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PATIENT FACING SYSTEMS

Efficient Framework for Identifying, Locating, Detecting and Classifying MRI Brain Tumor in MRI Images

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Abstract

Image processing has plays vital role in today's technological world. It can be applied in numerous application areas such as medical, remote sensing, computer vision etc. Brain tumor is caused due to formation of abnormal tissues within human brain. Therefore, it is necessary to remove affected tumor part from the brain securely. Among various medical imaging techniques Magnetic Resonance Imaging (MRI) employs a vital role to generate images of internal parts of human body. Image segmentation is one of the challenging tasks in today's medical field. An effective segmentation using MRI slices can help to identifying the tumor with its actual size and shape. To meet this requirement, a novel method called Adaptive Convex Region Contour (ACRC) algorithm is presented. Here, Support Vector Machine (SVM) is utilized for slice classification whether it is normal or abnormal. After obtaining SVM results, abnormal slices are involved in segmentation process. Since, human body is having complicated 3D anatomical structure naturally. Unfortunately, MRI slices are yields only 2Dimensional images. The actual shape of tumor cannot be clearly visualized in 2D form. Hence, transformation from 2D to 3D is essential which helps the doctors during surgery. The Rapid Mode Image Matching (RMIM) algorithm has to be followed for 3D reconstruction modeling. After building 3D model, the original volume of the tumor is estimated. The precise experimentation was implemented in MATLAB simulation environment. The obtained results are confirmed that proposed method has better accurate results compared to existing methods.

Keywords Brain tumor · MRI slices · Image classification · Adaptive convex region contour (ACRC) · 3D reconstruction and volume estimation

Introduction

Brain tumor is an uncontrolled growth of tissues inside the brain which leads potential life threatening. Depending upon the characteristics of tumor growth it is classified using grading system. The grades are refers to the way of tumor tissues are look through microscope and also indicates its aggressiveness. This grades are defined by experienced doctors, low grade represents least aggressive while high grade represents most aggressive. The different grade level of tumor is identified through scanned images of MRI slices. Most of the medical images are highly affected by noise which reduces quality of image. Therefore, denoising and enhancement techniques are necessary in the medical field.

Image pre-processing is the primary step in image analysis which can be used to remove unwanted noise from an image. The medical MRI images are affected by noise that reduces accuracy of the image. There are several filtering techniques are designed for eliminate this noise. The filtering techniques are namely mean filter, median filter, Gaussian filter, min and max filter. Among them combining both mean and median filtering are used to remove the noise in MRI images in [1]. Median filters are highly efficient for reduction of impulse noise for an image. Based on correlation between pixels and noise levels the image noise can be removed. For low noise level mean method is to be performed and for high noise level

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an adaptive weighted median filter is to be used [2]. Weiner filtering technique has been used to for obtaining improved image resolution [3]. The conventional median filters with windowing with different sizes are applied in cascaded form for removal of salt and pepper noise [Ali Ahmed]. For image enhancement, adaptive median filtering [4] is presented; noise is detected by median filtering with adaptive window. In window level, center value of pixel closer or same as median value.

Features are the key factor which used to describe the natural properties of an image. Texture based feature extraction [5] is designed for representing descriptive nature of the image. Texture co-occurrence matrix is formed using hybrid features set from the image. Except that, Gray Level Co-occurrence Matrix (GLCM) is introduced in [6, 7]. This approach has less computational complexity compared to others.

In image processing, one of the major difficulty is the segmentation of obtained image where the boundaries of objects such as abnormal region in medical research. The image segmentation is defined as the process of separating an image into various parts or regions. The main objective is to simplify or change the representation of the image into something else which is easier and more meaningful to analyze. Result of this process is used to locate objects and boundaries in images. SVM is a novel machine learning method and is mainly depends on the theory of statistical. SVM compromises both the study capability and the model's complexity that's why it is used in wide range of research areas. The problems with small sampling, nonlinearity and high dimension can be effectively solved by SVM method by using the optimal hyper plane with linear detachable properties. However, this method requires a large amount of feature values which may cause interference to the classification result. In the segmentation, it can able to attained suspicious region of brain tumor in 2D format, however it is not convenient for know the clear view of tumor.

Generally, a human body has complex 3Dimensional (3D) structure. Transformation of 3D structure into 2D form causes incorrect disease diagnosis. Hence, it is necessary to transform segmented tumor area into 3D visualization. Here, for higher understanding MRI tumor 2D images are combined to create a 3D format. Through the appropriate MRI slice selection, 3D modeling is constructed by using cubic reconstruction scheme. And finally, tumor volume is calculated.

The remaining of research work is organized as follows. The works related to brain tumor segmentation and 3D reconstruction is discussed in section II. The necessity and materials required for proposed approach is described in section III and IV respectively. In section IV, the proposed work is explained. Experiment evaluation is illustrated in section V. Finally, a conclusion is ended with in section VI.

Related works

There are several algorithms and techniques have been developed for the detection of tumor in human brain. This approach mainly involves investigation about segmentation of tumor area effectively. A review of anatomical structure modeling from medical images is presented in [8]. In Aravind Kumar et al [9] had proposed robust method for automated lung nodule diagnosis from ct images that based on fuzzy systems. They designed Computer Aided Diagnosis (CAD) system that uses wavelet technique for input CT image enhancement. Feature extraction process can be simple done by extraction of shape, texture or color. Mohanaiah et al [10] utilized a Gray level Co-occurrence Matrix (GLCM) feature extraction scheme of image texture features.

For segmentation, region growing method is followed which provides more stable with respect to noise than gradient and Laplacian methods. Michal Garland et al [11] had proposed a surface simplification model which reduces the quadric errors in image. This algorithm produces high quality approximations of polygonal models quickly. The result of pair contraction was improved the vertices and achieves optimized approximation. Paul Joseph et al [12] recommended a novel K-means clustering algorithm with morphological filtering approach. In K-means clustering method, the input images into clusters based on estimation of center of clusters. After that, morphological filters are used to preserve shapes and structures through morphological operations. The convex active contour model has been presented based on region and boundary of an image [13]. Patil et al [14] had investigated the problem of brain tumor extraction from MRI scan images by using MATLAB software. They discussed a Watershed method for segmentation, a grey-level image may be seen as a topographic relief. From tat the pixels are considered as its altitude in the relief. Several watershed lines methods are established in digital image processing. For representation of graph few are defined on nodes or on edges, sometimes hybrid lines are both on edges and nodes. Nandha Gopal et al [15] had suggested a clustering algorithm, Fuzzy C Means along with intelligent optimization method to diagnose tumor via MRI images. In their study, an intelligent system as CAD (Computer Aided Detection) model is designed to extract suspicious portion of tumor along with optimized technique such a genetic algorithm and Particle Swarm Optimization. The genetic algorithm used to estimate the optimized threshold value for tumor segmentation whereas PSO is a population-based stochastic optimization algorithm is used to detecting the position of tumor by factors such as particles area and velocity. PSO method improves global optimization solution compared to other methods.

