Brain tumor detection and classification with feature extraction and reduction using DWT and PCA

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Abstract

The central control unit of human body is brain. The tumor is not diagnosed in early stage then it affects the brain means it causes the death of the patient.Magnetic Resonance Image (MRI) doesn't produce any harmful radiation and it is a better method for area calculation as well as classification based on the grade of the tumor. Nowadays there exists no automatic system to detect and identify the grade of the tumor. This paper proposes brain tumor classification which is divided into four phases as pre-processing, segmentation, feature reduction and extraction, classification. Segmentation of brain Tumor is a one of the basic steps in detection and classification of tumor. Median filter is used to eliminate the noise and Combination of K means cluster and otsu binarization is used to segment the brain tumour. DWT (Discrete wavelet transform) and GLCM (Grey Level co-occurrence matrix) used for transform and spatial feature extraction and PCA (Principal component analysis) reduces the feature vector to maintain the classification accuracy of brain MRI images. For the performance of MRIs classification, the significant features have been submitted to KSVM (kernel support vector machine).The proposed system will reduce processing time and better accuracy can be achieved. The proposed method is validated on BRATS 2015 dataset.

Keywords: *DWT, PCA, GLCM, Segmentation, MRI image, tumor detection,otsu binarization, SVM.*

I. INTRODUCTION

Thebrain tumor means formation of abnormal cells in the brain. There are two main kinds of tumor those are Benign and malignant. The benign tumor is also called primary tumor and malignant tumor is called secondary tumor.The American Brain Tumor Association and World Health Organization consider the tumor in four grades those are grade I and grade II and are also known as low-grade tumors and grade III and grade IV and are called high-grade tumors.The low-grade tumors are also called benign tumor which grow slowly and the high-grade tumors are also called malignant which grow rapidly[2]. It is significant to detect brain tumor at the early stage and it is necessary to identify the tumor area and segment the tumor images.

Computed Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Magnetic Resonance Imaging (MRI) are Medical Imaging techniques. These techniques provide valuable information about shape, size, location and metabolism of brain tumors assisting in diagnosis. Magnetic resonance imaging (MRI) and computed tomography (CT) scans are two diagnostic modes which show the internal structure of the brain. Operator performance causes noise in MRI images and this noise leads to inaccuracies classification. MRI is considered as the standard technique due to its high-quality soft tissue contrast resolution and, image manipulation, uses non-ionizing radiation and multi plane imaging technique.[12]

During image acquisition, coding and transmission the noise is always present in digital images. So, in image processing filter methods are mainly used to suppress either the high frequencies in the image means smoothing the image or low frequencies in the image means detecting the edges in the image. There are different types of image noise filtering methods in image processing those are Median filter, mean filter, bilateral filter, weiner filter, Anisotropic filter and Gaussian filter. If salt and pepper noise is present in image then meadian filter is good methods, poisson noise is present in image then mean filter is good method and speckle noise is resent in image then weiner filter method is good. [19]. Averaging filter gives the good result by computing MSE. Median filter removes the noise based on PSNR [10]. It is not easy to detect and classify the brain tumors. Due to the misplaced edges, noise, low contrast of medical images it is hard to get information from these images [18]. It includes few processes, such as image segmentation, enhancement, feature selection and extraction, feature classification and reduction.

Image segmentation is partitioning a brain image into multiple segments which are uniform and homogenous with respect to some characteristics such as colour, intensity or texture. Segmentation techniques are threshold method, edge-based segmentation, region-based segmentation, clustering based segmentation, watershed-based segmentation and artificial neural network based segmentation.

Clustering is grouping similar data together and reduces data dimension and it learns the shape of dataset by repeatedly moving its neurons closer to the data points. Clustering methods are k-mean clustering, improved k-mean clustering, Fuzzy C-mean and improved Fuzzy C-mean clustering. In K-means, data will be included in one particular cluster. In FCM, data can be included in all existing clusters, but with varying degrees of membership in a range of values [01]. the execution time is less in K-Means compared to Fuzzy C Means clustering technique, because the number of iterations of K-Means is less than Fuzzy C Means clustering[3]. Clustering is one of the unsupervised segmentation methods. K-means and Fuzzy C-means algorithm are two mostly used clustering techniques. K-means clustering is an effective way that uses a fixed number of clusters prior to classify a set of data [16].

