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# Investigating Brain Tumor Segmentation and Detection Techniques

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**Abstract**

Brain tumor is a life-threatening problem and hampers the normal functioning of the human body. For proper diagnosis and efficient treatment planning, it is necessary to detect the brain tumor in early stages. Digital image processing plays a vital role in analysis of medical images. Segmentation of brain tumor involves separation of abnormal brain tissues from normal tissues of brain. In the past, various researchers have proposed the semi and fully automatic methods for detection and segmentation of brain tumor. In this article, the different techniques available for segmentation have been presented. This article focuses on the work done by many researchers in the past to partially or fully automate the job of segmenting the brain tumor. The consolidated details of the reviewed literature have been tabulated. Simplicity and degree of human supervision decides the clinical acceptance of a particular segmentation technique.



*Keywords:* Brain; Brain Tumor; Classification; Digital Image Processing; Medical Image Analysis; Segmentation.

## 1. Introduction

Brain is the most crucial organ of the human body. Generally, it is regarded as the governing point of human body.

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Almost each and every vital activity of human body is controlled by the brain. Brain is considered responsible for governing emotions, movement, intelligence, speech, memory, senses, thought, physical activity, taste, creativity, etc. [1]. Thus, any kind of mishap or harm to this vital organ will disturb the proper functioning of human body and will result in abnormal routine. It is thus crucial to take utmost care of this precious organ.

Among the various problems to the brain, the most common and the life-threatening problem these days is that of the brain tumor. Every year, nearabout 11,000 persons are being diagnosed of the brain tumor [2].

Brain tumor is an anomalous lump of flesh comprising of uncontrolled growth and multiplication of cells [3]. Depending upon the cell type the brain tumor originates from or where they are positioned inside the brain or their rapidness for growth and expansion, their exists around 130 different types of brain tumors [2]. But the broad classification categorizes the brain tumor into two classes, i.e., primary brain tumor and secondary brain tumor. Primary brain tumor is the one that stems inside the brain. Secondary brain tumor, on the other hand, originates in some other body part such as lung and then drifts to the brain generally via stream of blood [3]. The characteristic features of primary and secondary brain tumor are shown in Fig. 1.

The primary tumors are additionally classified as benign or malignant (cancerous). The characteristic features of benign and malignant tumors are shown in Fig. 2. Metastatic or secondary tumors are generally cancerous and malignant [3].

Around 1,50,000 patients with cancer are affected with metastatic brain tumors every year [3]. Thus, it is very important to pinpoint and diagnose these brain tumors as early as possible. Since the tumors vary largely in terms of their stature, form and presence, thus it is very difficult to take accurate measurements so as to properly diagnose the tumors. Advanced imaging techniques are available to recognize brain tumors. Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI) are the most commonly used diagnostic tools. Examination of chemical profile of tumor and determination of type of lesions detected in MRI can be done using Magnetic Resonance Spectroscopy (MRS). Persisting brain tumors can be detected using Positron Emission Tomography (PET) scan [3].

Thus, digital image processing enacts a crucial role in analysis of medical images for timely and efficient planning of treatment. The basic purpose of any image processing application is to make use of image information in order to extract the needed attributes which can then be used by a machine to come up with the proper diagnosis [4]. The most commonly used steps of digital image processing so as to partially or fully automate the task of brain tumor detection includes pre-processing (image enhancement, denoising etc.), segmentation, feature extraction and classification.

This article is divided into four sections: Section II describes the different segmentation techniques available to segment the different tissue types in the human brain; Section III describes the work done by the researchers to partially or fully automate the task of brain tumor detection and finally Section IV concludes the paper.

