Multimodal Brain Tumor Segmentation using Neighboring Image Features

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***Abstract*—Brain tumor can grow anywhere in the brain with irregular contours and appearance. It is very hard to correctly segment the tumor tissues due to the similarity, noise, complex texture, poor sampling and image distortions. In this article, an enhanced novel technique for brain tumor detection is introduced by using multimodal (T1, T2, T1c, Flair) MR images. The proposed method consists of two main steps. In the first step, supervised binomial classification method is used to classify MR images into tumorous and non-tumorous by extracting Discrete Cosine Transform (DCT) features and applying k-nearest neighbors (KNN) classifier. In the second step, segmented the tumor by manipulating image intensity values and used neighboring image features along with the actual image features. We further enhanced the tumor segmentation by applying region-growing algorithm. The proposed method is tested on MICCAI BraTS 2015, a well-known standard dataset. Receiver Operating Characteristic (ROC), Dice Similarity Coefficient (DSC) and Mutual Information (MI) are used to measure the performance and achieved 96.91% accuracy for the binomial classification and 93.22% accuracy for the tumor segmentation.**

***Index Terms*—Multimodal Brain Tumor Segmentation; KNN; DWT; MICCAI BraTS.**

I. INTRODUCTION

The brain is a very complex part of the human body which contains billions of neurons to process information and operates different body organs. The human brain has three parts: the cerebrum, the cerebellum, and the brainstem [1]. The brain is shielded by a protective skull which prevents direct damages and injuries to the brain. The skull protects the brain but it still can be affected by internal neurological changes or damages. The most common problem is known as tumors. These damage the brain cells and have become the leading cause of death across the world. Images are important in the field of medicine and for diagnosis of different injuries. X-ray images, Computerized Tomography (CT) images and Magnetic Resonance (MR) images are routinely used in hospitals. The development of medical imaging technology is rapidly inline with the advancement of computing technology [2]. There are several advantages to using medical imaging. First, it speeds up the analysis workflow where images are produced more quickly. Also, there is no need to archive films of medical images [3]. In addition, the computer provides possibilities to improve the usefulness of the medical images.

MR Imaging (MRI) is an imaging method usually used in radiology to visualize the internal structure and functionality of the body. An MRI machine contains a powerful magnet which works along with neutrons and protons dipole moment. It generates detailed anatomical information of soft tissues in humans [4]. An MRI scan can be used for disease detection and has proven successful in detecting heart abnormalities and brain tumors.

Brain MRI is a test that uses the magnetic field, radio waves, and a connected computing device to yeild images of the brain tissues. Four different types of brain MR images are produced based on the MRI signal frequency and magnet field strength: longitudinal relaxation time (T1) weighted, T1-contrasted, transverse relaxation time (T2) weighted, and Fluid-attenuated inversion recovery (Flair) images [5]. These four different types of MR images are produced by using different pulse orders and by altering the imaging constraints. In MR images, tissues with T1 are dark, tissues with T2 are bright and tissues with Flair shows water and macromolecules more clearly [6]. MRI uses magnetic field instead of radiation, which makes it a different technique from the CT scan. The MRI can detect swelling, tissue inflammation, bleeding, and tumor.

Tumor segmentation is a critical task due to the complex anatomy of the brain's structure and the skull. Most brain MR scans are highly correlated and low contrast, which make segmentation more difficult. Correct segmentation of MRI plays a significant role for a meaningful analysis because most MR images are low contrast images, and brain tissue classes can easily overlap [7]. The complexity and inconsistency of the brain anatomy make the MR image segmentation more difficult. Image segmentation divides images into parts based on the properties of an image, such as gray level, texture, and shape of the different objects in the image.