The feature extraction can be done by using Gray Level Co-occurrence Matrix (GLCM) and Discrete wavelet transform (DWT). Spatial feature extraction can be done by using GLCM and transform feature extraction can be done by DWT. The high dimensional space patterns can be made by statistical method known as principal component analysis (PCA). The multidimensionality and number of variables can be reduced by PCA and it enables the exploring of date in an easy way [20]. The classifier on the basis of machine learning comprising of supervised and unsupervised learning has become popular in recent years. K-NN, SVM and ANN are included in supervised learning. Self-organization feature map (SOFM) and fuzzy c-means are included in unsupervised [4]. The advantageous features of SVM are regularization, low test error rate, kernel trick and absence of local minima.

The tumor classification and detection has been done by employing various techniques till now. But these techniques have drawbacks such as lack of accuracy, intensity inhomogeneity, noise, time complexity, computational complexity, feature selection, extraction and reduction, etc. DWT with KSVM classifier is proposed to overcome these limitations and also classification of the tumor is done with high accuracy by using this classifier, which denoising and segment the image, extract and reduce the feature, select the proper features for accurate classification of the tumor as benign and malignant tumor from MRI image.The international Association of cancer registries (IARC) reported that brain tumor cases in India in this is 24,530 (13,840 men and 10,690 women) and 3,08,102 (1,68,346 male cases and 1,32,414 female cases) in worldwide.

II. LITERATURE SURVEY

Bangare et al., (2015) They proposed K means and FCM for segmentation of brain tumor and they used Magnetic Resonance Imaging (MRI) and CT-Scanned images.They gave the output of the K-Means algorithm is used as input to this Fuzzy C-Means algorithm and they did area calculation.

Shree, N. et al., (2018) The proposed method consists of preprocessing which improve the signal-to-noise ratio. Next, they used DWT decomposes the images and textural features were extracted from GLCM followed by morphological operation. Probabilistic neural network (PNN) classifier is used for the classification of tumors from brain MRI images. They collected 650 samples from the 25 images of DICOM (digital imaging and communications in medicine) dataset, of which 18 are infected and others normal for the analysis. They achieved accuracy of nearly 100% for trained and 95% was achieved for tested dataset.

Sharma et al., (2019) proposed Differential Evolution algorithm along with OTSU method and collected 56 MRI images of 56 patients consisting 18 patients who are healthy and 38 brain tumor patients and gained 94.73% of accuracy.

Chaudhary et al., (2020) They proposed K-Means for segmentation and DWT is used to extract features. For the classification between malignant and benign tumor SVM is applied at last. They used 6 images for testing their code from Rajendra institute of medical science and they achieved 94.6% of accuracy.

Ansari M et al., (2020) proposed median filtering to denoise the image and Morphological Operation for Image Segmentation. The DWT and GLCM is utilized for feature extraction and SVM are utilized for segmentation of brain tumor as benign and malignant. They used 5 MRI images for testing their code these images are JPEG/JPG format and they achieved 98.91% of accuracy.

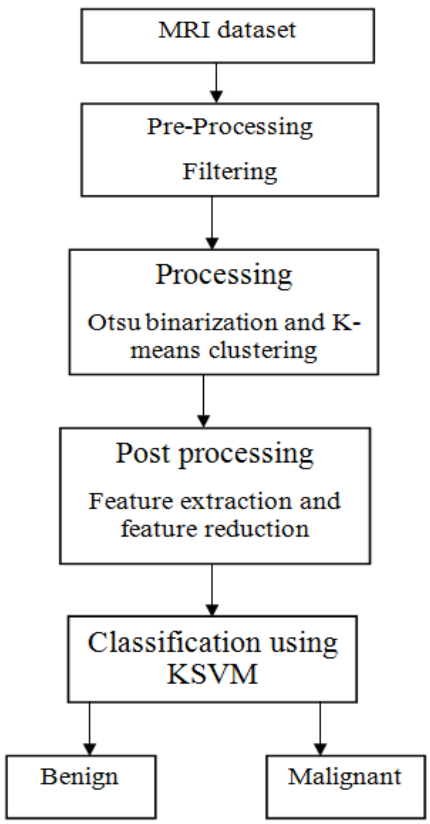
Gokulalakshmi et al., (2020) proposed SVM classifier and K-means clustering for classification.For feature extraction Grey-Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transformation (DWT) are used. They collected 750 samples of 30 images from DICOM dataset and They achieved 94% of accuracy.