The Fuzzy C Means (FCM) algorithm for image segmentation was presented in [16, 17]. They used an empirical method called Hierarchical Self Organizing Map to detect tumor in brain that can be segmented based on Low Depth of Field Images. This technique is popular one that can be widely used in different tasks such as image processing, pattern recognition, data mining, generating expression for data recognition, etc. The extraction of 3D target or object is most important in medical analysis. And segmentation of affected anatomical region of tumor is major issue. The detection and extraction of tumor part from MRI scan image of patients is critical task is faced by doctors. High resolution MRI images provide an anatomical data of tumor and discover abnormalities. Selvanayaki et al [18] proposed a meta-heuristic algorithm such as Ant Colony optimization (ACO), genetic algorithm (GA) and Particle swarm optimization (PSO) for effective tumor segmentation in 3Dimension. They investigated 42 slices of brain tumors from real patients and enhanced technique was provided advanced system automated detection of brain tumor. Vahid Soleimani et al [19] had followed Ant Colony Optimization for brain MRI image segmentation and tumor diagnosis. It is used to obtain the precious threshold value for tumor segmentation. In this algorithm, the pixels are considered as food for ants and pheromone on the pixels that is effective on other ant's movement. The distribution of pheromone is helpful for improving accurate threshold value Due to emerging growth o medical field requires advancement method to avoid those issues. Matei et al [20] had initiated semi-automatic region growing segmentation approach in order to segment spinal cord and testing outcomes are involving other organs such as parotid glands (i.e) threat areas. The modelization of these risk areas is very critical since tumor area is large.

Problem statement and definition

The research on Medical field is one of the emerging technologies for the past ten decades. Brain tumor is part of this field. Brain tumor is one reason for human death rapidly. Hence, it is necessary to well known about the reason for causing tumors and medical experts started doing an efficient research work on classification of MRI slices whether it is normal or abnormal. After classification, the abnormal slices are should involved in segmentation process. Earlier stage diagnosing of tumor can helpful for doctors in future process. There are tremendous amount of segmentation techniques are designed for effective process. However, each of techniques is meet their own merits and demerits. To mitigate this limitation, Adaptive Convex Region Contour (ACRC) algorithm is to be followed in this work. Brain tumor can be diagnosed and analyzed using MRI images which provide resultant images as 2Dimensional. The original shape and size of the tumor does not clearly visualize in 2D image. Hence, it is necessary to convert 2D segmented image into 3D. The 3D reconstruction process can be done by using MRI slices. At first, Preprocessing and enhancement techniques are used to improve the image quality. In this stage, given images are resized, color transform without any loss of information. For image enhancement, weighted median filtering technique has been used for noise removal with contrast improvement. Next, image useful features are extracted using Gray Level Co-occurrence Matrix (GLCM) depends on similarity and dissimilarity between the pixels. These extracted features are given input to SVM (Support Vector Machine) classifier that categorizes the abnormal MRI slices. These classified abnormal slices are only involved under the process of segmentation. Then, segmented image is visualized in 3D format using rapid mode image matching (RMIM). Finally, volume of tumor can be estimated.

Materials and methods

The each part represents the material from the collected MRI dataset of the patients; the followed algorithm can execute the fragmentation of MRI image. First the input dataset of images are resized of 256 × 256 pixels. Around MRI sample slices of 1–41 images as an input data set from patients and must be evaluated. During the preprocessing the MR image can be resized, the noise from the image is filtered and smoothness of the image can be improved by using the process of image enhancement. Feature extraction that can be done by Gray Level Co-occurrence Matrix (GLCM) method. After Support Vector Machine classification, the image can be predicted either normal or abnormal. The abnormal (malignant) portion of image can be segmented effectively by Adaptive Convex Region Contour (ACRC) algorithm. The outcome can be viewed in 3Dimension for further treatments.

Proposed implementation

The proposed system has been explained in different stages like Preprocessing, Enhancement, Feature Extraction, Classification, Segmentation and 3D reconstruction modeling. The Block diagram for the proposed methodology is shown in the Fig. 1.

(i) *Pre-processing and Enhancement*

Pre-processing is the first stage of image analysis where image is resized as 256 × 256 pixels without any loss of information. Image denoising is significant task which removes unwanted noise while preserving image features. Different filtering techniques are used in image processing which enhances the image quality. Here, weighted median filtering technique is utilized for MRI slices noise removal and enhancement. The mechanism of weighted median filter is similar to median filter; only key difference is the mask place is replaced with weighted value. Assume 3X3 weighted mask is

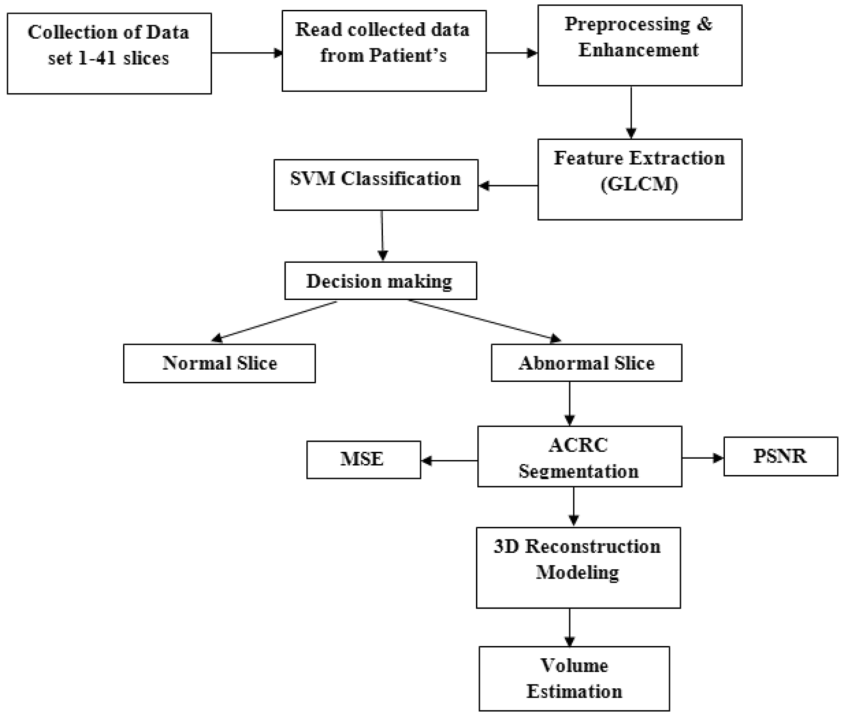

Fig. 1 Block diagram for the proposed methodology

performed. Initially place the mask at left hand corner. After convolution, resultant pixels are arranged in either ascending or descending order. Select the median value from the total values. This process is continued up to mask throughout the image.