Brain tumor segmentation, from the scanned data, is useful for identification and diagnosis of various types of tumors. In this research study, an enhanced technique for brain tumor segmentation by using multimodal MR images is introduced. The proposed method consists of two main steps. The first step uses supervised binomial classification method to classify MR images into tumorous and non-tumorous. In the second step, segmented the tumor by manipulating tumorous image intensity values and used neighboring image features along with the actual image features. Tumor segmentation is further enhanced by applying region-growing algorithm. The paper is ordered as follows; in section II background of recent literature on tumor detection is discussed. Section III presents the proposed method for tumor segmentation using neighboring image features. Section IV and V confer to the performance measures and results respectively. The study is concluded in section VI.

II. BACKGROUND

Classification of brain MR images into tumorous and non-tumorous images and further segmentation of tumorous part is a complicated task. Number into methods are proposed in current studies but still it is lacking in optimal solution. Image segmentation is crucial for several medical image processing applications that are being used for the analysis of image structure and diagnosis of various disorders. Different segmentation and classification techniques are presented by the researchers.

Rexilius et al. presented a new region growing technique for segmentation of brain tumor [8]. A probabilistic model is applied to achieve the initial tumor segmentation, which is further enhanced by region growing to give better segmentation results. Distance information is combined with probability model to make the algorithm more flexible for segmentation. Data is varied across the subjects to make the model robust. Global affine and non-rigid registration methods are used to register multi-spectral histograms gathered from patients' data with a reference histogram. Experiments are performed on patient's datasets with varying the size, location, shape and texture of the tumor. Quratulain et al. segmented the brain tumor after extracted first order brain MRI features by using texture analysis and classifying images [9]. She used first-order and second-order features such as mean, skewness, variance, entropy, energy, and kurtosis, along with second-order features like inertia, max probability, and correlation. First order features were obtained from the histogram of the brain MR image, while second order features were extracted from the Gray-level spatial co-occurrence matrix. Ruan et al. discussed a supervised machine learning technique to track the tumor volume [10]. Four different modalities are used for segmentation. The complete process is categorized into two main steps. In the first step to make it efficient and reducing computational time, only T1 modality is used to identify the abnormal area. In the second step, the abnormal area is extracted from all modalities and fused to segment the tumor. SVM is used in both steps to segment the entire tumor.

Corso et al. used multimodal brain dataset of 20 experts annotated glioblastoma multiforme (GBM) gathered from different sources [11]. Pre-processing is performed on all the four modalities T1, T1C, T2 and FLAIR. A top-down model based approach is used to distribute the product over a generative model, where classification and segmentation are performed. In the second step, input a sparse graph is given to graph cut method, where each edge uses features to find similarity between neighboring nodes having the affinity. Segmentation by weighted aggregation (SWA) is used in graph cut method to provide the multi-level segmentation of data, where each voxel is classified into one of the three (active tumor, necrotic or edema) classes and at a higher level these voxels are combined as a single segment. Zhu et al. [12] proposed a semi-automatic brain tumor segmentation method, in which initial segmentation is performed through ITK-Snap tool. Voxel based segmentation and deformable shape based segmentation are combined into the software pipeline. Voxel based is used as an automatic segmentation and deformable shape based segmentation manually refine it. GBM patients' dataset with T1C and T2 modality only is used and results are further refined by using post-processing step. Anisotropic diffusion based brain MR image segmentation technique is proposed by Arfan et al. by using multi-phase segmentation and visualization [13].

Fluid vector flow (FVF) is the technique introduced to discuss the problem of unsatisfactory capture range and weak convergence for concavities [14]. FVF showed improvement over gradient vector flow (GVF), boundary vector flow (BVF) and ACM on different datasets to get concave shapes and capture great range. The dataset used for experimentation is either collected from an online repository or synthetic images. Harati et al. demonstrated an improved fuzzy connectedness (FC) method, where seed values are chosen automatically to segment the tumor region [15]. To define an object in an image, the strength of connectedness between every pair of the image element is calculated, which is determined by considering all possible connected paths among the pair. Results are accessed based on similarity index (SI), overlap fraction. The method is useful to predict the size and position of brain tumor automatically. Automatic segmentation is performed using the random forest (RF) [16], where features extraction is performed after pre-processing. Features for classification include MR sequence intensities, neighborhood information, context information and texture.