Chander P et al., (2020) proposed adaptive K-Means clustering algorithm for segmentation and SVM classifier is used for classification.Discrete Wavelet Transformation (DWT) and Grey-Level Co-occurrence Matrix (GLCM) are utilized for feature extraction. Forty MR images of malignant and Benign tumor are collected from Harvard University medical Image Repository. They achieved 99.7% of segmentation accuracy and 93% of Classification accuracy.

Gokulalakshmi et al., (2020) Proposed K-means clustering for segmentation, Discrete wavelet transformation (DWT) and gray-level co-occurrence matrix (GLCM) is used for feature extraction, and SVM is used for classification of brain tumor. They collected 750 samples from DICOM dataset and they achieved 93.3% of accuracy.

III. METHODOLOGY

Figure 1: Steps for tumor detection and classification



The analysis of proposed system consists of various steps such as pre-processing, segmentation, feature extraction and classification. In the preprocessing stage, for extracting the noise, median filter is applied to the image. Ostu's thresholding is also applied to determine the threshold. In the segmentation stage, for the purpose of segmenting tumor, K-means clustering is applied. In the third stage different types of features are extracted. Finally,in the classification stage the type of tumor images can be identified[6].

1) Dataset: Collected 100 multi-modality MRI images from BRATS 2015 benchmark. MRI scanned images are either color, Gray-scale or intensity images with size of 220×220.if it is Gray-scale image, a Gray-scale converted image is defined by using a large matrix whose entries are numerical values between 0 and 255, where 0 corresponds to black and 255 corresponds to white. Image segmentation and edge detection is considered as two main stages for brain tumor detection.

2) Pre-Processing

The MRI images are taken as the input image data set in which the MRI image gives detail information about the brain. The input dataset is kept in the form as, X= {x1, x2, ….. xn}. The images are collected from the BRATS dataset. After preparing the dataset, Preprocessing is the first stage in this system. Magnetic resonance images can be affected by several types of noise and suffer from resolution degradation. [21].

It is the primary stage which is used to remove the unwanted noise from an image like patients name, age, address and other extra details are removed during this process. The image is resized and conversion of RGB to grayscale is performed. Due to thermal effect, there may be noise during MRI scanning, and it is necessary to eliminate this noise. The Median filter is nonlinear filter which is used to remove noise without affecting image information and it provides high resolution result compared to other filters such as spatial filter, mean filter, bilateral filter, weiner filter, Anisotropic filter and Gaussian filter and adaptive filters.The gray scale images consist of Salt and Pepper noise, this noise is removed by using median filter.

3) Processing

Image Segmentation is performed by two steps those are Otsu binarization and K -means clustering. Selecting proper segmentation method is difficult task because of the great verities of the lesion shapes, sizes, and colors along with different skin types and textures. The drawback of FCM clustering for image segmentation is that its objective function does not take into consideration any spatial dependence among pixels of image but deals with images the same as separate points. Second drawback of FCM clustering method is that the membership function is mostly decided by $d(xk$, Vi), which measures the similarity between the pixel intensity and the cluster center. Higher membership depends on closer intensity values to the cluster center. Hence membership function is highly sensitive to noise [18]. They can be broadly classified as thresholding, edge-based or region-based, supervised and unsupervised classification techniques

