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Brain Tumor Detection and Segmentation by Intensity Adjustment

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Abstract

In recent years, Brain tumor detection and segmentation has created an interest on research areas. The process of identifying and segmenting brain tumor is a very tedious and time consuming task, since human physique has anatomical structure naturally. Magnetic Resonance Image (MRI) scan analysis is a powerful tool that makes effective detection of the abnormal tissues from the brain. Among different techniques, Magnetic Resonance Image (MRI) is a liable one which contains several modalities in scanning the images captured from interior structure of human brain. A novel hybrid energy-efficient method is proposed for automatic tumor detection and segmentation. The proposed system follows K-means clustering, integrated with Fuzzy C-Means (KMFCM) and active contour by level set for tumor segmentation. An effective segmentation, edge detection and intensity enhancement can detect brain tumor easily. For that, active contour with level set method has been utilized. The performance of the proposed approach has been evaluated in terms of white pixels, black pixels, tumor detected area, and the processing time. This technique can deal with a higher number of segmentation problem and minimum execution time by ensuring segmentation quality. Additionally, tumor area length in vertical and horizontal positions is determined to measure sensitivity, specificity, accuracy, and similarity index values. Further, tumor volume is computed. Knowledge of the information of tumor is helpful for the physicians for effective diagnosing in tumor for treatments. The entire experimentation was implemented in MATLAB environment and simulation results were compared with existing approaches.

Keywords MRI brain tumor · K-means clustering · Fuzzy C-means · Active contour by level set · Edge detection and intensity adjustment

Introduction

With increasing development in image processing technology, significance of medical field has made a great impact on many researchers. Currently, numerous methods such as Computed Tomography (CT), X-ray, Ultrasound (US) Positron Emission Tomography (PET) and Magnetic Resonance Image (MRI) are in use. Among them, MRI is the one frequently used in brain tumor diagnosis. The physicians plan for treatments by evaluating the current status of tumor depending upon the recorded value in diagnosing process. The proper treatment of tumor is based on tumor level and size while type and location are also most important. The determination of tumor as benign and non-benign is a critical one. The tumor may cause uncontrollable growth of abnormal tissues within the brain. The non-benign tumor must be removed carefully without affecting any normal tissues and possibly it may grow again. The non-benign tumors are often called as 'Malignant' tumors that affect the function of neighborhood cells in brain. It arises mainly owing to growth of abnormal tissues that have proliferated in an uncontrolled manner. Based on their behavioral properties, it can be classified to two categories namely, primary and secondary tumors. The primary tumors appear around the brain, nerve cells or glands, whereas the secondary tumors arise from other tissues in the brain. Sample of brain tumor is shown in Fig. 1.

Brain tumor is a group of abnormal tissues that spread within the brain. It does not depend upon human age and it

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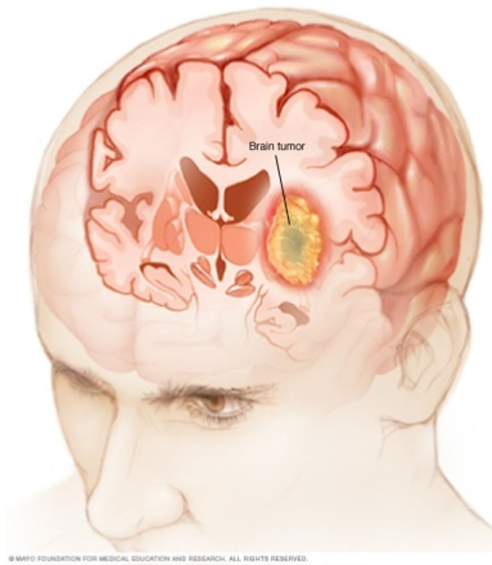


Fig. 1 Sample of brain tumor

occurs in any individual. This can be handled by many equipment techniques including radiotherapy or chemotherapy treatments. Additionally, the tumors are often classified as Benign or Malignant tumors. The key difference between them is that the benign tumors have homogeneous structure whereas malignant tumors have heterogeneous structure. Their individual properties also vary. Benign tumors are pulverized radio-logically / surgically and malignant tumors are dealt with chemotherapy/radiotherapy. For effective dealing of the brain tumor, MRI technique furnishes with vast information of brain such that every area of tumor can be detected easily. The physicians define the stages of brain tumor level in terms of grades as Grade I, II, III and IV. The main differences among the grades are described in detail in Table 1 as shown below.