III. PROPOSED METHOD

The proposed method consists of two main steps. In the first step, supervised binomial classification method is used to classify MR images into tumorous and non-tumorous by extracting Discrete Cosine Transform (DCT) features and applying k-nearest neighbors (KNN) classifier. In the second step, ignored the non-tumorous images and segmented the tumor part from the remaining images. To enhance the segmentation, manipulated image intensity values and used neighboring image features along with the actual image features. We further enhanced the tumor region by applying region-growing algorithm. From the segmented tumor boundaries, tumor size is measured and tumor location is identified. Figure 1. describes the workflow of the proposed system. The workflow diagram shows a multi-step process consisting of MRI image acquisition, preprocessing, feature extraction, feature selection, classification and segmentation. In the preprocessing step, the acquired 3D MRI file are converted from MetaImage (mha) format to 2D grayscale format and enhanced the images by histogram matching. The features are extracted by using DCT and normalized for binomial classification. The tumorous images are further enhanced by manipulated intensity values. Threshold based segmentation is done by using previous two and next two images as reference along with the actual image. The tumor segmentation is further enhanced by applying region-growing algorithm by taking initial segmented tumor part as seed. Based on the segmented tumor part form the MR images, tumor size and location can be measured which will help to the radiologists in decision-making.

A. *Feature Extraction*

In the proposed methods, texture features are extracted by using DCT which isolate images into parts depending upon the image visual features. Top low frequency coefficients are selected as features vector. DCT features extraction technique is selected based on performance measures for the binomial image classification [17]. The discrete cosine transform shares a similarity to the discrete Fourier transform (DFT) being used to transform images from a spatial domain to a low-frequency domain. 2D-DCT is most commonly used for image and signal processing due to its substantial compaction property. One dimensional DCT of N data points is defined in Equation 1, where F is the linear combination of the basis vectors.