Let the input image is represented as f(x, y) and the filtering window size of 3 X 3. The similarity value of each pixel point within the window size is calculated. The window is moved across each pixel x(m, n) at location (m, n). Each window W^3 (m, n) and arrange the pixels in ascending order. The weights of corresponding pixels are denoted as w_k. Then, grey value after filtering the noise pixels is calculated as

$$g(x,y) = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} w_k f(x,y) \quad (1)$$

Where w_k is the weighting function

(ii) *Feature Extraction*

The feature extraction is used to deduce the amount of resources needed to representing the given data. The number of factors is involving when evaluating the large amount of data to be efficient. This is one of the most serious problems in that process. It is used to define the objects of image such as shape, pixels, quality and dissimilarity. In our approach we use Gray Level Co-occurrence Matrix (GLCM) to extract the features of the image. The GLCM algorithm was proposed by Haralick. The pixel which having the same gray levels, the positions of that pixels are stored in GLCM matrix. The statistical characteristics of it with functional attributes are discussed below.

(i) Average or Mean

The mean value of MR image can be evaluated as calculating the rate of the entire pixels, which are divided by the

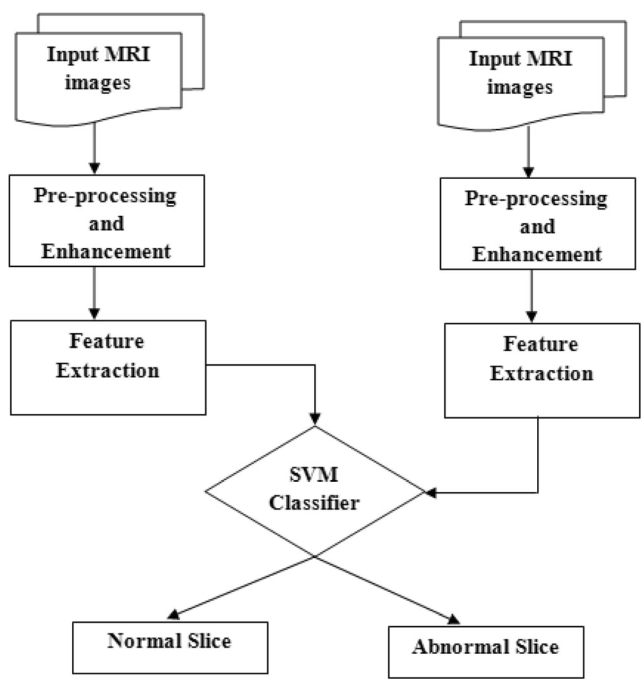

Fig. 2 SVM classifier

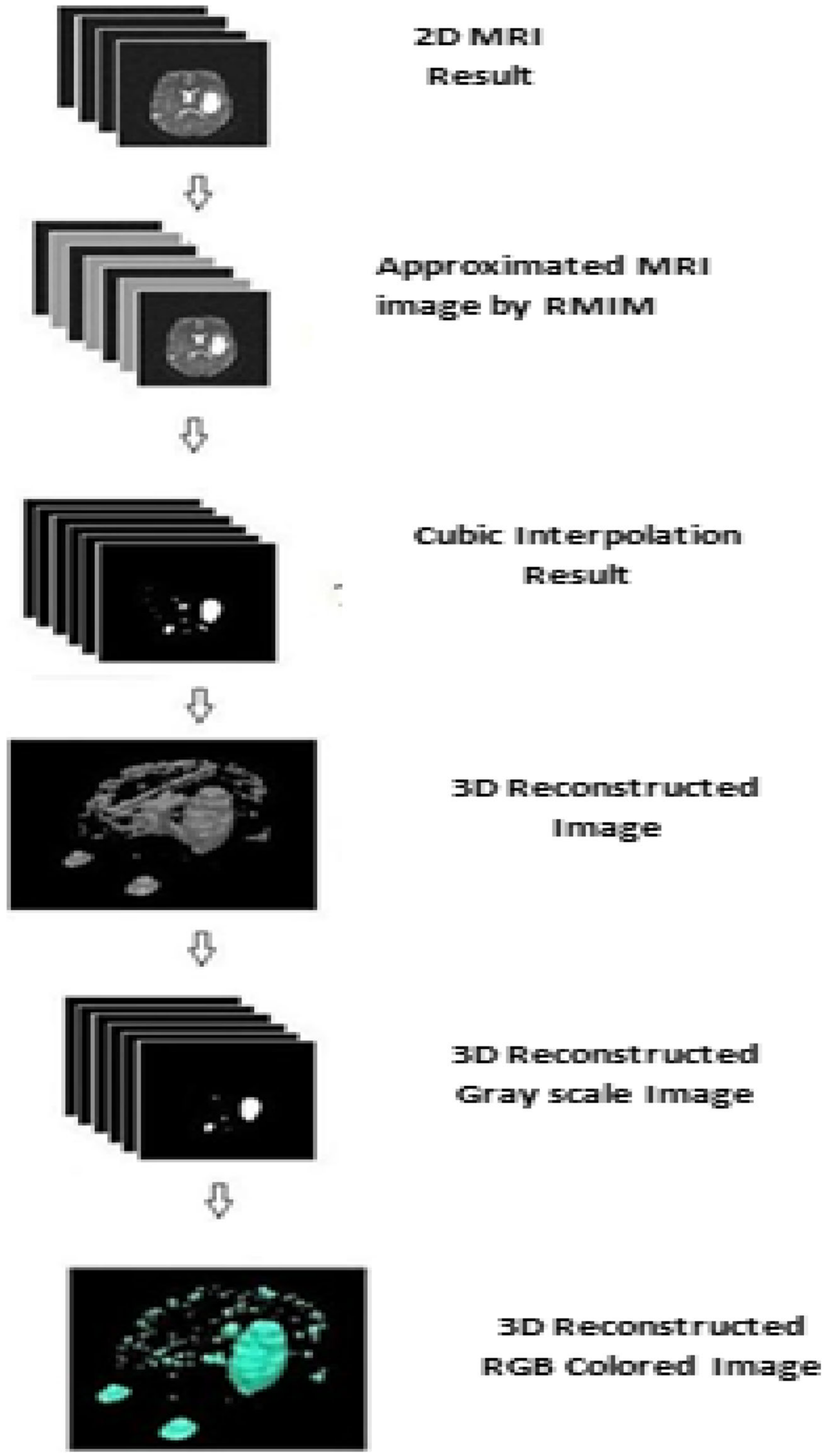

Fig. 3 3D Reconstruction process

total amount of pixels of an image. The mathematical representation of Mean value is given by the following equation.

$$M = \left(\frac{1}{m \times n}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y) \tag{2}$$

(ii) Standard Deviation (SD)

It is the next essential moment explaining the prospect allocation of an examined populace and determines homogeneity. The superior rate signifies enhanced level of intensity, elevated boundaries in dissimilarities of an image.

$$SD(\sigma) = \sqrt{\left(\frac{1}{m \times n}\right)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}(f(x,y)-M)^2} \quad (3)$$

(iii) Entropy (E)