In today's emerging world, digital image processing plays a pivotal role in many applications. Pre-processing is the primary stage for an image analysis employed to remove noise from an image. In addition, the unwanted noise and artifacts like patients name, age, address and other extra details are removed during this process. The image is resized and conversion of RGB to grayscale is performed. Due to thermal effect, there may be noise during MRI scanning, and it is necessary to eliminate this noise. The weighted median filter is used to remove noise without affecting image information, which provides high resolution result compared to other filters such as median, spatial and adaptive filters. Image enhancement process and Brightness Conserves Dynamic Histogram Equalization (BCDHE) technique are used to improve image qualities that are performed after completion of pre-processing. In the proposed work, a tracking algorithm is followed for pre-processing. The enhanced images are fed into KMFCM technique, in which a cluster numbers N, maximum iterations and termination parameter after completion of pre-processing and enhancement are set.

Next, feature extraction is executed which captures visual information of image in order to retrieve with index for further analysis. The image extracted results are analyzed under various statistical measurements and are used to take decision regarding pathology of tissues. However, texture features yield highly precision value, which is mainly applied in a real world image pattern recognition applications. Among many image extraction methods learnt, Adaptive Gray-Level Co-Occurrence Matrix (AGLCM) approach is identified as a statistical method to extract crucial image features and spatial relationship among the pixels. After extraction, an important feature is fed into SVM classifier. Then Support Vector Machine (SVM) with kernel classifier, which is necessary for classifying image as either normal or abnormal is built. Segmentation process is employed after detecting abnormal tumor.

Generally, image processing faces difficulty during segmentation of the particular region from whole image. Image segmentation is defined as the process of partitioning a whole image into several set of images in terms of multiple regions having similar properties. It includes image gray or intensity level, texture, color, contrast, coarseness and brightness. This process is helpful for easy image analysis under meaningful way. An effective segmentation process called active contour by level set is followed in the proposed approach. It can be used for effective image segmentation and boundary tracking. After that, segmentation part is improved by intensity adjustment which improves quality of image.

The remainder of research work is carried out as follows: The relevant papers of research work are briefly discussed in Section II. In Section III, necessity, importance and problem definition are reported. The required

Table 1 Grade levels of brain tumor

S.No	Grade Level	Tissues Status In The Body
1	I	Harmless Growing slowly
2	II	Venomous Act as a normal tissue
3	III	Appearance is varied Abnormal tissues grow highly
4	IV	Appeared as abnormal tissues Fast Growing

materials and methods of proposed work are illustrated in Section IV. A brief explanation of the proposed methodologies is illustrated in Section V. In Section VI, simulation results obtained from MATLAB environment are demonstrated. The conclusion is summarized in Section VII.

The comparison between Magnetic Resonance Image (MRI) and Computer Tomography (CT) is discussed below.

MRI versus Ct and X-ray

This section makes a comparative analysis among Magnetic Resonance Image (MRI), Computer Tomography (CT) and X-ray. X-ray is a type of radiation treatment, whereby the rays are passed through human body. By this process, it is easy to view dense objects like body bone but difficult to view light dense objects. However, it is very difficult to diagnose the bone degeneration, bone fractures and specific location of tumor. A Computer Tomography (CT), often called as CAT scan, is a sophisticated technique employed for producing high quality images. It takes 360 degree internal structure of organs such as brain, heart, etc. The approximated MRI images can be obtained by combining properties of CT and X-ray technologies to produce effective image while a cross sectional view of body part being scanned. Commonly, organs and tissues within the body have some magnetic properties. This technique comprises a hybrid powerful magnet in addition to radio waves. Automated computer system, which utilizes these features, makes exhaustive details of organ structure in the body. After that, MRI result outcomes are viewed as a cross section as “slices” to know which part is being scanned. The major advantage of MRI technique is its frequent diagnosing of the bone and joint problem. Therefore, the proposed research is carried out by using Magnetic Resonance Image (MRI) for analysis.