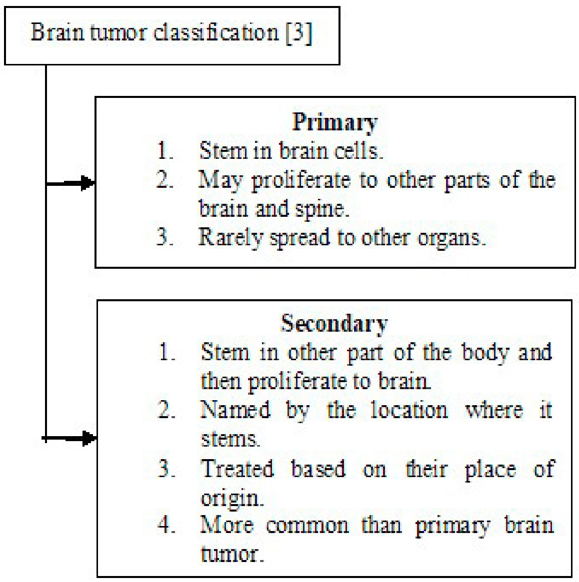


Fig. 1. The brain tumor classification into primary and secondary brain tumors.

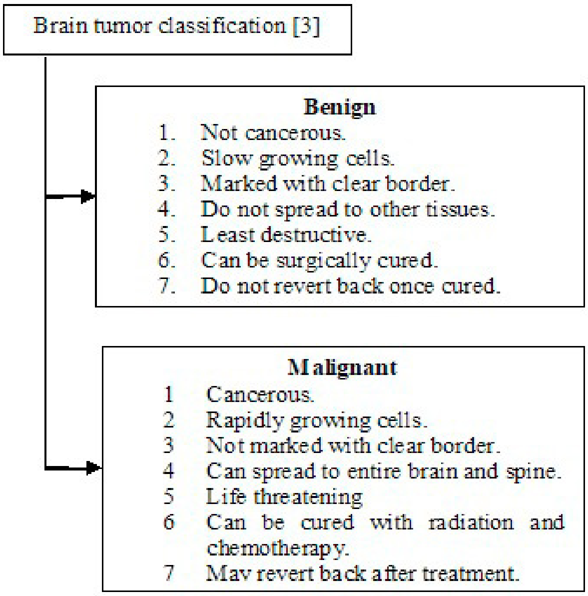


Fig. 2. The brain tumor classification into benign and malignant tumors.

## 2. Segmentation Techniques

Image segmentation is defined as the method of segregating the image into mutua1ly exclusive and exhaustive sectors being uniform corresponding to some predefined standard. Segmentation in the light of brain tumor comprises of distinguishing the abnormal tissues from normal tissues of brain [5].

Segmentation techniques are generally divided into the following categories [6]:

- Thresholding techniques,
- Region growing techniques,
- Edge based techniques,
- Clustering techniques,
- Watershed technique,
- Deformable model-based techniques.

### *2.1. Thresholding Techniques*

Thresholding is the most common technique used for segmentation. Depending upon the selected threshold value, the image is partitioned in two classes – one with the pixel values greater than or equal to the threshold value and the other with the pixel values less than the threshold value. Thresholding techniques are of three types – local, global and adaptive. In local thresholding, local properties such as standard deviation or local mean value of various regions of image are used for selecting the threshold value. In global thresholding, for the whole image single value of threshold is selected on the basis of histogram of image. In adaptive or dynamic thresholding, local threshold values are chosen independently for each pixel [6].

The segmentation result greatly depends on the threshold value. Selection of inappropriate threshold value results in improper segmentation. Various methods have been proposed in order to automate the threshold selection process such as Otsu's thresholding. Thresholding techniques disregard the spatial details of the image resulting in noise sensitivity [7].

### *2.2. Region Growing Techniques*

In the region growing segmentation technique, the images are partitioned by organizing the nearest pixel of similar kind (homogeneity, texture, intensity levels and sharpness). This process begins with the selection of some initial seed point based on predefined law. Accordingly, the neighboring pixels on the basis of homogeneity criteria are added progressively to the seed [7].

This approach is quite simple and it can correctly partition the image pixels with similar properties to form large regions. As this technique takes into consideration the spatial details of the image, it is less noise sensitive and results in better segmentation compared to histogram thresholding approach [7]. Spatially separated regions and regions with similar properties are properly segmented using this approach. Connected regions are also generated by this technique [6].