- Threshold segmentation
- Water shed segmentation
- Gradient Vector Flow (GVF)
- K-mean Clustering
- Fuzzy C-means Clustering

3.1) Otsu method:

Otsu binarization was used to convert the image into its binary format and it automatically finds the binarization threshold. It is commonly used thresholding technique. It is used to automatically perform clustering-based image thresholding, or, the reduction of a gray-level image to a binary image in computer vision and image processing. Otsu's thresholding technique is based on a discriminant analysis which partitions the image into classes C1 and C2 at grey levels 'k' such that C1={0,1,2,…….k} and C2={k+1, k+2,…….L-1} where, 'L' is the total number of gray levels of the image. Let 'n' be the total number of pixels in the given image and 'ni' be the number of pixels at the ith grey level. The probability of occurrence of grey level is defined as,

$$P_i=\frac{n_i}{n}$$

C1 and C2 are two classes representing the region of interest and the background.

The probabilities of classes C1 and C2 are,

$$P_1(k)= \sum_{i=0}^{k} P_i$$

$$P_2(k)= \sum_{i=k+1}^{kL-1} P_i = 1 - P_1(k)$$

The mean intensity values of these two classes are

$$m_1(k)=\frac{1}{P_1(k)}\sum_{i=0}^{k} i.P_i$$

$$m_2(k)=\frac{1}{P_2(k)}\sum_{i=k+1}^{L-1} i.P_i$$

Where m1(k) and m2(k) are object's center grey and background center grey.

3.2) K-means clustering

K-means, as the most famous clustering algorithm, was used for further processing of the binary image and it is an unsupervised iterative clustering technique and it separate the given data into K predefined distinct clusters. The cluster is defined as a collection of data points exhibiting certain similarities Clustering the image means grouping out the pixels depends on some characteristics. In K-means clustering the number of clusters k has to be defining first. The cluster centers k has to be chosen randomly. Then distance between these cluster centers and pixels are calculated. Every pixel is individually compared with all cluster centers with the help of distance formula. The pixel is moved to particular cluster which has shortest distance among all. This process is continuous until the clustering criterion converges. The objective function describing k-means clustering can be written as:

$$S= \sum_{b=1}^{k}\sum_{a=1}^{x} ||x_a^{(b)} - c_b||^2$$

Where $|x_a^{(b)} - c_b||^2$is the predefined distance from data point $x_a^{(b)}$and cluster center c_b. S is the indicator of the distance of the N points from their respective cluster centers. Partition the data set by using these following points:

1) Each data point belongs to a cluster with the nearest mean.

2) Data points belonging to one cluster have high degree of similarity.

3) Data points belonging to different clusters have high degree of dissimilarity.

The algorithm steps of k-means clustering can be expressed as:

Step 1:

1) Choose the number of clusters 'K'

2) Randomly select any 'K' data

Step 2:

1) Select cluster centers in such a way that they are as farther as possible from each other.

Step 3:

1) Calculate the distance between each data point and each cluster center.

2) The distance is calculated either given distance function or by using Euclidean distance formula.

Step 4:

1) Assign each data point to some cluster.

2) A data point is assigned to the cluster where center is nearest to that data point.

Step 5:

1) Recomputed the center of newly formed clusters.

2) The center of a cluster is computed by taking mean of all the data points contained in that cluster.

Step 6:

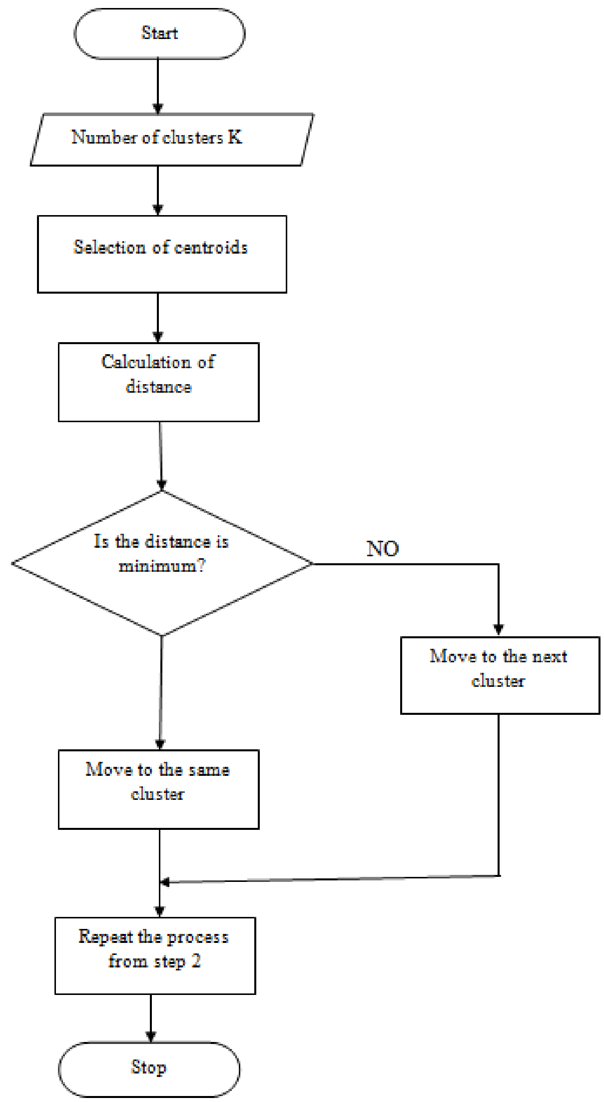
1) Keep repeating the procedure from Step 3 to Step 5 until any of the following stoping criteria is met.

2) Center of newly formed clusters do not change

3) Data points remain present same cluster.

4) Maximum numbers of iterations are reached.

Figure 2: Flow chart of K means clustering



4) Post Processing

Post processing employs to main parts: Feature Extraction and Feature Reduction.

4.1 Feature extraction

Feature extraction is process of extracting quantitative information from an image such as color features, texture, shape and contrast. Here we used DWT (discrete wavelet transform) for transform feature extraction and GLCM (gray-level co-0ccurrence matrix) for Spatial feature extraction.

4.1.1) Spatial feature extraction using GLCM

GLCM is a statistical method to obtain the relative pixel position of an image. This texture-based feature extraction technique was first introduced by R.M. Haralick. It measures the occurrence of a pixel i of intensity I in relation to other pixel j at a distance d and angle Ө.The total number of occurrences of a pixel i becomes an element of the GLCM. After calculating GLCM, features are determined from the resultant matrix. In this study, we measured contrast, correlation, energy and homogeneity.

There are two types of features is there

1) The Intensity Based Feature

2) Texture Based Feature

1) The Intensity Based Feature

The intensity-based feature is most commonly used features compared to texture-based features in image processing algorithm. Mean, standard deviation, variance, median, skewness and kurtosis are considered as the intensity-based features. The two dimensional function of the image is denoted by f(a,b), intensity level is denoted by h(i), N is denoted by the total number of gray levels in the entire image and p(i) denotes the probability density

- Mean

Mean is defined as the average level of intensity of image and It clearly shows that the mean is a function probability density.

$$\mu = \sum_{i=0}^{N-1} i, p(i)$$

- Standard Deviation

The mean value of the pixels and their probability densities are used to measure the standard deviation

$$\sigma = \sqrt{\sum_{i=0}^{N-1} (i-\mu)^2 \,. p(i)}$$

- Entropy

The uncertainty in the random variable is measured by the entropy. It depends on the probability density p(i).

$$En = -\sum_{i=0}^{N-1} p(i) \log_2[p(i)]$$

- Variance

The variation in the intensity is measured with the help of variance. It is also calculated by squaring the standard deviation.

$$\sigma^2 = \sum_{i=0}^{N-1} (i-\mu)^2 \,. p(i)$$

- Kurtosis

The histogram flatness is measured by kurtosis and it depends on the standard deviation, mean and probability density.

$$\mu^4 = \sigma^4 \sum_{i=0}^{N-1} ((i-\mu)^4 \,. p(i)) - 3$$

- Skewness

Symmetry of an image is defined by the skewness and It is denoted by μ3.

$$\mu^3 = \sigma^{-3} \sum_{i=0}^{N-1} ((i-\mu)^3 \,. p(i))$$

2) Texture Based Feature

The higher order description of an image is offered by the texture features. It provides the details about spatial distribution of tonal variations or gray tones. The texture -based feature extraction includes the homogeneity and similar regions of an image. The gray matter, white matter, cerebrospinal fluid and tumor region are classified from the MRI by this feature.