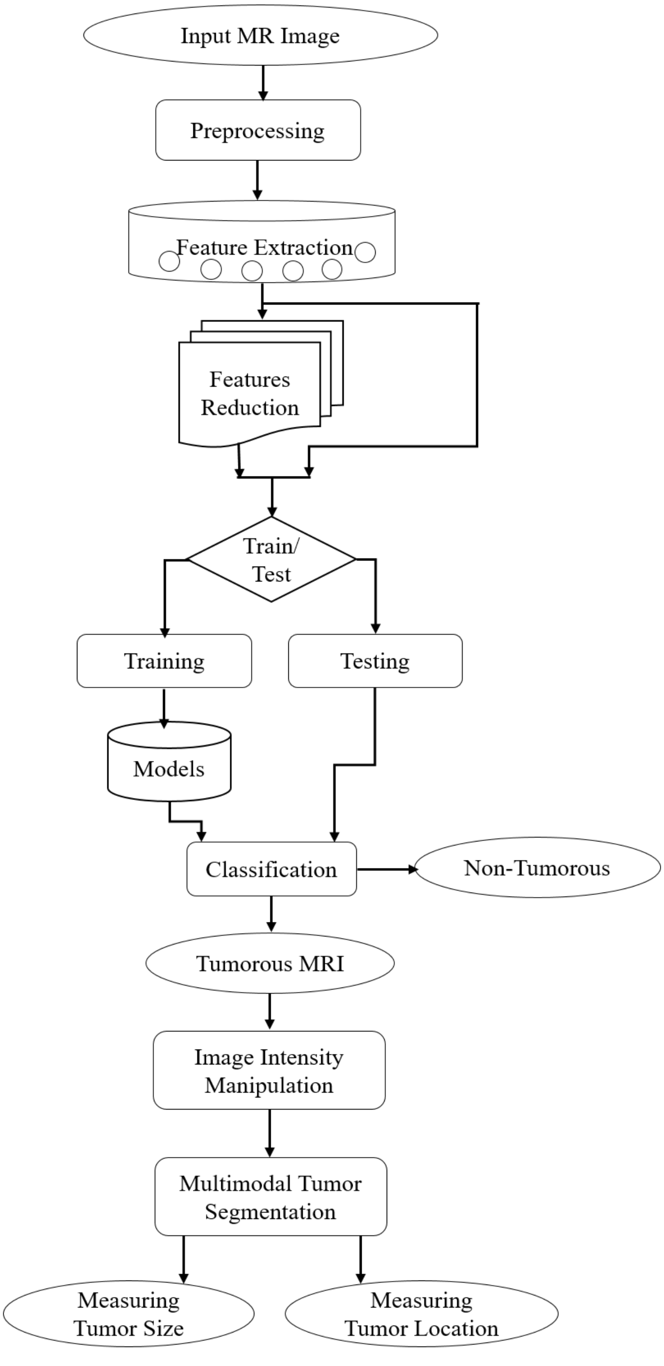

Figure 1: Workflow diagram of Proposed Method

$$F(\mu) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} A(i).\cos\left[\frac{\pi.\mu}{2.N}(2i+1)\right] f(i) \tag{1}$$

One-dimensional DCT is applied to each row and column of F to obtain two-dimensional DCTs. 2-dimensional discrete cosine transform of *n x m* image is defined in Equation 2.

$$F(\mu,v) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \left(\frac{2}{M}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \Delta(i).\Delta(j).\cos\left[\frac{\pi.\mu}{2.N}(2i+1)\right]\cos\left[\frac{\pi.\mu}{2.M}(2j+1)\right].f(i,j) \tag{2}$$

where $0 \leq u \leq N$, and $0 \leq v \leq N$ while Inverse 2D DCT transform is simple F-$I(u,v)$.

$$\Delta(\varepsilon) = \begin{Bmatrix} \frac{1}{\sqrt{2}} & for\ \varepsilon = 0 \\ 1 & otherwise \end{Bmatrix} \tag{3}$$

Two-dimensional (2D) discrete cosine transform is used to compute the DCT features of the brain MR image. We applied the natural logarithm on each absolute element value of the corresponding element. The 2D DCT of the image is calculated and selected the top left low frequency coefficients as feature vector which is shown in Figure 2. Different experiments are done by selecting different low frequency coefficients like top 5, 7, 10, 15 and 25 as features set for the classification to find the best feature set to achieve maximum classifier accuracy. Based on the experiments, feature set of top 15 low frequency values are selected by achieving best classifier accuracy.

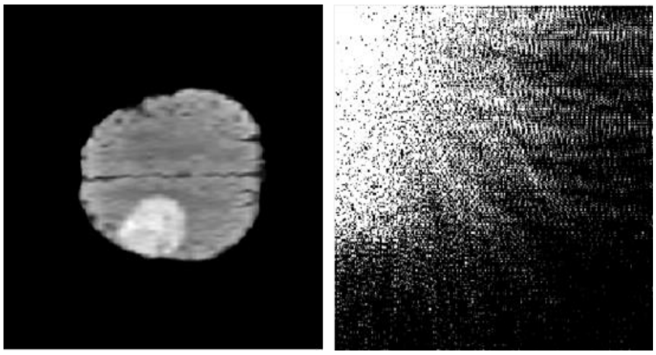

Figure 2. 2D DCT (Log abs) of the MR Image. The left image shows the original MRI image while right image show the 2D DCT of the MR image where low frequency coefficients can be seen at the top left corner.

