Automatic Multimodal Brain Image Classification using MLP and 3D Glioma Tumor Reconstruction

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***Abstract*—This research study discusses an enhanced technique for multimodal brain image classification using Multilayer Perceptron (MLP) and introduces tumor location identification and tumor volume measurement techniques. Brain tumor classification and segmentation is an important task in medical image processing. In the proposed method, brain MR image features are extracted by using discrete wavelet transform (DWT) along with absolute Gaussian smooth filters. Supervised binary classification has been used to separate tumorous and non-tumorous images by MLP. The tumor part is segmented from MR images by employing anisotropic diffusion filters (ADF). The boundaries of all segmented tumors are used for volume measurement and 3D reconstruction of the tumor. Based on the 3D tumor model, location of the tumor inside brain is calculated which can help the radiologists in decision making. The proposed technique has been tested on MICCAI BraTS 2015 data. Results show an accuracy of 92.59% in classification of MR images and 90.12% in tumor segmentation and its volume measurements.**

Keywords— Tumor Classification; 3D tumor Reconstruction; MICCAI BraTS; Discrete Wavelet Transform (DWT); Multilayer Perceptron (MLP); Anisotropic Diffusion Filters (ADF)

I. INTRODUCTION

Image segmentation and classification plays a pivotal role in the modern medical industry. Medical Resonance Imaging (MRI) is a medical procedure used by radiologists in which powerful magnetic fields, radio waves, and computer systems are used to acquire images of various parts of human body. These images can be used to diagnose different kinds of medical conditions. Brain MRI uses large magnets to locate the position of cells in the brain, which are captured by antennas and plotted on a computer system. This method can provide information related to many medical conditions of the brain e.g. tumors, cysts, bleeding and other abnormalities. The scans provided by brain MRI scans can also be converted to three-dimensional (3D) images which can help to pinpoint different faults accurately.

Tumors in brain cells have irregular growth as compared to healthy brain cells. Brain tumors can be classified into two types, tumorous and non-tumorous. The tumorous brain cells are cancerous and can grow rapidly, affecting the neighboring tissues and leading to serious health issues. There are many types of brain tumors based on size and shape which makes the process of identification and treatment very difficult.

In image processing, feature extraction techniques are employed to extract the feature vectors from complex images [1]. Various techniques provide image feature vectors which can be used to classify and segment the images into different types. DWT is one of the methods used for image classification [2] and segmentation. Supervised and unsupervised classification [3] are two approaches commonly used for classifying images. In supervised classification, the input features of an image are categorized by determining resemblance with training set [4]. The Brain MR images can be classified into tumorous and non-tumorous groups by using a supervised classifier. The training data can be acquired from actual patients that are diagnosed with brain tumors. Once the images are classified into tumorous and non-tumorous images, the tumor location can be identified through image segmentation.

Brain tumor segmentation, from the scanned data, is useful for identification and diagnosis of various types of tumors. Manual segmentation by radiologists and doctors has several limitations i.e. time consuming and irreversible. Various methods are presented for MR image segmentation including segmentation by Markov random field, prior information, support vector machines and fuzzy based approaches [5].

II. RELATED WORK

Automated detection of brain tumor is a critical task in medical image processing and a considerable amount of work has been done in this area in the recent years [6]. An automated approach for brain tumor detection is proposed in [7], wavelet transformation has been applied on the input images to categorize them into four sections of various sharpness. The images are clustered using k-means and a wavelet decomposition is applied afterwards to extract the brain tumor location. The proposed method is tested and analyzed on a different type of wavelets, and the results indicate a better performance regarding the number of tumorous images detected and their perceived visual quality. A three-stage process is presented in [8] to find abnormalities in brain MRI scans. The authors have used various techniques such as feature extraction, image transformation and image segmentation by using fuzzy logic to evaluate the overall quality of proposed method. Two

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metrics i.e. False Alarm (FA) and Missed Alarm (MA) are used to calculate the performance of detected brain tumor images. The results are compared with various existing methods used for the tumor detection and the proposed method gives relatively smaller values of FA. The MA values, however, are high because the method is not able to handle the symmetry of brain tumor around the center vertical line.