- Inverse Difference Moment (IDM)

The local homogeneity of an image is calculated by IDM. It takes two images and parameters that specify the viewing condition. IDM is local homogeneity and it is high when local gray level is uniform and inverse GLCM is high.

$$\text{IDM} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{1}{1+(i-j)^2}, p(i,j)$$

- Contrast

The intensity variation of threshold and its nearest pixel is determined by contrast.

$$\text{Contrast} = \sum_{n=0}^{N-1} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2$$

- Correlation

It is used to measure the relationship between the threshold and nearest pixel.

$$\text{Correlation} = \frac{1}{\sigma_a \sigma_b} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i,j) p(i,j)^2 - \mu_a \mu_b$$

- Energy

Sum squared of GLCM elements.It is also called as angular second moment or uniformity

$$\text{Energy} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2$$

- Homogeneity

Homogeneity is calculated by the energy. It measures the variation in image intensity.

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{p_{i,j}}{1+(i-j)^2}$$

4.1.2) Transform feature extraction using DWT

In this stage, discrete wavelet transform (DWT) technique was applied to the segmented image to extract the features. Here first converting images from the spatial domain to frequency domain. Then actual DWT is performed by filtering the image using two filters those are low pass filter and a high pass filter, in both the vertical and horizontal direction. Here the image is divided into four coefficients: LL,LH, HL and HH in every DWT level. The LL sub-bands come from using the lowpass filter in the horizontal direction and the lowpass filter in vertical direction, and these sub-bands are known as the approximation coefficient. The other sub-bands are known as detailed coefficients and more detailed information is extracted from the tumor using DWT.

4.2). Feature Reduction Using PCA

Extra unnecessary features will increase the classification complexity, require more storage memory and prolong the computational time. Thus, feature reduction is considered as a part of our proposed system. Principal Component Analysis (PCA) is one of the popular methods to reduce the dimensionality of wavelet transform. PCA is used to reduce the dimension of data according to their importance and variance. The PCA method makes the components of the input feature set perpendicular, and then it rearranges them in terms of the highest variation. The component with a low variation in the feature set are removed. PCA allows the identification of standards in data and their expression in such a way that their similarities and differences are emphasized. Once patterns are found, they can be compressed, i.e. their dimensions can be reduced without much loss of information. Such a reduction is advantageous for image compression, data representation, calculation reduction necessary in subsequent processing, etc.

5) Classification

The original support vector was developed by Vapnik which is a binary classification method to minimize structural risk. SVM is based on supervised techniques which can be used to one-class classification problem to multiple-class classification problem [13]. SVM can be used as a kernel machine. The main impact of kernel trick is that in a transformed feature space kernel allows to fit the maximum-margin hyperplane. A kernel support vector machine (KSVM) was finally applied for MRI classification. There are several families of SVM such as auto scale, box constraint, and kernel. The kernel support vector machine was selected due to its wide range of kernel functions, such as linear, polynomial, and gaussian radial basis function (GRB). In this study, SVM with linear kernel is used to separate the images into two classes. The form of linear function is shown by using the following equations:

$$\alpha(m)=w^T \varphi(m) + c$$

where w, T is the hyper plane parameter and φ(m)function maps the vector m into higher plane. Training samples are separated by hyper plane using,

$$\alpha(m)=w^T \varphi(m) + c = 0$$

So, based on the high plane two classes are separated.

Performance analysis:

Arrangement, understanding, accuracy of the present system and sensitivity of the model are finding out by using these relations.