B. Binomial Classification

We go through several classification methods including support vector machine (SVM), Naïve Bayes classifier, K-nearest neighbor (KNN) and multi-layer perceptron (MLP) and based on the performance outcomes, selected KNN classifier in our proposed system [18 - 21]. KNN is characterized by being instance-based learning and supervised classifier. New instance queries result to the classification of the majority of K-nearest neighbor category. It uses training samples and attributes to classify a new object, and it then determines which are the nearest neighbors of any instance through correlation e.g. cosine, hamming, city block distance, or euclidean distance. The K-nearest neighbor does this on a 'random', 'nearest', or 'consensus' rule, with ties broken randomly. What makes K-nearest neighbor significant is that since its process of classification involves analyzing a small group of objects that are similar, it is found to be very useful for multi-modal classes wherein several objects with independent variables possess varying characteristics on various subsets. It has a record of being accurate even when targeting a class that is multi-modal. On the other hand, this ability to quickly compute for similarities means the K-nearest neighbor treats all features as equal when it computes for similarities. This leads to classification errors and inadequate measures of similarity, especially when it involves only a small subset of features for classification. Several experiments are performed on the acquired MICCAI BraTS 2015 datasets for binary classification [22].

C. Multimodal Tumor Segmentation

The brain images are manipulated by changing the intensity values to enhance them. We used previous two and next two images as reference along with the actual image for the segmentation. For the initial segmentation, converted the grayscale MR image into binary image by using automatic thresholding technique. The threshold of the grayscale image is calculated by using the Otsu's method [23]. A constant value is added to the initially calculated threshold value by the Otsu's method. Morphological operations are applied for further enhancement of the binary image. To remove the non-tumor part from the binary image, calculated the total number of objects in the binary image and selected an object based on its shape properties. Figure 4 describes the results of the initial segmentation and further explained in experimental results section.

D. Tumor Segmentation Enhancement

The initial segmented tumor part is enhanced by applying the region-growing algorithm on the initial extracted tumor part. The region growing algorithm works based on the connected set of pixels in the image [24]. In this method, the initial segmented brain tumor part is used as seed cluster and minimized the intra-cluster distance and maximized the inter-cluster distance. Figure 4(g) shows the enhanced segmented part of the brain tumor by using region growing algorithm.

IV. PERFORMANCE MEASURES

The proposed method is evaluated on the MICCAI BraTS 2015 datasets. The performance is measured by utilizing Receiver Operating Characteristic, Mutual Information and Dice Similarity Coefficient.

A. Receiver Operating Characteristic (ROC)

ROC is used to measure the performance of the proposed method based on the True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). Accuracy, Sensitivity, and Specificity of the test is measured based on the ROC outcome table as shown in the Equation 4, 5 and 6.

$$Accuracy = \frac{(TP + TN)}{(P + N)} \tag{4}$$

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{5}$$

$$Specificity = \frac{TN}{(FP + TN)} \tag{6}$$

From the ROC outcome table, calculated different performance matrices which include Accuracy, Sensitivity, and Specificity of the simulated and real MRI datasets outcomes and compare the results. Figure 3 describes the ROC based binary classification outcome table to predict TP, FP, TN and FN.

	Predicted (P')	Predicted (N')	Total
Actual (P)	**TP**	**FP**	P
Actual (N)	**FN**	**TN**	N
Total	P'	N'	

Figure 3. ROC based binary classification outcome table

B. Mutual Information (MI)

MI is used to compute the performance of the outcome based on the joint probability distribution. It is a qualitative measure that how much a random variable correlates with the other random variable. The mutual information of two class problems can be measured by considering them as random variable X, Y and by using joint probability distribution equation.

$$MI(X,Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \times \log \left(\frac{p(x,y)}{p(x)p(y)} \right) \tag{7}$$

where $p(x,y)$ is joint probability distribution of X and Y.