Related works

Aslam [1] et al had suggested an advanced edge detection algorithm called Sobel edge detection for tumor segmentation. Their proposed approach comprises sobel edge operator information with image dependent threshold method in several regions by using closed contour algorithm. The affected tissues (tumors) are extracted based on image intensity level within the closed contours. In the paper [2] et al had proposed a Computer aided system method which follows Multi thresholding dependent K-Means algorithm, to detect area and shape of the tumor. Lakra [3] et al revealed a comparative analysis of familiar segmentation technique from MRI images. Among them, they used Genetic algorithm with improved KSW entropy evaluation technique to attain a low error value. The Entropy value is selected by deriving a threshold and KMW Entropy value is modified upto two times to collect the maximum information. In addition, they use Fuzzy C [26] and K-means Algorithm for analyzing clustering of MRI data to segment many abnormal tissues automatically and simultaneously. The segmentation process is done based on threshold level and maximum value of threshold level depends on the amount of information collected from the object and image background.

Chadded [4] had proposed a novel method for automatic feature extraction in tumor MRI images [27] which use Gaussian mixture model (GMM) especially for Glioblastoma. The proposed model (GMM) has certain special features and contains both features of principle component analysis and wavelet features. Further, they added a new task to recognize the Glioblasma by T1, T2 weighted MRI images. Through the simulation applied in the proposed study, the obtained performance level is 92.73% and 97.05% respect to T1 and T2 images. While most of the proposed methods follow, after segmentation the tested images [28] undergo image classification of normal or abnormal. But, Devkota [5] et al had introduced a new innovative method, Computer aided detection approach, by using Mathematical morphological method, to recognize abnormal tissue which causes tumor in its prior stage. Further, the elimination of noise and other unwanted artifacts are done in image pre-processing. After that, image segmentation process will be executed via region of interest, and statistical image features are extracted.

Olenska [6] et al had investigated several diagnosing methods for detection of Neoplasm’s. The scanned MRI patient’s information details are correlated with descriptive variables to determine the incidence of neoplasm’s in specified brain region. Their proposed study demonstrated the number of people affected by neoplasm’s indicating gradual increase percentages. Praveen [7] et al had prescribed a hybrid based approach in classifying the brain tumor from MRI images. Raj [8] et al had introduced proposed system that categorizes status of brain tumor in multiple stages. In the first stage, the whole brain region is segmented from the human skull part while in other region input image is still present. Then, as a usual process like pre-processing, feature extraction and classification are performed. Their proposed segmentation process involved different algorithms such as Otsu’s method, K-Means clustering and Watershed segmentation, texture filter and few other segmentation approaches.

Sudharani [9] et al had revealed Morphological based automatic brain tumor detection and also separation of non-enhancing tumors from the healthy tumors in brain that can be done by performing localization process. This localization process easily predicts the position of affected tumor and provides full references for statistical analysis. In addition, a new mechanism is introduced to measure the area of affected tumor region. In morphological processing, a filter is used to remove low frequency component from the input MRI images. Traditionally, single scale framework network is followed to detect and segment the abnormal tissues from the brain. Zhao [10] et al proposed an automatic brain tumor segmentation system which is based on the Convolutional neural network (CNN) that considers both local features, input image and global region features. This system has three peculiar frameworks called Multi-scale CNN and high level three scale of image information are taken, and both are tested and trained. Moreover, pixel classification is done by estimating integrated information collecting from the proposed network.