The term Entropy is defined as a quantity to describe the amount of information which must be coded, having a very little contrast and large runs of pixels with the same quality of image. Mathematically, it can be represented as follows

$$E = -\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\log_2 f(x,y) \quad (4)$$

(iv) Skewness (SK)

The Skewness of the image are depends on the geometric moments of that image. It can be used to calculate equilibrium and the arbitrary variable X is representing the skewness of an image is given by

$$S_k(X) = \left(\frac{1}{m \times n}\right)\frac{\sum(f(x,y)-M)^3}{SD^3} \quad (5)$$

(v) Kurtosis (SK)

In digital image processing the value of kurtosis can be used to interpret as combination with noise and resolution. The kurtosis of an image is symbolized as Kurt(X) and is given as

$$K_{urt}(X) = \left(\frac{1}{m \times n}\right)\frac{\sum(f(x,y)-M)^4}{SD^4} \quad (6)$$

(vi) Energy (En)

The term energy is defined as the quantity of pixels, which are doe to recurrences of the image. It can be used to differentiate the similar appearance of the image and it can be represented as

$$En = \sqrt{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f^2(x,y)} \quad (7)$$

(vii) Contrast (Cn)

The properties of contrast is used to determine the strength of the pixel and its neighbors pixels in an image and it is represented as

$$C_{on} = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1}(x-y)^2 f(x,y) \quad (8)$$

(viii) Inverse Difference Moment (IDM)

It computes the restricted homogeneity of an image. IDM might be particular or an array of values in order to verify

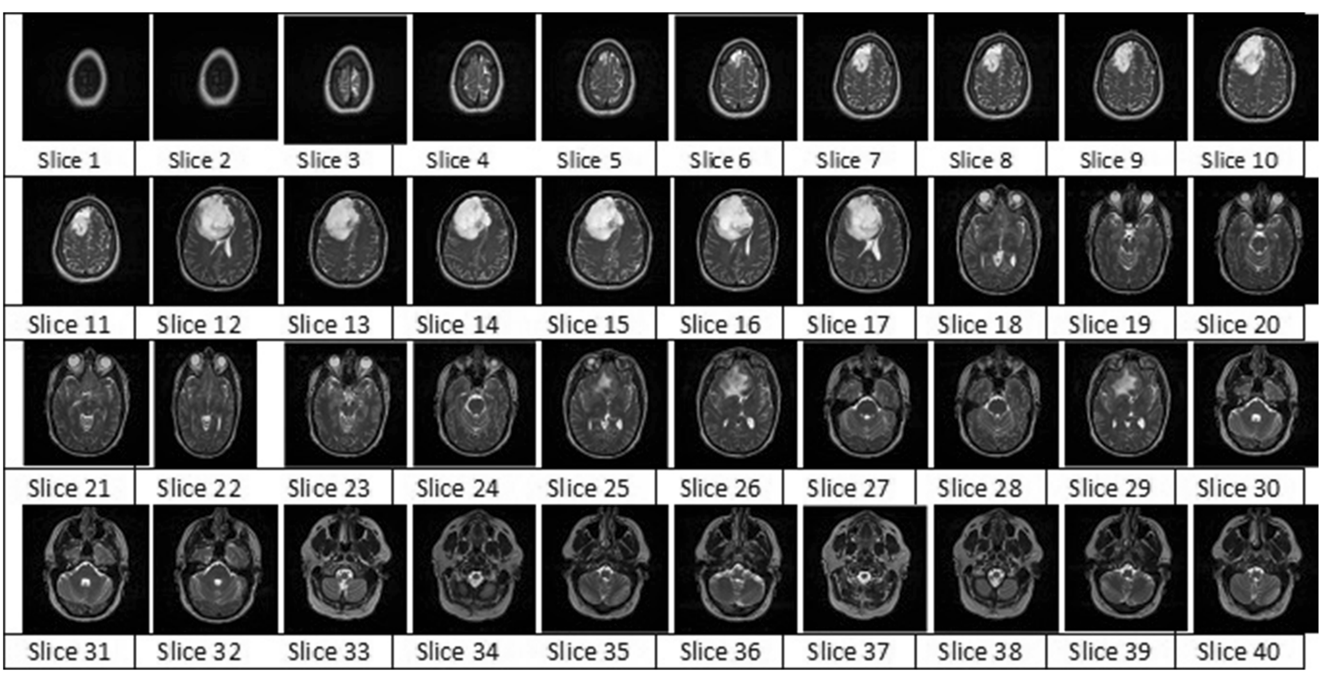

Fig. 4 Dataset of MRI brain images

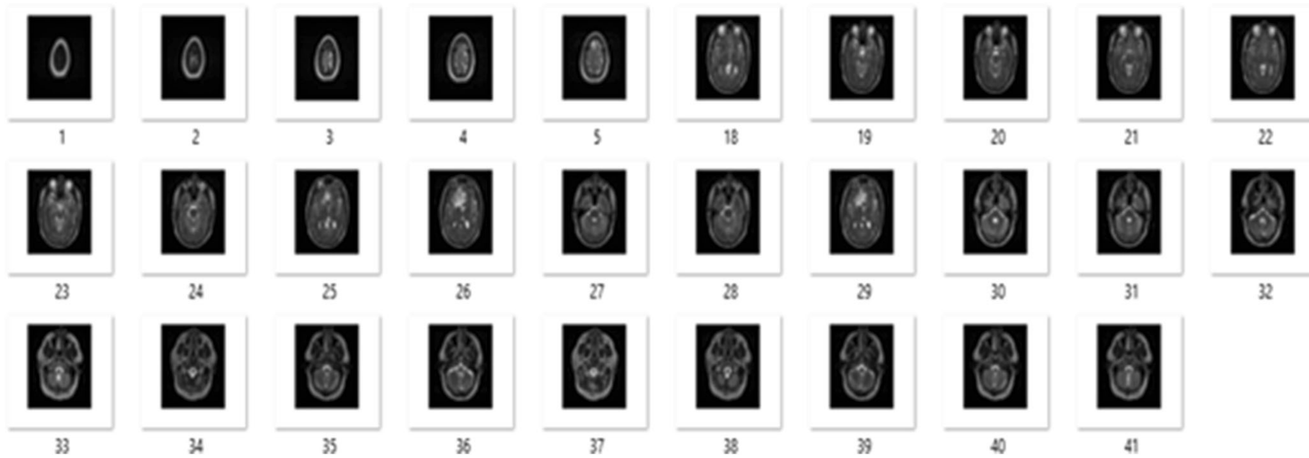

Fig. 5 Normal MRI images

whether the image is quality or non-quality.

$$IDM = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} \frac{1}{1+(x-y)^2} f(x,y) \tag{9}$$

(ix) Directional moment (DM)

It is defined as keeping the image to measures which is done by regarding the arrangement based on the position of the pixels in an image. It is given by

$$DM = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)|x-y| \tag{10}$$

(x) Correlation (C_{corr})

The spatial correlation among the pixels in an image is given in the following equation

$$C_{corr} = \frac{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\big)x,y\big)\ f(x,y)-M_xM_y}{\sigma_x\sigma_y} \tag{11}$$

Where,M_x, σ_x are the mean and standard deviation in the parallel spatial area whereas and M_y, σ_y are the mean and standard deviation with corresponds to the perpendicular spatial factor.