The main limitation of this approach is that it can result in a hole in the deduced shape and can also generate disconnected area [7].

### *2.3. Edge Based Techniques*

In an image, boundary or edge is defined as the intensity gradient of the local pixel or group of pixels [6]. Edge based techniques figure out the image pixels that corresponds to the edges of the object visible in the image. Thus, a binary image with the located edge pixels is produced. This technique makes use of different edge operators such as Laplacian, Sobel, Canny, Prewitt, etc. Edge based techniques are suitable for simple and noiseless images. For the noisy images, these techniques can result in extra or missing edges [8].

These techniques are computationally fast and no prior information regarding content of image is required. The basic problem encountered by these techniques is the edges not enclosing the whole of the object [6]. The other limitation of these techniques is that they are not capable of generating required results in cluttered background [8].

### *2.4. Clustering Techniques*

The clustering approach for segmentation classify the data into groups on the basis of attributes, features and characteristics. Thus, a cluster constitutes groups of similar data. These are unsupervised techniques and do not require learning data. The techniques based on clustering takes less time to generate segmented data. The commonly used clustering techniques are K-means clustering and Fuzzy C Means (FCM) clustering [7].

### *2.5. Watershed Techniques*

This technique makes use of image morphology. Here, corresponding to each object, at least one marker or seed point needs to be selected [6]. This method groups image pixels based on their intensities. Pixels with resembling intensities are assembled together. Two basic methods are used for applying watershed approach – in the first method, the calculated loca1 minimum of image gradient is selected as a marker and then merging is performed. In the second method, watershed transformation is performed using markers, making use of the explicitly defined marker positions. The major drawback of this technique is that it suffers from the problem of over segmentation and under segmentation [9].

### *2.6. Deformable Model Based Techniques*

In these techniques, the segmentation problem is formulated as an optimization task where an appropriate energy function is optimized to obtain the boundary of segmentation [10]. Deformable model or snake model based methods are categorized into two classes: free form models and shape models. In shape models, parameterized pattern of a particular structure is used to include the previous information of the global structure. In free form models, such as snakes, previous information generally comprises of local continuity and smoothness constraints resulting in no explicit global structures [11]. Deformable model based techniques used for segmentation includes random field methods, Active Contour Models (ACM) and level set methods [10].

The deformable or snake models are best suitable for recovering objects with anonymous topologies. The mathematical formulation of deformable models makes it easy to integrate in a single extraction process the image data, knowledge based constraints and required contour properties [11].

The main limitation of these models is their ability of handling only simple topology objects. The other limitation is the sensitivity of the snake to the initial conditions because of non-convex nature of energy function and the contraction force arising from the internal energy term [11].

## 3. Related Work

A large amount of work has been done by the various researchers to partially or fully automate the task of brain tumor segmentation and detection. The work of the various researches is discussed below:

Shivhare, Sharma and Singh [12] presented a fu1ly automated strategy for segmentation of brain tumor by making use of parameter free K-means clustering algorithm and mathematical morphological operations like dilation and ho1e fi1ling. The proposed strategy is used on training dataset of Brats 2015. The tumor segmented using the presented approach is correlated with the ground truth result available in the dataset. The obtained results showed 75% of Dice Similarity Coefficient (DSC) with the available ground truth.

Jagan [13] presented a novel approach for segmentation of tumor where acquired image is pre-processed using anisotropic filter. Then FCM approach and improved Expectation Maximization (EM) approach are applied to perform initial segmentation. Next, superior segmentation is performed using suggested approach. The work of the suggested technique is correlated with FCM clustering approach and improved EM approach in context of segmentation accuracy. The proposed approach resulted in average 97.98% segmentation accuracy calculated over 10 patients and outperforms the FCM clustering and improved EM methods.