Arfan et al., proposed a different technique that uses fuzzy curvelets, Discrete Cosine Transform (DCT) and Support Vector Machines to categorize the MR images as benign (non-cancerous) and malignant (cancerous) [9]. In initial stages, noise is removed from the images using fuzzy curvelets and features are extracted from the denoised image using DCT. Afterwards, the features are fed to an SVM for classification. Fuzzy based clustering algorithms are used to segment the images and detect brain tumor. A comparison of different image transformation techniques, to extract tumor features from MR image, is provided in [10]. The authors de-noise image in the initial stage and use DCT and DWT to obtain relevant characteristics of the input image, which are later segmented using neural network techniques to find the brain irregularities. Sensitivity and accuracy metrics are used to study the performance of DCT and DWT on tumor detection.

Brain's lateral ventricular (LaV) deformation can cause errors in accurate detection of brain tumors. This deformation is introduced as part of the feature set during feature extraction of MR images and modeled through 3-D viewing in [11]. The improvement in brain tumor segmentation using Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), with the inclusion of this new LaV deformation feature is reported. Brain template LaVs are obtained dynamically with the help of brain hemisphere symmetry, and the model is aligned and represented in 3-D to avoid any compression effect errors in the feature data for tumor classification. Quratulain et al. proposed brain MR image classification using first order and second order texture features [12]. Six first order and seven second order texture features have been extracted. Ensemble based classification is used to classify the MR images based on extracted features. A multi-phase segmentation process, to find the brain tumors using texture analysis, is adopted. The authors were able to achieve high accuracy for the classification of tumorous images. A multi-phase brain image segmentation method is presented in [13] that overcome different intricacies of 3D volume segmentation for the brain. Contours of various parts of the brain are stacked over to get the 3D model. The method provides substantial results that help in detection of brain tumors. A multi-phase ADF based segmentation of brain parts from the MR image is also proposed. Further, the tumor is detected by using the fuzzy c-mean.

III. Proposed System

The proposed fully automated system consists of four main stages including feature extraction, classification, segmentation and 3D modeling. In the first stage, features are extracted using DWT and afterwards the features set is reduced based on feature coefficient values. In the second stage, multilayer perception classifier is applied to the images for grouping them into tumorous and non-tumorous images. In the third stage, the tumorous images are segmented using ADF and further region-based active contours algorithm are applied for enhancement. In the final stage, tumor and brain volume of the Glioma tumor along with its location is measured and reconstructed as a 3D model. The workflow process of adopted strategy is depicted in Fig. 1.