(xi) Coarseness

It is the process of determinant of the quality of smoothness of an image (i.e) it is a textual; analysis of MR images. It can be defined as follows:

$$C_{cness} = \frac{1}{2^{m+n}} \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y) \tag{12}$$

Away from each other, subsequently the quality evaluation constraints are moreover required to guarantee enhanced outcome analysis on brain MR images.

(xii) Structured Similarity Index (SSIM)

It is a perceptual metric which indicates the dreadful conditions in image eminence that could be sourced by data density or failures in data communication. It is termed as

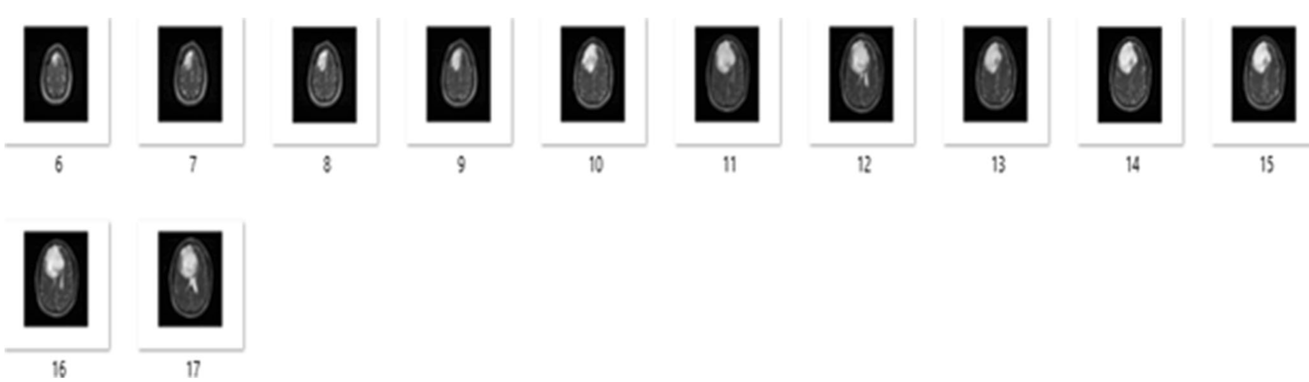

Fig. 6 Abnormal MRI images

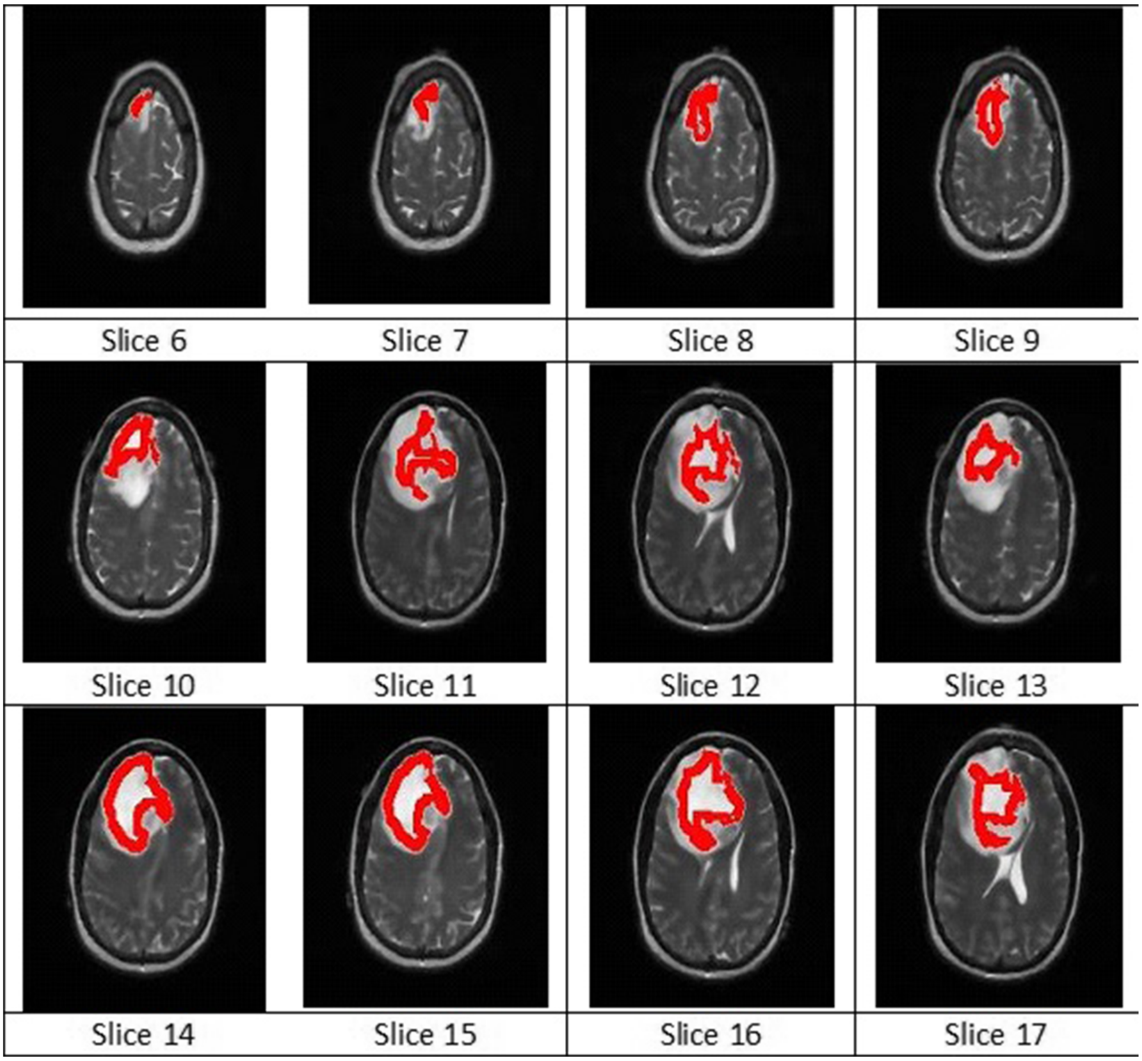

Fig. 7 Detected tumors from the dataset

$$SSIM = \left(\frac{\sigma_{xy}}{\sigma_x\sigma_y}\right)\left(\frac{2\overline{xy}}{\left(\overline{x}^2\right)\left(\overline{y}^2\right)+C_1}\right)\cdot\left(\frac{2\sigma_x\sigma_y}{(\sigma_x)^2\left(\sigma_y\right)^2+C_2}\right) \tag{13}$$

An advanced rate of SSIM specifies enhanced maintenance of luminance, dissimilarity, also structural content.