Filho et al. [14] presented an Optimum Path Snakes (OPS) based adaptive and parameter free algorithm for segmenting medical images. Initially, pre-processing is done to extract the features such as texture using HU moments, Gray Level Co-occurrence Matrix (GLCM), Human Density Analyse (HDA) and statistical moments. Then, segmentation is done using OPS method. The performance evaluation metrics such as Hausdorff distance (HD), Dice Coefficient (DC), and processing time are calculated. For lung segmentation, the proposed approach is compared with the existing vector field convolution method and gradient vector flow method. For brain segmentation, the proposed approach is compared with watershed method, region growing method and Level Set algorithm based on Coherent Propagation Method (LSCPM). The proposed technique outperforms the existing methods. This approach is not application specific and is not limited to particular image type.

Dandu et al. [15] presented a Statistical Region Merging (SRM) and Back Propagation Neural Network (BPNN) classification based approach for segmentation of pancreatic and brain tumor. In this approach, first the image is pre-processed using Decision Based Couple Window Median Filter (DBCWMF) method. Next, segmentation is carried out using SRM. Then, features are extracted using Cat Swarm Optimization (CSO) and Scale Invariant Feature Transform (SIFT) techniques. Then, BPNN classifier is used for classification. In the proposed approach, DBCWMF performs better than median and PGPD filter and BPNN classifier performs better than Artificial Neural Network (ANN) and AdaBoost classifier. The suggested method outperforms the existing methods in context of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), accuracy, precision, specificity and recall performance evaluation metrics.

Suneetha and Rani [16] suggested a nove1 technique for detection of brain tumor in early stages. In the proposed approach, acquired brain MRI images are pre-processed using Optimized Kernel Possibilistic C-means Method (OKPCM). Then, image enhancement is done using adaptive Double Window Modified Trimmed Mean Filter (DW-MTMF). Finally, image segmentation is performed using region growing technique. The suggested OKPCM technique is correlated with K-means, CLOPE and FCM techniques in context of processing time and accuracy. The proposed OKPCM results in higher accuracy as compared to other methods. But, in context of processing time K-means method is faster. The proposed DW-MTMF filter is compared with the mean, BM3D and median filter in terms of MSE and PSNR. DW-MTMF performs better than the other filters. The proposed region growing segmentation method is compared with k-Nearest Neighbors (k-NN), edge detection and fuzzy techniques in terms of accuracy and error rate. The region growing approach outperforms the other methods.

Amin et al. [17] presented an unsupervised clustering approach for brain tumor detection. Initially, lesion enhancement is carried out using histogram matching method. Then, the lesion is segmented using an unsupervised clustering (C) method with C=5 clusters. Then, feature extraction is carried out where four texture features Gabor Wave1et Features (GWF), Histogram of Oriented Gradient (HOG), Local Binary Pattern (LBP), and Segmentation based Fractal Texture Analysis (SFTA) are extracted. The fused feature vector is then created by fusing these four features. Then tumor classification is done using Random Forest (RF) classifier. The proposed approach is evaluated on BraTS 2012, BraTS 2013, BraTS 2014, BraTS 2015 datasets and is compared with the techniques like Conditional Random Fields (CRF), deep Convolutional Neural Networks (CNN), CNN, Otsu clustering, U-net based fully CNN, random decision forest based, 3D CNN in context of Area Under Curve (AUV), sensitivity, accuracy, specificity, Negative Predictive Value (NPV) and Positive Predictive Value (PPV) as performance measures. The proposed approach outperforms the existing methods.

Raju, Suresh and Rao [18] presented a Bayesian fuzzy clustering based approach for segmenting and classifying brain tumor. In the suggested approach, segmentation is carried out using Bayesian fuzzy clustering method. Then, the scattering transform, the wavelet transform and the information theoretic measures are used for the extraction of features. Finally, classification is done using multi Support Vector Neural Network (SVNN) classifier in which weights are trained using Harmony Crow Search (HCS) optimization method. The performance of the suggested Bayesian HCS multi SVNN approach is evaluated against the existing kNN, Neural Network (NN), multi Support Vector Machine (SVM), multi SVNN techniques using sensitivity, accuracy, and specificity as performance metrics. The proposed approach excels the existing methods.