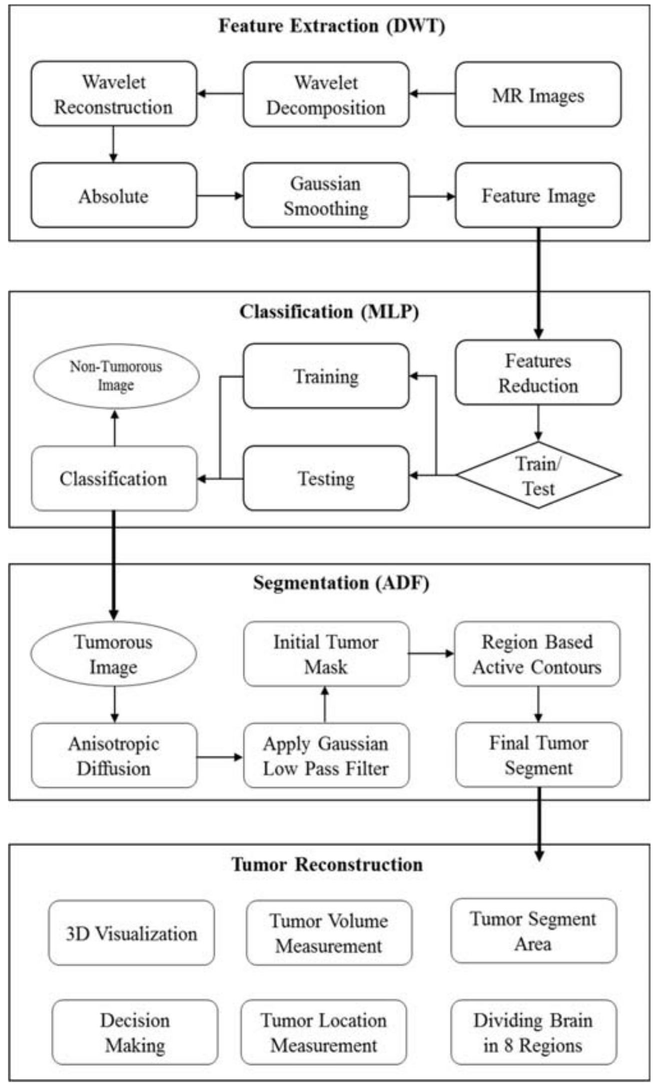

Fig. 1. Workflow process of the proposed system

A. Feature Extraction (DWT)

DWT is used for numerical and functional analysis in data compression, image processing, and signal processing. In image processing, wavelets are used for analysis of image textures based on their wavelet coefficients known as a feature vector [14]. In DWT, image is divided in to different frequencies using linear transformation. The four sub-bands generated are HH, HL, LL, and LH, where HH, LH, and HL represent detail coefficients and LL is for approximate coefficients.

In proposed model the brain MRI features are extracted using level 3 DWT. Fig. 2 show the process of 3 level DWT approximation and detailed coefficients.

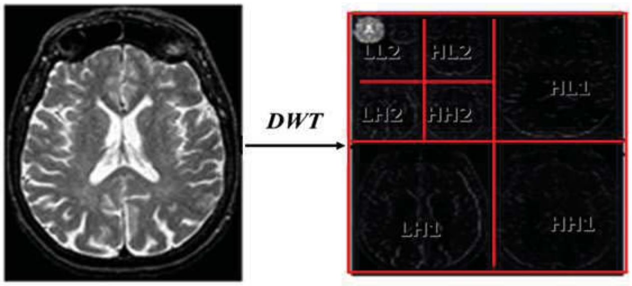

Fig. 2. DWT 3 level schematically for Brain MRI

B. Binary Classification (MLP)

Multilayer perceptron (MLP) is a type of neural networks which is widely used to remove noise from input features set. In brain MR images, tumorous and non-tumorous data is not linearly separable. The MLP algorithm is used for supervised learning [15]. It is comprised of an input layer, intermediate hidden layers and the output layer. Excluding the input nodes, all the other nodes act as neurons (processing elements), having a nonlinear activation function.

Several experiments are conducted to choose the best number of sigmoid nodes, learning coefficient and number of iterations for the MLP. With a careful analysis of results, seven sigmoid nodes, 1000 iterations, and learning rate value of 0.2 are selected. 1550 MRI scans have been used for the training of classifier while testing is done on 10 different patient cases with flair MRI images. Each case has 155 MRI scans and on average 92.59% accuracy is achieved.

C. Brain Tumor Segmentation (ADF)

The brain tumor segmentation is done by using ADF and active contour models. Initially, the image is dispersed using ADF technique, then centroid and origins of all the segments inside the image are used to remove the non-tumorous parts and detect the tumor segment. To make the edges of the images fuzzier and smoother, non-Linear anisotropic diffusion filter was used on the images [16]. Also, to degrade the gradient monotonically, diffusion function was applied to the image. This required updating each pixel of the image by considering its own position with reference to the four neighboring pixels. 2D ADF is used to offset the non-tumorous part. The diffused image is divided into different segments by using simple average threshold.