(xiii) Dice Coefficient

Dice coefficient is used to analyze the evaluation of two images when they overlap with each other. Mathematically, it is represented as

$$Dice(A, B) = 2 \times \frac{|A_1 \wedge B_1|}{(|A_1| + |B_1|)'} \tag{14}$$

(xiv) *SVM Classification*

The novel SVM algorithm was given by Vladimir.N. Vapnik also its contemporary edition were extended by Cortes in the year1993. The SVM is a systematic algorithm of learning technique and is used to correlate the n- order problem from the one-order problem. With the help of SVM's kernel utility is used to differentiating the linear functions from the non-linear functions. The Gaussian kernel functions are utilized in this study. There are several classifiers are used for medical analysis such as SVM, K-nearest Neighbor, Artificial Neural Network, Probabilistic Neural Network, etc. They can be used in object recognition, face identification, text classification and Digital data identification. Each method has its own strengths and weakness in implementation. Among these SVM has used to implement in various applications and that gives high accuracy to others. The SVM

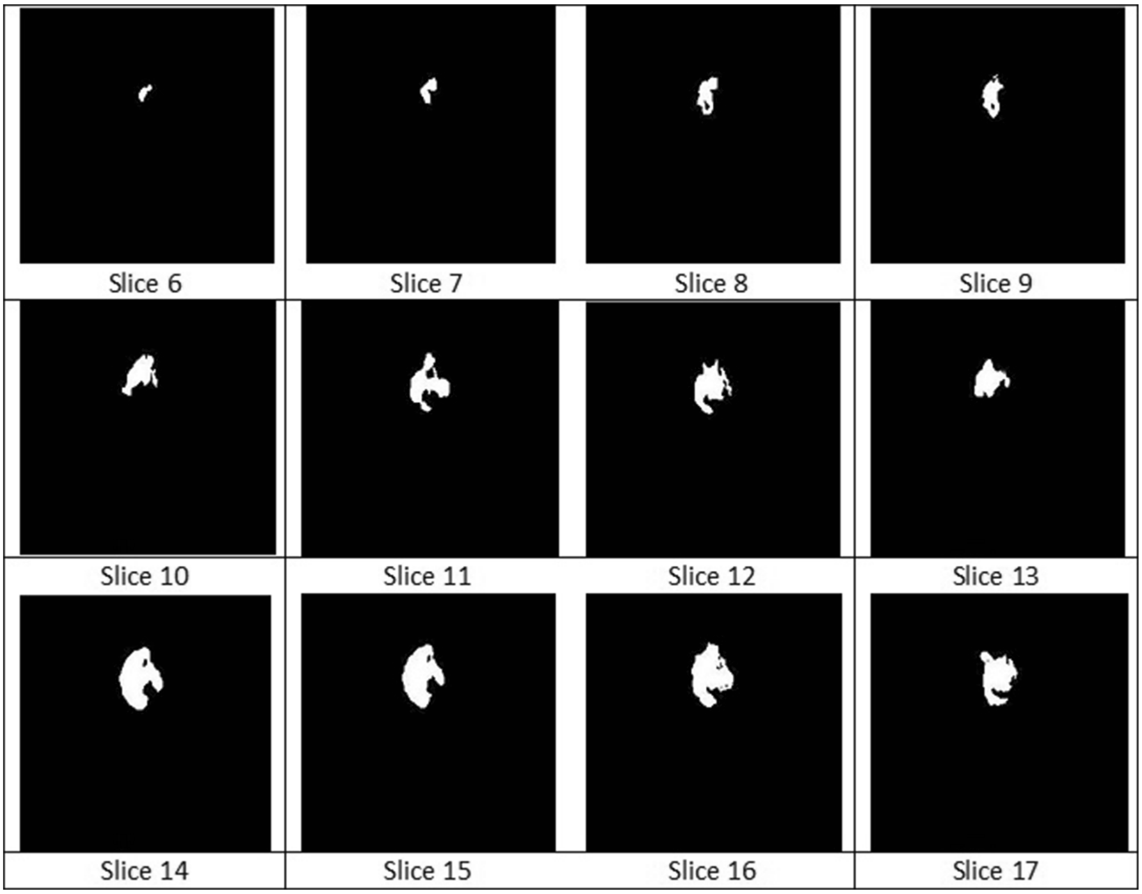

Fig. 8 Segmented tumors from the dataset

classification process has been divided into two stages (i.e.) one is training part and another is testing part. In training part, the input MRI data are given for training where data is known to classifier. The unknown input data are given in second part that can be performed after completion of training stage. Overall efficiency of Support Vector Machine is depends on precious rate of training process. The Fig. 2 shows classification process of SVM approach.

The Support Vector Machine (SVM) which took input of extracted feature set, through it classifies the normal and

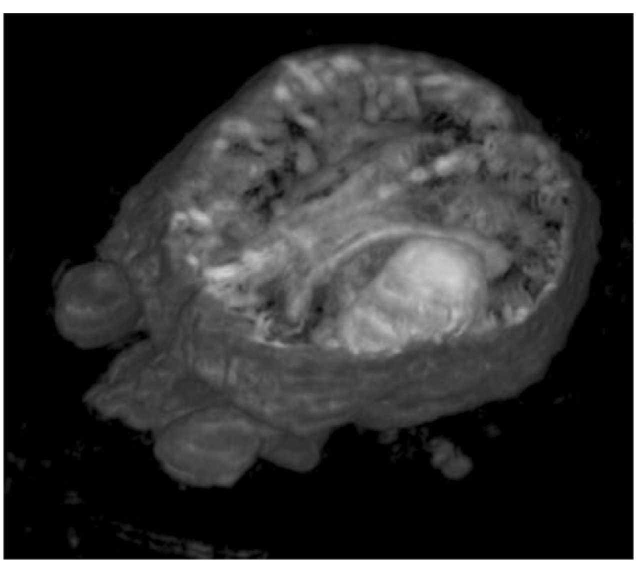

Fig. 9 3D MRI tumor image in gray scale form

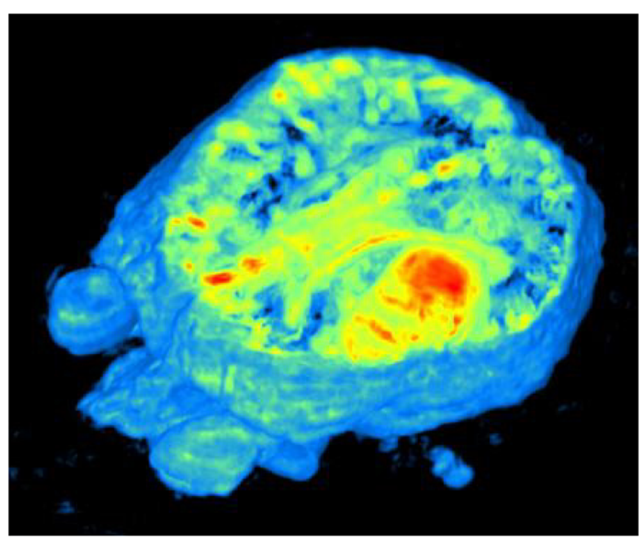

Fig. 10 3D MRI tumor image in RGB colored form

Table 1 Comparison of performance metrics

Performance metrics	Reference paper [2]	Proposed (Weighted median filter)
MSE	35.4196	36.563
PSNR	18.6689	19.69

abnormal slices. Before involving the process of classification, it must be trained with known data (ground truth images). Here, totally forty one MRI slices are consider for analysis. After classification it is found that image 6 to image 17 are identified as abnormal slices while remaining slices are normal.