Deepa and Emmanuel [19] presented a fused feature Adaptive Firefly Backpropagation Neural Network (AFBNN) approach for brain tumor detection. Initially, the image is pre-processed using the average filter. Then, the texture features like orientation, locality and frequency are extracted using the Gabor Wavelet technique. Then, the most relevant features are selected using Kernel Principle Component Analysis (KPCA). Notable information is provided through feature fusion using Gaussian Radial Basis Function (GRBF). Finally, classification is done using AFBNN classifier. The proposed approach is validated using BRATS 2015 dataset. The proposed approach is evaluated for performance using sensitivity, accuracy, and specificity as performance metrics against the Naïve Bayes, SVM and Linear Discriminate Analysis (LDA) classifiers. The proposed approach excels the other classifiers.

Lim and Mandava [20] presented a multi-phase technique for segmenting the multisequence image of brain tumor. The proposed technique consists of three stages. In the initial stage, random wa1ks technique is used for modelling the information. In the second stage, information is fused using weighted averaging approach. The last stage involves the extraction of visual objects using Information Theoretic Rough Sets (ITRS). Brain tumor dataset of MICCAI is used for testing the proposed strategy. The suggested method is correlated with the simple averaging and Principal Component Analysis (PCA) fusion techniques. The performance of the presented strategy is evaluated using DICE metric and resulted in average DICE accuracy of 0.7 for high grade tumor and 0.63 for low grade tumor.

K, T and S [21] presented an efficient approach for detection of brain tumor. Initia1ly, the acquired MRI image is denoised by using Poisson Unbiased Risk Estimator- Linear Expansion of Thresholds (PURE-LET) transform. Next, the features are extracted using a combined technique of Modified Multi-Texton Histogram (MMTH) and Multi-Texton Microstructure Descriptor (MTMD). Then, the performance is compared using a combination of two another technique of feature extraction – Gray Level Run Length Matrix (GLRLM) and GLCM. Finally, the features so extracted are used to train the classifiers such as kNN, SVM and Extreme Learning Machine (ELM) which are then used for image classification. The result of the suggested approach is correlated by using three classifiers in context of accuracy, specificity, and sensitivity as performance evaluation metrics. The precision of proposed strategy with kNN classifier is 80%, with SVM classifier is 95% and with ELM classifier is 91%. Thus, the proposed approach with SVM classifier shows higher accuracy than the remaining two classifiers.

Nanda et al. [22] presented a hybrid K-means Galactic Swarm Optimization (GSO) approach with Otsu's entropy as a fitness function for the purpose of determining the position, form and shape of brain tumor. The proposed approach is correlated with the existing approaches such as K-means, GSO and Real Coded Genetic algorithm for performance using the Normalized Root Mean Square Error (NRMSE), PSNR, Structured Similarity Index Measure (SSIM), Otsu's measure and computational time as the performance measures. The suggested technique excels the existing approaches for all the performance measures taken except the computational time. The presented approach is computationally more expensive than the existing techniques.

Vishnuvarthanan et al. [23] presented an automated method for segmenting the tumor and tissues which is based on the clustering and optimization techniques. Skull stripped brain MRI image is taken as input to this approach. Contrast limited adaptive histogram equa1ization method is used to pre-process the skull stripped image. Then, Modified Fuzzy K-means (MFKM) technique is adopted to carry out the clustering. Next, optimum value of threshold is identified using Bacteria Foraging Optimization (BFO) algorithm. The result of MFKM method is re-evaluated using the identified threshold value. The proposed approach is correlated with the existing MFKM, Particle Swarm Optimization (PSO) based FCM and conventional FCM techniques. The work of the suggested method is assessed using PSNR, MSE, sensitivity, Jaccard Index (JI), specificity, Dice Overlap Index (DOI), storage requirement and computational time as performance metrics.