Here ADF is used to strengthen integration smoothing and in parallel inhabiting integration smoothing, as mentioned in Eq. (1) [17].

$$\frac{\partial}{\partial t} I(x',t) = \nabla.\left(c(x',t)\nabla I(x',t)\right) \tag{1}$$

Where $\mathrm{I}(x',\mathrm{t})$ is the brain image and x' and t stands for the image axes, t describes the number of iterations and $\mathrm{c}(x',\mathrm{t})$ points to the diffusion function which is represented in Eq. (2).

$$\mathrm{c}(\mathrm{x}',\mathrm{t}) = \exp\left(-\left(\frac{\nabla \mathrm{I}(\mathrm{x},\mathrm{t})}{\sqrt{2}\mathrm{K}}\right)^2\right) \tag{2}$$

The diffusion constant, represented in the Eq. (2) as K, which will affect the filter's behavior. The diffused MR images after utilizing anisotropic diffusion can be seen in Fig. 4 (ADF Images). Afterwards, parts of the brain are segmented using an automated threshold value. The histogram of the diffused image is calculated and the Gaussian curve is fitted on it, in order to enhance the visual presentation of the results [18]. The Gaussian filter is applied first, followed by the automatic threshold technique, which is used to convert the gray level image into a binary level image. Binary segments that are generated using automatic threshold includes holes, which are further filled using morphological operations. After all gaps and spaces are filled, the image undergoes erosion; a process in which non-tumor parts are removed. Then, a center point of the brain image is picked and used as reference point. Based on the detected object area and roundness of the shape, the non-tumor parts of the image are removed. The next step involves dilating the image. To do this, the isolated brain image is subtracted from the original eroded image. In the end, we follow the original image's boundary and map it before extracting the boundary on the initial tumor region as shown in Fig. 4 (Initial Tumor Segment).

Sometimes, the generated mask does not completely fit the original tumor mask, and some tumor parts fall outside the actual tumor boundary. To solve this problem, the active contour model algorithm was introduced by Kass, et al. [19]. The final

Algorithm 1: Tumor Segmentation and Reconstruction

Input: *Tumorous MR Image I of size m x n*
Output: *Segmented Tumor Boundary*

Read MR Image (I)
Initialize constants: num_iter, delta_t, kappa
Initialize 2D convolution masks
for j=1: num_iter
  Apply imfilter using convolution masks on Image I
  Apply diffusion coefficient function
  Reconstruct Image I using Discrete PDE solution
end
Apply 2-D FFT on Image I
Shift the DC component to the center of Image I
Apply Gaussian Low Pass Filter
Calculate inverse Fourier transform
Calculate mean thresh and Standard deviation of image
Convert image to binary by applying the threshold
Apply Morphological operations to enhance
Trace tumor boundary from binary image
Output Segmented Tumor Boundary

outcome i.e. brain tumor boundary is shown in Fig. 4 (Enhanced Tumor Boundary) based on proposed Algorithm 1.

D. 3D Glioma Tumor Reconstruction

Brain tumor size, location and shape are very important for decision making by the radiologists. The proposed system introduces a new method which measures the volume of the brain and tumor very accurately and construct a 3D model based on the tumor volume and location. Brain tumor location is measured by proposing a new technique and dividing the whole brain into eight different parts; Front Right Side, Central Right Side, Back Right Side, Central Back Side, Back Left Side, Central Left Side, Front Left Side and Central Front Side. Fig. 3 describes the brain distribution into eight parts. The location of brain tumor and the coordinates of its center is measured on the basis of this distribution.