Soltaninejad [11] et al had presented a fully automated system for detecting an abnormal tissue from the brain, which uses Fluid Attenuated Inversion Recovery MRI images. The proposed system is built by following a super-pixel technique that utilizes novel image features like intensity, Gabor, curvature and fractural analysis. Finally, the normal and abnormal brain tissues are classified by Support Vector Machine (SVM) and results are compared with existing extremely randomized tree based classifier. Bahadure [12] et al had implied a paper, in order to improve accuracy and decrease complexity during the medical image segmentation. To implement this, they proposed a Berkeley wavelet transform for tumor segmentation. After that SVM classifier is used to classify a segmented image while relevant features of corresponding images are extracted in each segmented tissue. Through simulation, the proposed system is has the capacity obtained to 94.2% of specificity, 97.72% of sensitivity and average of 0.82% dice similarity index coefficients value.

Varuna Shree [13] et al had concentrated on noise eliminating technique by which crucial image features can be extracted by using gray-level co-occurrence matrix (GLCM) features. Discrete Wavelet Transform (DWT) based brain tumor segmentation is applied to decrease complexity which improves performance. The proposed system follows the morphological filtering which can remove the unwanted noise precisely after segmentation. Finally, classifier is designed based on probabilistic neural network which is used to train and test MRI images accurately. Dhage [14] et al had suggested a watershed management based segmentation to differentiate the abnormal issue from healthy one from brain. And also proposed watershed management effectiveness is really helpful to know about exact location of tumor. The issue is segmented after detection. The connected component labeling algorithm will further improve the segmentation results in terms of tumor area, eccentricity, perimeter, entropy and other crucial values.

Cui [15] et al presented an automatic segmentation of Brain vivo Gliomas from MRI images which are constructed in Deep cascaded neural network. This network comprises two sub-networks namely tumor localization network and intra tumor classification network. Highly sensible results are obtained from this process. The main advantage of our proposed system is its capability to merge different regions of tumor images together whereas other methods are imbalanced due to this reason.

There are different kinds of efficient classification methods developed by well-known experts to eliminate unwanted tissues from brain. Kumar [16] et al had suggested a hybrid approach to classify MRI brain tumor images into either normal or abnormal. The Hybrid framework contains Discrete Wavelet Transformation technique to extract the image features. Genetic algorithm of principle component is applied to diminish the number of features used for analysis. Through their approach Root Mean Square (RMS) error rate is reduced. Sheikh Abdullah [17] et al had proposed an innovative classification technique which follows a potential Vector Quantization in order to segment affected part of normal tissues in brain. The proposed system is built on Euclidean distance mechanism to measure the distance between input and codebook vector that makes a highly accurate framework. The input images are collected from University Kebangsaan Malaysia Medical Center that sets UCI benchmark data to their research. In addition, they perform pre classification with Multi-randomizing data sets and this will increase the overall performance of the proposed classifier model.

Computer aided diagnostics are valuable and mainly applied in a medical image analysis. Roy [18] et al had presented a reliable automatic system for tumor segmentation, which also estimated the volume of detected tumor. Their proposed methodology mainly focused several phases of MRI image segmentation, area determination and especially for tumor volume calculation. 3D volumetric of segmented part from the 2D images is calculated with known value of each lesion. In the paper [19] et al had implemented a new image processing method for brain tumor detection. Their scheme uses thresholding algorithm and comparative study of brain tumor detection is also explained briefly. The image boundary extraction was done by sobel edge detection operator.

Swamy [20] et al had designed an intelligent system which is robust and follows an innovative algorithm in order to diminish the effect of denoising and blurring from image. In addition, their approach followed an effective filtering process which is a dynamic one to improve its performance efficiency. Further, we use hybrid self organizing MAP with Fuzzy C-Means algorithm which offers identification of tumor and best segmentation process inside the tissue of brain. Ilhan [21] et al had recommended a novel threshold based approach to segment the MRI brain tumor. Morphological operations are used to find the edge boundaries precisely and to eliminate skull part from the brain. This mechanism uses two common operators such as dilation and erosion; both are applied in binary and gray-scale images. Finally, the removed skull images are subtracted from the original input image.