(iii) *Adaptive convex region contour (ACRC) Segmentation*

Image segmentation is the process of partitioning a image into multiple segments. Here, adaptive convex region contour (ACRC) has to be followed. At first, region based approach which generates the initial boundary and then convex active contour is applied to optimize the contour. The proposed method has two terms namely boundary tem and region term. The region term has image properties like color and texture while boundary term holds difference value of adjacent pixels.

Initialization of contour

The region based approach is used for initialization of contour. In this method, the pixels similarity and spatial dissimilarity is measured. Based on this value pre-segmented image will be obtained. Hence, the pre-segmented output image is being obtained by initializing the contour. Here, geodesic method [21] to be used for contour initialization because it eliminates small cut problem during segmentation. The result of geodesic method is represented as probability map P(x) and the values lies between [0, 1]. It indicates the pixel x which belongs to the foreground region. The distance of pixel x either foreground or background is measured as $D_F(x)$ and $D_B(x)$ correspondingly.

Convex active contour model

The convex active contour model has followed two terms such as region term and boundary term. The foreground and background seed provides information of color distributions of foreground and background. The Gaussian mixture models [Ankita] has been used for foreground and background separation for image segmentation.

Regional term formulation

The Gaussian model of foreground and background region seeds are represented as Pr(x|F) and Pr(x|B) which is the probability value of pixel x. It is given by

$$P(F)(x) = \frac{-\log\Pr(x|F)}{-\log\Pr(x|F)--\log\Pr(x|B)} \tag{15}$$

And

$$P(F)(x) = \frac{-\log\Pr(x|B)}{-\log\Pr(x|F)—\log\Pr(x|B)} \tag{16}$$

The image regional information is derived from foreground and background is transformed as regional term of convex active contour model as

$$hr(x) = P_B(x)-P_F(x) \tag{17}$$

However, the above equation is not applicable for foreground and background color models. To avoid this problem, tradeoff factor α is introduced with an condition $\alpha \in [0, 1]$. The probability of region term is defined by

$$\mathrm{hr(x)} = \alpha(\mathrm{PB(x)-PF\ (x)}) + (1-\alpha)(1-2\mathrm{P(x)}) \tag{18}$$

And α is the distance between foreground and background region.

$$\alpha = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left|\frac{\log\mathrm{P_r(x_i|F)}-\log\mathrm{P_r(x_i|B)}}{\log\mathrm{P_r(x_i|F)}+\log\mathrm{P_r(x_i|B)}}\right| \tag{19}$$

Where, n represents number of pixels in the given image.

Table 2 Comparison of result parameter with PSO [18], ACO [18], GA [18] and ACRC (Proposed)

Haralick or GLCM features	PSO [18]	ACO [18]	GA [18]	ACRC (Proposed)
Sum average or Mean	0.0776	0.0776	0.0773	0.0770
Contrast	0.0440	0.0440	0.0440	0.0438
Inverse Distance Moment	0.1927	0.1927	0.1900	0.1895
Correlation	0.0575	0.0575	0.0573	0.0570
Entropy	0.1478	0.1473	0.1461	0.1502

Table 3 Error and accuracy rate analysis in 21 patients data sets compared with reference paper [23]

Images	Actual tumor value (AV)	Estimated Value (EV)	Difference = AV-EV	Error(%)	Accuracy rate(%) (Proposed)	OTSU's Method [22]
Image 6	23638mm^3	23,958 mm^3	320 mm^3	1.3	98.9	98.7
Image 7	14,586 mm^3	14,796 mm^3	210 mm^3	1.44	98.99	98.66
Image 8	24,001 mm^3	24,299 mm^3	298 mm^3	1.24	99.1	98.76
Image 9	13,361 mm^3	13,524 mm^3	163 mm^3	1.22	99.7	99
Image 10	32,987 mm^3	33,314 mm^3	327 mm^3	1	89	85
Image 11	540 mm^3	621 mm^3	81 mm^3	15	98.5	97.5
Image 12	7811 mm^3	7998 mm^3	187 mm^3	2.5	95.8	98.83
Image 13	14,652 mm^3	14,824 mm^3	172 mm^3	1.17	95.6	94.2
Image 14	1298mm^3	1373 mm^3	75 mm^3	5.8	99.2	98.3
Image 15	6677 mm^3	6792 mm^3	115 mm^3	1.7	99.3	98.8
Image 16	20,923 mm^3	21,177 mm^3	254 mm^3	1.2	99.43	98.38
Image 17	7084 mm^3	7202 mm^3	118 mm^3	1.62	99.25	98.18

Boundary term formulation

The boundary term of convex contour model is discussed below. The boundary function fb is defined as

$$\mathbf{fb}(\mathbf{x}) \quad = \frac{\mathbf{1}}{\mathbf{1} + |\nabla \mathbf{I}(\mathbf{x})|\ \mathbf{2}} \tag{20}$$

I(x) is denotes intensity of the image. The Gaussian model with probability map is defined to edge detection is stated as

$$\mathbf{fb} = \boldsymbol{\beta} \cdot \mathbf{fc} + (\mathbf{1} - \boldsymbol{\beta}) \cdot \mathbf{fe} \tag{21}$$

where fc and fe are Gaussian probability map results of edge detection. And $\boldsymbol{\beta}$ is the edge tradeoff factor that is $\beta \in [0, 1]$.

(iv) *3D Reconstruction Modeling*

Since single patient consists of multiple MRI brain scanned images of many slices, hence its reconstruction takes enormous amount of computational time and makes algorithm complexity. To mitigate this problem, rapid mode image matching (RMIM) algorithm is applied to select an approximate MRI slices. The RMIM is based on number of matching points between two consecutive MRI slices that depends upon distance between them. If the distance is large, there is less matching points between them and vice versa. The matching points are calculated on the basis of same intensity value and neighboring pixel values of those two images are considered. The image connects properly when number of matching points is high, which results in obtaining accurate 3D reconstruction modeling. The step by step procedure of RMIM algorithm is depicted below.