	Brain Region		Brain Region
(A)	Front Right Side	(E)	Back Left Side
(B)	Central Right Side	(F)	Central Left Side
(C)	Back Right Side	(G)	Front Left Side
(D)	Central Back Side	(H)	Central Front Side

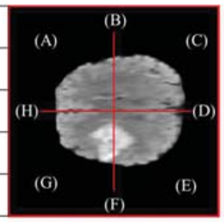

Fig. 3. Distribution of brain into eight parts

Fig. 4 (3D Model) show the reconstruction of the brain tumor and the different measurements based on the proposed segmentation and classification methods. It describes the 3D modeled shape of the brain tumor along with the volume of the tumor and brain. The proposed method (Algorithm 2) automatically determines the tumor location based on the defined parameters and provides the central axis value of the tumor. It will also calculate the proportion of tumor volume to brain volume and total tumorous MR images to total MR image.

IV. EXPERIMENTS AND RESULTS

For experiments, we used MICCAI BraTS 2015 MRI dataset which contains Low Grade Glioma (LGG) and High Grade Glioma (HGG) for training with annotated data and testing cases without annotated data [20]. Each case contains T1, T2, T1c and Flair sequences type MR images and each sequence type has 155 scans. During the experiments, total 1550 MR images are used for classifier training including 483 tumorous and 1067 non-tumorous images. Classification and segmentation testing is done using 10 cases of Flair sequence type. Each MR image size is 240×240 pixels with 1 to 6 mm slice thickness.

The superior performance of proposed method is justified by calculating dice similarity coefficient (DSC), mutual information (MI), specificity and accuracy [21] [22]. Table 1 describes the average performance measurements of used 10 MRI test cases for tumor segmentation. The results are validated based on the BraTS annotated tumor images.

Algorithm 2: 3D Glioma Tumor Reconstruction

Input: *Z number of MR Images for a Patient of size m x n*
Output: *Volume, Location and 3D of Tumor*

for i=1: Z
    Read Image i
    Calculate Area of Brain in i and store in Array K
    If (image I is tumorous)
        Calculate Area of tumor and save it an Array L
        Increment M
    End
End

Calculate the Volume of whole brain, based on individual brain areas stored in Array K

Calculate Volume of all tumor segments based on individual areas stored in Array L

Draw 3D tumor by extracting isosurface data from volume data

Calculate volume percentage % of tumor with respect to complete brain volume

Calculate tumorous images M percentage % with respect to total images Z

Calculate the 3D tumor point of center in X, Y and Z coordinates.

Divide the human brain in to eight parts.

Use nested conditionals to choose the tumor location out of 8 human brain parts by using 3D tumor central axis.

Table 1. Performance Measures of Tumor Segmentation

Data Source	**MICCAI BraTS 2015**	
Method	Proposed 3D Tumor Segmentation	Normal Tumor Segmentation
Accuracy	90.12 %	78.92%
Specificity	96.74%	87.22%
Sensitivity	94.72%	81.29%
DSC	90.43%	74.50%
MI	87.44%	66.86 %