C. Dice Similarity Coefficient (DSC)

Dice similarity coefficient is a statistical method used to measure similarity in between two classes. The equation is used to measures the dice similarity coefficient of two class problem.

$$DSC(X,Y) = \frac{2|A \cap B|}{|A| + |B| + 2|A \cap B|} \tag{8}$$

D. MICCAI BraTS Datasets

For experiments, a worldwide recognized MRI dataset named MICCAI brain tumor image segmentation (BRATS) 2015 [21]. The dataset contains a total of 384 training and testing samples of both Low-grade Glioma (LGG) and High-grade Glioma (HGG). There are 274 samples for training including 220 samples for HGG and 54 samples for LGG. Each training sample has 155 MRI slices for each T1, T2, T1c, Flair and annotated (labeled) images. Similarly, there are 110 samples in the testing dataset. Each testing dataset also has T1, T2, T1c and Flair images, each one having 155 images.

V. EXPERIMENTAL RESULTS

We applied the classification methods with a different number of features along with the different experimental and testing percentage of the data distributions. We used 18 patient sample datasets each one having T1, T2, Flair, T1c and annotated images. Several tests are performed with 5, 7, 10, 15 and 25 features dataset of DCT and based on the results, concluded top 15 features set produced best classification results. Table 2 describes the comparison of the classification performance by using purposed method along with the other recent work. A variable distribution of training, validation and testing percentages for the feature sets is used i.e. 80% versus 20%, 50% versus 50% and 66% versus 34% for training and testing respectively. Based on the computational power required for the experiments and the performance measures, we concluded that 80% for training and 20% for testing is most suitable for the classification. Using the proposed method, an accuracy of 96.91% is achieved for binomial classification. Table 1 shows the comparison of accuracy for different classifiers for binomial classification of tumorous and non-tumorous images.

For tumor segmentation, an accuracy of 93.22% is attained. Table 2 summarizes the experimental results for the brain tumor segmentation by using our proposed method (excluding non-tumorous images based on classification results) and the normal segmentation (applied for all tumorous and non-tumorous images). The results show that the proposed approached achieved higher accuracy for MICCAI BraTS datasets because only tumorous images segmented to extract tumor part. Figure 4 shows segmentation of the brain tumor where each row images are form the different patients dataset provided by the MICCAI BraTS where (a) shows the previous 2 images of actual image used as reference to enhance the segmentation, (b) shows the actual image for tumor segmentation, (c) shows next two images of actual image used as reference to enhance the segmentation, (d) displays the visual representation after manipulation the intensity values of the image, (e) shows the results after applying the proposed initial segmentation method and calculated the extracted clusters shape roundness values, (f) highlights the boundary of the initial segmentation, (g) shows the enhanced tumor segment after using region growing algorithm and (h) displays the actual tumor segment for the corresponding image as part of BraTS Annotated dataset.

Table 1
Comparison of different classification methods

Data Source	MICCAI BraTS 2015	
Method	Proposed Segmentation	Normal Segmentation
Accuracy	93.22 %	78.92%
Specificity	99.86%	87.22%
Sensitivity	95.52%	81.29%
DSC	90.87%	74.50%
MI	86.49%	66.86 %

Table 2
Experimental results' comparison of the proposed method

Classification Methods	Accuracy %
Support Vector Machine (SVM)	92.64%
Naïve Bayes	82.86%
K nearest-Neighbors (KNN)	96.91%
Multilayer Perceptron (MLP)	90.12%