1. True positive is at the abnormal condition, it’s identified correctly. x True negative is said like normal brain condition, it’s identified properly.
2. False negative is at the abnormal brain condition, it’s identified properly.
3. False positive is at the normal brain condition, it’s identified properly.

These parameters are mainly helped to check the classifier status in the model.

1) Sensitivity= True positive/100 %*(True positive +FN).

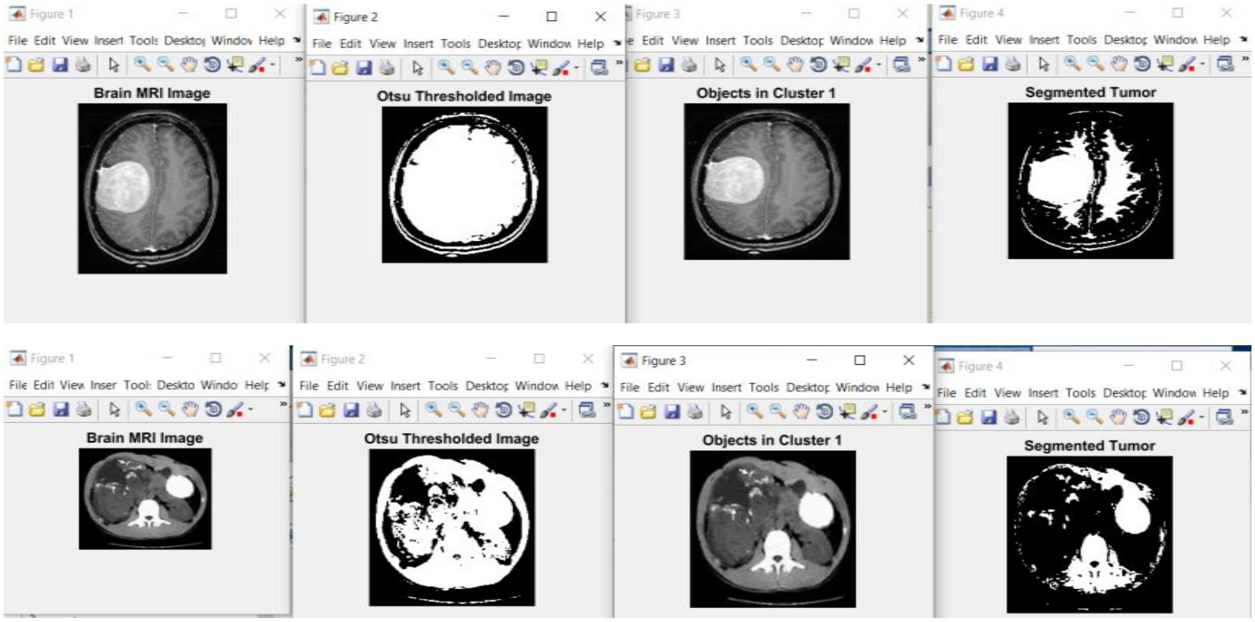
2) Specificity = True negative /100 %*(True negative +FN).

3) Accuracy= $\left(\frac{(TP+TN)}{(TP+TN+FP+FN)}\right)$ *100%

IV. RESULT AND DISCUSSION

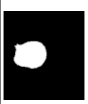
• This section presents experimental results of segmentation of brain tumor using K-means clustering and feature extraction and reduction by using PCA and GLCMto detect the infected region. We have collected 50 images of both normal and abnormal brain tumor images from BRATS 2015 dataset and applied K-means clustering algorithm to 30 MRI images to detect the infected region. Below table shows the result of pre-processing and segmentation for normal image, image with benign tumor and image with malignant tumor.

