classification approach for brain tumors from MR images in 2018 [26]. DWT based statistical features were extracted from preprocessed MR images. Anisotropic filtering and morphological processing were used for preprocessing. Machine learning technique, SVM, used for classification of benign and malignant tumors with 99.67% and 99.02% accuracy for respective classes.

In 2018 [34], Zia et al proposed a classification scheme for brain tumor MRIs. Features were extracted from the level-3 DWT of segmented images. A semi-automatic segmentation called LRBAC was used. Feature selection was done by PCA and the SVM showed 85.70% accuracy using RBF kernel and 10-fold cross-validation. The proposed methodology was tested using different datasets and different sized images.

In 2018 [31], Salman et al proposed a brain tumor classification scheme using a pre-trained neural network. The segmentation of the MR image was done by input cascade CNN and the VGG-19 was used as the pre-train neural network for deep feature extraction and classification. The proposed system gave 90% accuracy for the radio media dataset and 94.8% accuracy for the brain tumor dataset.

Mukambika et al proposed a classification model where segmentation was performed in a preprocessing step before feature extraction in 2017 [28]. 41 images T2 weighted images were taken and GLCM based features were extracted from level-2 DWT of the segmented image. The SVM based classifier gave 94 % and 82% accuracy for segmentation using the level set method and K-mean clustering respectively.

3.1 Review Table

Table 1. Review table of classification methodologies

Sl. No.	Authors	Paper	Methods used	Results
1	Ahmed et al[1]	A hybrid approach for automatic classification of brain MRI using genetic algorithm and support vector machine	DWT+GLCM+GA+SVM	- Classify benign or malignant - DWT improves accuracy - RBF kernel is better than polynomial and linear kernel - Accuracy 97.59%
2	Zhang et al [5]	An MRI brain images classifier via principal component analysis and kernel support vector machine	DWT+PCA+SVM	- Classify normal abnormal - GRB kernel bettre than polynomial and linear kernel - Accuracy 99.38%
3	El-Sayed Ahmed et al [6]	Hybrid intelligent techniques for MRI brain images classification	DWT+PCA+KNN	- Classify normal or abnormal - KNN outperforms ANN - Accuracy 98.6%
4	Zhang et al [7]	A novel method for magnetic resonance brain image classification based on adaptive chaotic PSO	DWT+PC A+ ACPSO-FNN	- Classify normal or abnormal - Hybrid classifier - Less computation time - Accuracy 98.75%
5	Othman et al [15]	Probabilistic neural network for brain tumor classification	PCA+PNN	- Classify meningioma or glioma - Require less training time - Accuracy varies 73%-100%
6	Nitish et al [21]	GLCM Textural Features for Brain Tumor Classification	GLCM+ FF-NN	- Classify 4 types tumor - Overall accuracy 97.5%
7	Ahmed et al [22]	.MRI brain tumor classification using support vector machines and meta-heuristic method	DWT+GLCM+SA+GA-SVM	- Classify normal or abnormal - Hybrid classifiers - Efficient in terms of computational time - Accuracy 95.65%
8	Ketan et al [23]	MRI brain cancer classification using hybrid classifier (SVM-KNN)	Skull Masking+ SVM-KNN	- Classify normal or abnormal - Hybrid classifiers - Accuracy 98%
9	Minz et al	MR Image Classification	GLCM+ AdaBoost	- Classify normal or abnormal

	[24]	Using Adaboost for Brain Tumor Type		- Accuracy 89.90%, sensitivity 88.23, specificity 62.5%
10	Jainy et al [29]	Segmentation, feature extraction, and multiclass brain tumor classification	SROI+PCA+ANN	- Classify 6 types of tumor including normal - PCA improves classification accuracy - Overall accuracy 91%
11	Vani et al [32]	Automatic Tumor Classification of Brain MRI Images using DWT Features	DWT+GLCM+KNN	- Classify 3 type tumor including normal - KNN out performs SVM - Overall accuracy 88.89%
12	Akhtar et al[34]	A new rectangular window based image cropping method for generalization of brain neoplasm classification	LABRC+DWT+PCA+SVM	- Classify 3 glioma grades, - PCA improves classification accuracy, - Highest accuracy 85.70%, Sensitivity 92.23%, maximum specificity 93.93%

IV. CONCLUSION

A Brain tumors are one of the leading diseases in the world. So the identification and classification of tumors are important. MRI has a widely used modality for imaging brain. Extracting brain tumors is done by the segmentation process. But, the Selection of an appropriate segmentation technique largely depends on the type of images and application areas [48]. Hence for different types of brain tumors, different types of segmentation methods are required. Brain tumor classification from MRI can be divided into three phases. The first phase preprocessing includes processes like segmentation, Noise removal, resolution enhancement, skull masking. Anisotropic filters are effective to remove noises from brain MR images. DWT is used widely to improve resolution and skull masking helps in excluding unwanted regions. As segmentation is not mandatory for classification, it is included in the preprocessing phase. The Second phase includes feature extraction as well as feature selection. Texture analysis, shape analysis, and domain transform are widely used for feature extraction purposes. For feature reduction, LDA, PCA, GA and DWT methods are used. DWT can be considered as preprocessing as well as a feature extraction technique. The third phase is classification in which brain images are classified based on the extracted feature set called feature vector. ANN, KNN, SVM, AdaBoost, etc are used as classification methods for brain MR images.

DWT based feature extraction are widely used for brain tumor classification. Texture analysis based on GLCM gives better features for classification where PCA reduces the feature vector maintaining the accuracy of classification of brain MR images. Shape features are important where segmentation has already been performed. The use of SVM along with appropriate kernel techniques can help in achieving high accuracy. The use of NN can also help in achieving high accuracy, but usually needed a large amount of data for training. High accuracy has been achieved to classify brain MRI as normal or abnormal, benign or malignant and low grade or high grade. But classifying the tumors into more particular types is also challenging.

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