Sompong and Wongthanavasu [24] presented a segmentation technique which makes use of cellular automata and improved tumor cut technique. In the proposed strategy, initially an image is transformed to the target featured image using GLCM based Cellular Automata (GLCM-CA). Then, the segmentation is carried out using improved tumor cut method. The proposed approach is tested on BraTS 2013 dataset for performance evaluation using DC, sensitivity, specificity, PPV as the performance evaluation metrics. The suggested method is correlated with the state-of-the art techniques which are carried out on the same dataset. The suggested approach excels the state-of-the art approaches.

Vishnuvarthanan et al. [25] presented an unsupervised learning technique with clustering strategy for identifying and segmenting the brain tumor. The brain MR image is initially skull stripped using Brain Extraction Tool (BET) and Region of Interest (ROI) based brain mask. Next, initial clustering, dimensionality reduction and prototype preparation is carried out using Self Organizing Map (SOM). Then, the segmentation is performed using Fuzzy K-means (FKM) method. The efficiency of the suggested approach is assessed by utilizing MSE, PSNR, DOI, JI, storage requirement and computational time against the conventional FCM algorithm. The proposed SOM-FKM technique excels the convention FCM approach.

Zhang et al. [26] presented a Multilayer Perceptron (MLP) approach for detection of pathological brain. In the first step, feature extraction is carried out where 12 Fractional Fourier Entropy (FRFE) features are extracted. In the next step, MLP classifier is used for classification. Optimal hidden neuron number is determined using pruning technique. Three pruning techniques are compared – Kappa Coefficient (KC), Bayesian Detection Boundaries (BDB) and Dynamic Pruning (DP). The training of weights and biases is carried out using Adaptive Real- Coded Biogeography Based Optimization (ARCBBO). The obtained results depicted that the combination of FRFE, KC, MLP and ARCBBO obtained better average accuracy 99.53%. The proposed approach is compared with SVM and native Bayesian classifiers and it outperforms the other two classifiers.

A complete review of the work performed by the different researchers in the area of partially or fully automating the task of brain tumor segmentation and detection is summarized in table 1.

## 4. Conclusion

Brain tumor is an unexpected lump of flesh where cells grow and multiply uncontrollably. It is a very common and devastating problem these days. The proper diagnosis of brain tumor is difficult because of the complex structure of tumor in terms of their stature, form and presence. Manual detection of brain tumor by radiologists may be inaccurate and results can vary from one radiologist to another and may not necessarily guarantee proper diagnosis. Thus, some sort of automation is required to properly detect brain tumor.

Image processing is very important for analysing medical images. Brain tumor segmentation is the method of segregating the normal brain tissues from abnormal tumor tissues. Various segmentation approaches has been discussed along with their advantages and shortcomings. A detailed review of the work performed by the researchers in the area of automating the task of detection and segmentation of brain tumor is presented. Simplicity and degree of human intervention decides the clinical acceptance of a particular segmentation technique.

This review has been done to focus on the future developments of medical image processing in healthcare and medicine, i.e., timely detection of brain tumor for proper diagnosis. The existing techniques employing pre-processing and segmentation phases for detection of brain tumor cannot distinguish whether the segmented region is normal or abnormal. And, the existing work that employs other phases also such as feature extraction and classification are able to classify the extracted region into normal or abnormal, but with less accuracy. So, this task will be continued to model advanced technique for automating the job of detecting the brain tumor resulting in better results in comparison to existing approaches.