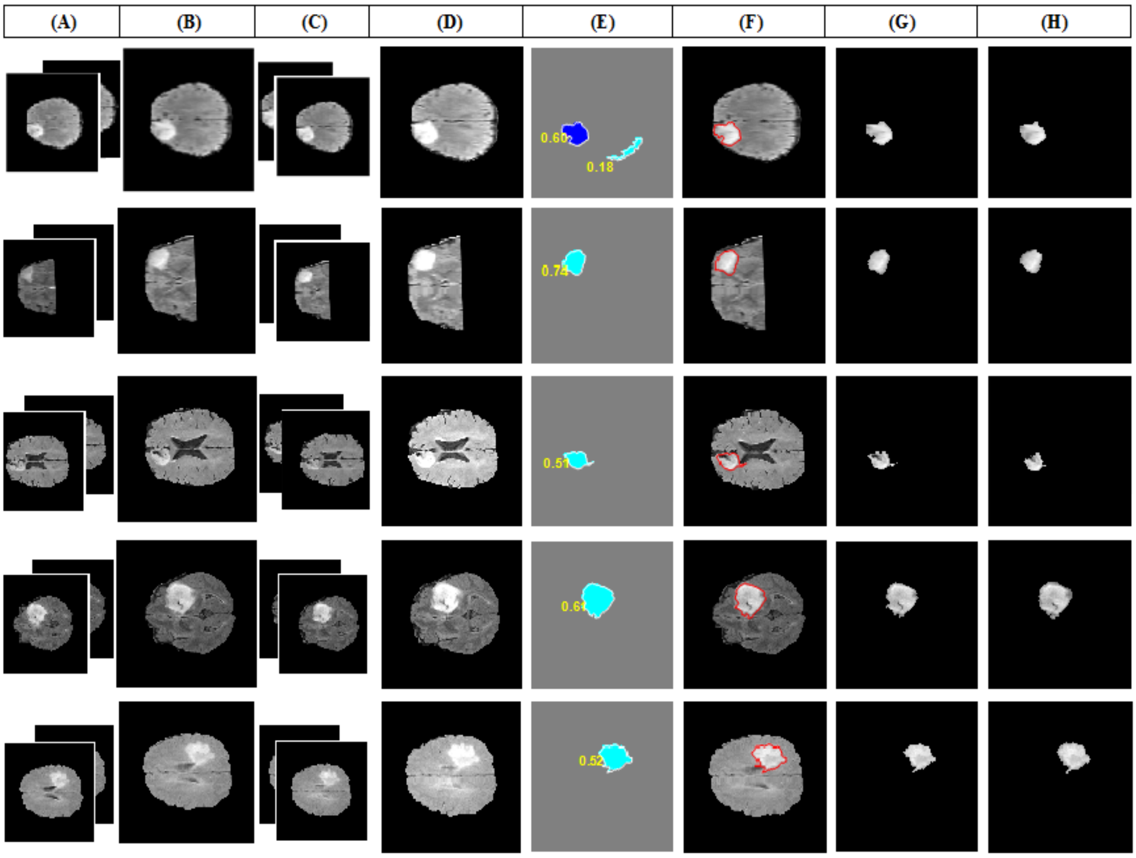

Figure 4. Experiment results of tumor segmentation over BraTS Datasets. Each row in the figure is representing different patient MR Images. (a) Previous 2 images of actual image used as reference to enhance the segmentation. (b) The actual image for tumor segmentation (c) Next two images of actual image used as reference to enhance the segmentation (d) Manipulated the Intensity values of the image (e) Applied proposed initial segmentation method and calculated the extracted clusters shape roundness values (f) Highlighted boundary of the initial segmentation (g) Enhanced the tumor segmentation by using region growing algorithm (h). Actual tumor segment for the corresponding image as part of BraTS Annotated dataset.

CONCLUSION

This research is about the problem of automatic and accurate brain tumor diagnosis and brain tumor region extraction for further analysis and cure. Manual extraction of brain tumor region by the radiologist is a time consuming and irreversible process. This problem is dealt as the image processing problem and the solution is determined using machine learning and computational intelligence techniques. For brain tumor segmentation from MR images, a multistep process is used. In the first step, classified the images into tumorous and non-tumorous images, after that, the images containing the tumor are improved by manipulating the intensities of the images. The tumor part from the images is detected by using the neighboring images information along with the current image is being processed. By using this method, the tumor region information is extracted with a higher accuracy rate as compared to the existing techniques. The correct derived brain tumor part can help the radiologists for locating brain tumor, boundary and size.

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