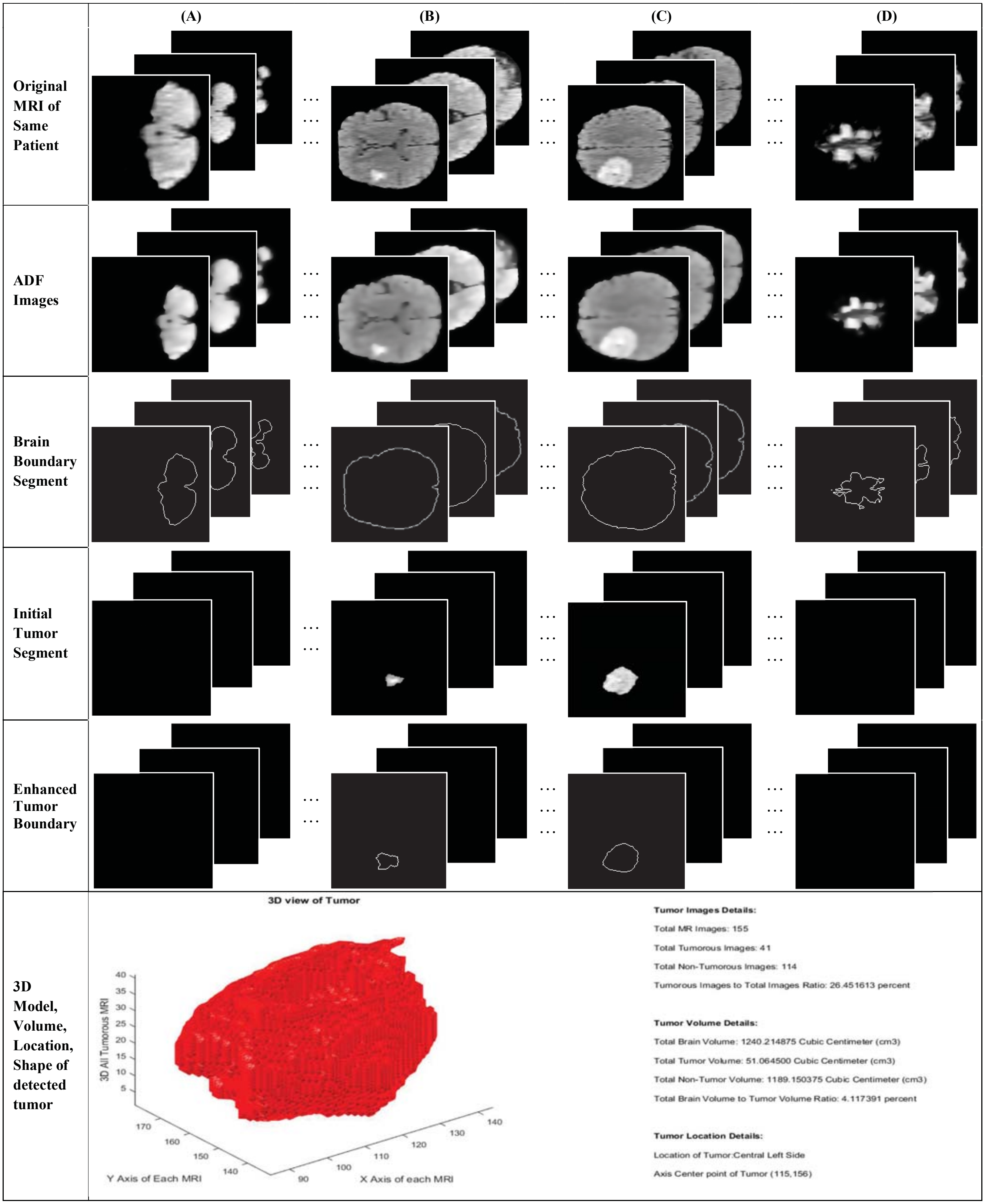

Fig. 4. Visual results of proposed automated brain tumor segmentation and 3D reconstruction by applying Flair MRI images as input

V. Conclusion

In this study, an automated brain tumor segmentation method is proposed which generates a 3D model of the tumor along with the volume and location with high accuracy. A multistep method is adopted in which features are extracted by DWT and brain MR images are classified into tumorous and non-tumorous type by using MLP. Tumorous images are extracted and segmented by ADF to detect the tumor region. The boundaries of segmented tumor are used to measure the volume of the tumor and its 3D reconstruction. Based on the 3D tumor model, the location of tumor, inside the brain, is calculated which can help the radiologists in decision making. The proposed techniques are tested on MICCAI BraTS 2015 data and an accuracy of 92.59% in the classification of MR images is observed. In tumor segmentation and volume calculations using the proposed methodologies, an accuracy of 90.12% is obtained. In contrast to available techniques, the results obtained through presented approach provide a better approximation in tumor location, volume and shape measurements.

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