Table 1. Centralized details of the related work

| S. No | Authors | Total images/ Patients | Pre-Processing | Feature Extraction | Reduction Technique | Segmentation | Classifier | Post Processing | Result |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Shivhare, Sharma and Singh [12] | BRATS 2015 dataset | NA | NA | NA | Parameter free K-means clustering | NA | Morphological operations such as dilation and hole filling | 75.06% DSC |
| 2 | Jagan [13] | 10 | Anisotropic Filter | NA | NA | FCM and improved EM | NA | NA | 97.98% segmentation accuracy |
| 3 | Filho et al. [14] | Lung CT Images: Normal=27 Fibrosis=21 COPD=24 Brain CT images=100 | NA | GLCM, HU moments, Statistical moments, HAD | NA | OPS | NA | NA | Lung CT images<br>Normal DC=0.93±0.01, HD=5.09±1.07<br>Fibrosis DC=0.93±0.01, HD=5.29±1.03<br>COPD DC=0.93±0.02, HD=4.90±2.02<br>Brain CT images<br>DC=0.83±0.07, HD=3.12±0.60 |
| 4 | Dandu et al. [15] | Medical Harvard School database and TCIA repository's database | DBCWMF | CSO-SIFT | NA | SRM | BPNN | NA | Brain / Pancreas<br>Accuracy= 95.56% / 90.2%<br>Precision= 99.45% / 92.86%<br>Specificity= 99.46% / 93.34%<br>Recall= 92.34% / 86.67%<br>MSE= 103.49 / 84.29<br>PSNR= 27.76 / 28.86 |
| 5 | Suneetha and Rani [16] | 457 | OKPCM, DW-MTMF | NA | NA | Region growing | NA | NA | Accuracy= 78.9%<br>MSE=26.4<br>PSNR=29.98<br>Error Rate=0.78 |
| 6 | Amin et al. [17] | 521 | Histogram matching | GWF, LBP, HOG, SFTA | NA | Unsupervised clustering (C) | RF | NA | BRATS 2012 2013 2014 2015<br>Sensitivity 98.6 98.5 85.3 98.5<br>Specificity 98.7 98.7 90.2 98.4<br>AUC 0.98 0.98 1.00 0.93<br>NPV 0.98 0.98 0.87 0.98<br>PPC 0.98 0.98 0.91 0.98<br>Accuracy % 98.9 91.0 95.0 92.0 |
| 7 | Raju, Suresh and Rao [18] | BRATS 2012 dataset | NA | Scattering transform, wavelet transform, | NA | Bayesian fuzzy clustering | HCS-multi-SVNN | NA | Accuracy=0.93<br>Sensitivity=0.96<br>Specificity=0.99 |

Table 1. Continued….

| S. No | Authors | Total images/ Patients | Pre-Processing | Feature Extraction | Reduction Technique | Segmentation | Classifier | Post Processing | Result |
|---|---|---|---|---|---|---|---|---|---|
| 8 | Deepa and Emmanuel [19] | 81 | Average filter | Gabor Wavelet | KPCA | NA | AFBNN | NA | Accuracy=99.84<br>Sensitivity=97.24<br>Specificity=99.85 |
| 9 | Lim and Mandava [20] | 30 | NA | ITRS | NA | Random walks | NA | NA | Dice accuracy= 0.7 for high grade tumor and 0.63 for low grade tumor |
| 10 | K, T and S [21] | Normal=67<br>Tumor=67 | PURE-LET | MMTH with MTMD, GLCM, GLRLM | NA | NA | kNN, SVM, ELM | NA | SVM / kNN / ELM<br>Accuracy= 95% / 80% / 91%<br>Specificity= 91 / 70 / 100<br>Sensitivity= 100% / 90% / 81% |
| 11 | Nanda et al. [22] | NA | NA | NA | NA | K-means-GSO | NA | NA | NRMSE=0.6782<br>PSNR=16.477<br>SSIM=0.56<br>Otsu's measure=1014.959 |
| 12 | Vishnuvart hanan et al. [23] | 38 | Contrast limited adaptive histogram equalization | NA | NA | BFO-MFKM | NA | NA | Sensitivity=0.97<br>Specificity=0.93<br>PSNR=57.93<br>MSE=0.106<br>DOI=40% |
| 13 | Sompong and Wongthana vasu [24] | 55 | NA | GLCM-CA | NA | Tumor cut | NA | NA | Dice metric whole tumor=0.84<br>Core tumor=0.79 |
| 14 | Vishnuvart hanan et al. [25] | 38 | BET and ROI based brain mask | NA | NA | SOM-FKM | NA | NA | MSE=2.15<br>PSNR=40<br>DOI= 48% |
| 15 | Zhang et al. [26] | NA | NA | FRFE | NA | NA | KC-MLP | NA | Accuracy=99.53% |

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