A cubic interpolation technique has been utilized for 3D reconstruction, which uses 3D modeling tool called as Slicer

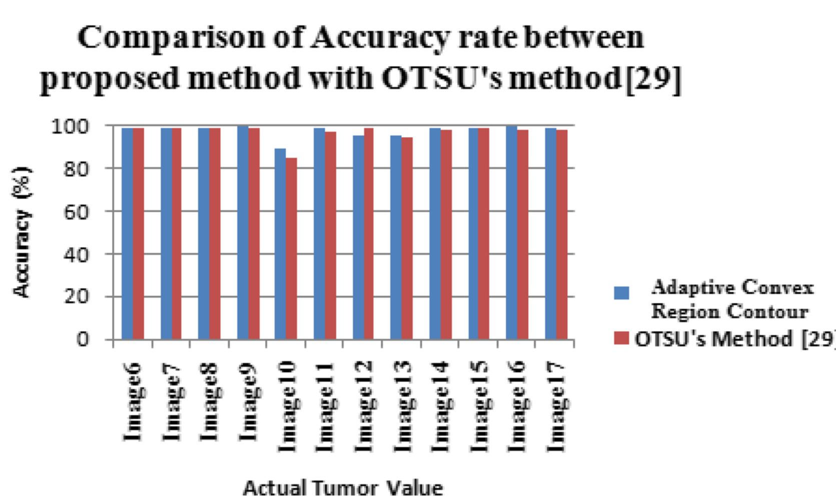

Fig. 11 Comparison of accuracy rate of proposed method (ACRC) with OTSU's method [23]

4.3.0. In this technique, the curve around the segmented area is identified initially which is known as main slice. The boundary of tumor is defined by using this initial curve in the main slice. The shape of tumor was varied from one patient's to another. Hence, it is possible to determine the shape of the tumor via tumor curve while slices are interconnected. This process will continue until all the input MRI images are interconnected by matching points. Then, tumor curve create an exact 3D shape of the tumor. The cubic interpolation function with 2D co-ordinates are given as

$$f(x,y) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} a_{i,j}\, x^i y^j \tag{22}$$

And

Similarly, Corresponding Cubic interpolation function with 3D co-ordinates is given in Eq. (22).

$$f(x,y,z) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\sum_{k=0}^{l-1} a_{i,j,k} x^i y^j z^k \tag{23}$$

The above function creates a spline curve by using calculated values from that function. This value contains information about matching points calculated by using RMIM method. The overall 3D reconstructed process is shown in Fig. 3. The MRI reconstructed image of MRI is showin in Fig. 3. Where initially 2D MRI results are collected and completed of approximated MRI image by RIMM and interpolation completed for next process and finally 3D RGB image reconstructed obtained by proposed approach.

Tumor volume estimation

The volume of the tumor is calculated after completion of 3D reconstruction modeling. Since brain tumor does not have definite shape, volume calculation of irregular object is a critical task. To overcome this limitations, a bounding cube has been utilized, which as a closed cube and contains irregular shape objects. The tumor volumes were calculated using three different shapes like ellipsoid, sphere and cylinder and formula for each is described with its length, height and width of the cube.

$$Elipsoid, V_E = \frac{4}{3}\pi\left(\frac{L}{2}.\frac{W}{2}.\frac{H}{2}\right) \tag{24}$$

$$Sphere, V_S = \frac{4}{3}\pi\left(\frac{W}{2}\right)^3 \tag{25}$$

And

$$Cylinder, V_C = \pi\left(\frac{W}{2}\right)^2 .L \tag{26}$$

Where W=Width, H=Height and L = Length.

Result analysis

The MRI slices were obtained from the dataset containing both normal and abnormal images which are taken from the website. The collected dataset of MRI slices is given in the Fig. 4.

After pre-processing and enhancement stage, MRI slices are classified into normal or abnormal slices by using SVM classifier. The following Figs. 5 and 6 shows output of SVM classifier.

It can be noted from the dataset that images from 6 to 17 contains tumor. Hence, these images are classified as abnormal images.

These abnormal images are taken into account for further processing. The tumors from these abnormal images are detected and segmented using ACRC algorithm. Figure 7 shows the output of detected tumor. Figure 8 shows the output of segmented tumor.

After completing segmentation process, through 3D reconstruction modeling tumor volume can be calculated. The proposed work taken 40 slices of real data set from patients, in which each tumor part has been converted from 2D format to 3D and volume calculation is also done. The 3D reconstructed tumor is represented in gray scale form and colored image is shown in Fig. 9 and Fig. 10 respectively.

Performance measures

The proposed methodology performance was evaluated in terms of Mean Square Error (MSE) and Peak Signal to Noise Ration (PSNR) is discussed below.

Mean Square Error (MSE)

In statistics it is defined as the measures of averages of squares of the errors or deviations. It is the difference between the estimator and what is estimated. The MSE is a measure of the quality of an estimator—it is always non-negative, and values closer to zero are better. It is represented as

$$MSE = \frac{1}{M \times N}\sum\sum\left(f(x,y) - f^R(x,y)\right)^2 \tag{27}$$

Peak Signal-to-Noise Ratio (PSNR)

It is computed to evaluate the eminence copy of advancement in an image which can be defines as follows

$$PSBR\ in\ dB = 20\ \log_{10}\frac{(2^n - 1)}{MSE} \tag{28}$$

For the small value of MSE, this results in higher value of PSNR. Therefore, it is further improvement in the signal to noise ratio of the image. Lesser rate of MSE and superior value of PSNR specify enhanced signal-to-noise ratio.

The comparison table of mean square error (MSE) and peak to signal noise ratio (PSNR) is given in the Table 1.

The extracted features results are compared with other existing scheme is given in the Table 2.

The comparison of determined tumor volumes are compared with existing method [22], actual tumor size with estimated value, percentage of error rate and accuracy is listed in Table 3.

The accuracy rate of proposed method is compared with OTSU's method [23] is illustrated in the Fig. 11.

Conclusion

In today's world, Image processing plays a vital role in variety of different application. The application of image processing can be useful in most of the areas such as electronics, medical and sensing field. Especially in medical application of diagnosing purposes the image segmentation process is widely used. We are collecting a set of forty one slices of brain tumor parts of the real patients. The main features of image is selected from the collected data. The process of Feature Extraction can be done by using GLCM algorithm. Thus results in it reduce the computational complexity. The performance of SVM can be improved by taking features of points, whereas traditional SVM requires sampling data of the whole. The SVM involves a different kernel functions that can be used to classify the MRI image as either Normal or Abnormal by using Adaptive Convex Region Contour (ACRC) algorithm. Next, the segmented tumor part is converted from 2D into 3D format by applying rapid mode image matching (RMIM) algorithm and cubic interpolation technique. Then volume of the tumor was estimated by using bounding cube. Through the simulation result, it is confirmed that proposed method achieved more efficiency than others.

Compliance with Ethical Standards

Conflict of Interest This paper has not communicated anywhere till this moment, now only it is communicated to your esteemed journal for the publication with the knowledge of all co-authors.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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