Figure 3: Brain MRI image with segmented region



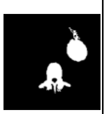
The extracted GLCM features are tabulated in the below tables

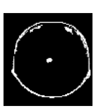
TABLE 1. EXTRACTED GLCM FEATURES OF BENIGN TUMORS

Segmented Image	Mean	Standard deviation	Entropy	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Energy	Homogeneity
	0.0031107	0.0897	3.17346	0.008047	0.92046	7.32819	0.469022	-0.05 768	0.20884	0.7621	0.93516
	0.002352	0.08978	3.2698	0.00805	0.89742	7.95668	0.8863	0.49259	0.2717	0.76857	0.933815
	0.0030015	0.08976	3.555	0.008019	0.9178	6.36606	0.6499	0.4729	0.2414	0.74403	0.927651
	0.0025096	0.08978	3.31556	0.008063	0.90325	6.2320	0.312064	0.56309	0.21607	0.75480	0.9324

	0.002068	0.089709	3.5182	0.008030	0.88497	6.7672	0.4413	0.5461	0.22497	0.7691	0.9365
	0.00253	0.08978	3.07565	0.008056	0.9041	7.7971	0.57742	-0.26010	0.2558	0.7557	0.93142
	0.00352	0.08975	3.1562	0.008027	0.92911	7.485	0.5212	-1.03921	0.23415	0.75299	0.93153
	0.00069	0.0898	2.7464	0.00806	0.71864	10.970	0.7365	0.119006	0.2689	0.78615	0.94095
	0.003412	0.08975	2.9949	0.00805	0.92697	7.68008	0.63176	0.3816	0.2433	0.7606	0.9344

TABLE 2. EXTRACTED GLCM FEATURES OF MALIGNANT TUMORS

Segmented image	Mean	Standard deviation	Entropy	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity
	0.00631	0.0896	3.2052	0.00802	0.9591	12.241	1.1048	1.2156	0.3059	0.1421	0.78623	0.9379
	0.004266	0.0897	3.6004	0.00805	0.940723	6.0137	0.5267	0.380124	0.2255	0.1345	0.7466	0.92985
	0.003651	0.08974	3.37095	0.00806	0.9314	7.3506	0.635	-0.1378	0.2433	0.09328	0.76129	0.93288
	0.00455	0.089699	3.0493	0.008057	0.9448	13.1916	1.063	0.272373	0.2745	0.11850	0.76973	0.9348

	0.00459	0.0897	3.5484	0.008069	0.9446	6.5235	0.6204	0.50303	0.244	0.1072	0.73102	0.9246
	0.00303	0.08976	3.6701	0.00802	0.9185	5.6209	0.41195	1.03495	0.2280	0.07693	0.75770	0.9319
	0.00424	0.08971	3.5516	0.00804	0.94033	6.0615	0.51043	0.31302	0.2314	0.10724	0.74181	0.9298
	0.003485	0.08975	3.524	0.00799	0.9284	6.522	0.4978	1.652	0.2517	0.07341	0.7402	0.9267
	0.00599	0.08965	32.6626	0.00805	0.95706	16.293	1.6119	1.2859	0.3073	0.1337 0.1337	0.7598	0.93335
	0.00283	0.08977	3.628	0.008036	0.9132	5.3238	0.3223	1.04188	0.2155	0.09508	0.73784	0.9274
	0.0053	0.08966	3.194	0.00805	0.9516	9.7318	0.9914	1.855	0.2786	0.1427	0.760	0.932
	0.0055	0.08965	3.1117	0.00803	0.95303	12.161	1.123	-0.56187	0.28699	0.0918	0.759	0.93197

V. CONCLUSION

Automatic brain tumor detection and classification is still a challenging task due to various factors. The brain MRI based tumor identification and grade classification method has been proposed in this paper. The initial pre-processing has been done with the help of median filter and Ostu's thresholding adopted for threshold determination. Now the pre-processed input MRI is segmented using K-means clustering algorithm. The key features extracted from segmented MRI using GLCM and DWT. The features are reduced with the help of PCA. Now the PCA output has been given as input to the SVM classifier. The classification of tumor into benign or malignant has performed using various kernels like RBF kernel, linear kernel and polynomial kernel. The proposed system was implemented using MATLAB 2016b. The use of SVM along with the appropriate kernel techniques can help in achieving high accuracy.Further work will be carried out classification by using KSVM and Will implement our proposed result step by step using GUI window.

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