In general, the previous Particle swarm optimization methods are trapped with local optimum points, but in certain applications they failed. To resolve this problem, Vijay [22] et al had suggested an improved version of Darwinian Particle Swarm Optimization method instead of traditional PSO algorithm. The proposed approach had taken image set of 101 brain MRI images comprising 87 MRI images with abnormal tissue and 14 MRI images without abnormal tissue. Harmony searching algorithm is one of the well-known optimization algorithms, which is recently applied in certain practical applications. This algorithm continuously revises the harmonic variables in given database. Yang [23] et al had recommended an improved version of harmonic algorithm which uses fuzzy clustering method in order to select premature optimum value for segmentation of MRI images. The proposed approach is highly accurate than the existing harmony searching algorithm.

Problem statement and definition

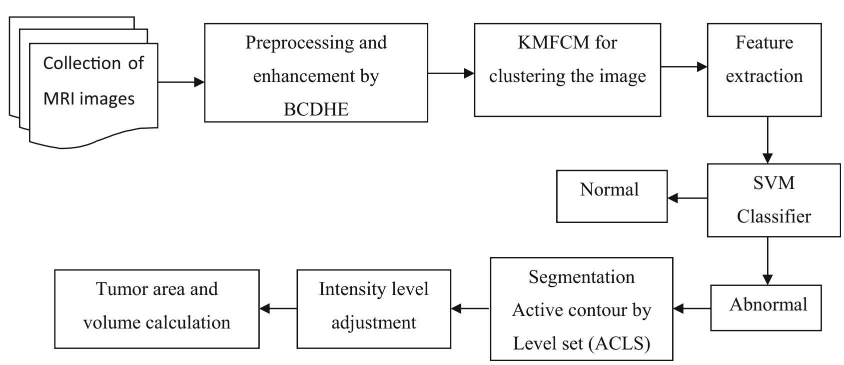
For the past two decades, growth of brain tumor has increased in an uncontrolled manner in different parts of human body, especially in brain. Generally, brain has a complicated framework of body, which is tightly connected within the skull. Hence, it is very difficult to diagnose the vulnerable diseases. In order to mitigate this issue, the proposed work introduces a hybrid energy efficient segmentation system and the process is done by adjusting intensity level of input image. On comparing to other various imaging techniques, MRI has been considered as preferable, since it furnishes versatile contrast of tissues and is a non-invasive process. Conventionally, neurologist segments the brain tumor that is performed manually by marking brain tumor region slice by slice. However, it is a time consuming, impossible and non-reproducible process.

Several tumor segmentation algorithms and techniques have been designed in order to differentiate abnormal brain tumor region from normal tissues. Among them, the proposed hybrid system utilizes Active Contour by level set (ACLS) algorithm for an effective segmentation of tumor region. After segmentation, a novel approach is used to estimate the volume of tumor. Next section describes essential materials, the places from which the sources were collected and the methods needed are described.

Materials and methods

This section presents required material and techniques, and the sources of MRI image dataset, which were collected from ANBU hospitals in Madurai. Totally, as an input data, sample of 40 slices, which are real data of patients, were collected and were utilized for the proposed hybrid segmentation system. Based on the symmetrical property, an MRI image has been identified as

Fig. 2 Block diagram of proposed hybrid energy efficient segmentation system (KMFCM)



either normal or abnormal one. This property will decide the image, either normal or abnormal. In pre-processing, input image was resized to 256 × 256 pixel sizes and noise was filtered out by applying weighted median filter. Image enhancement was done by Brightness Conserves Dynamic Histogram [29] Equalization (BCDHE) to improve the image quality. In the Feature Extraction, an Adaptive GLCM method was used to extract crucial features. The hybrid system follows Support Vector Machine (SVM) with kernel function in classifying normal or abnormal image. After classification, the abnormal image was involved in segmentation process. For efficient segmentation of tumor part, Active Contour by level set (ACLS) design was used. Finally, with the completion of segmentation process, volume of tumor can be estimated.

Proposed methodologies

The proposed methodology was carried out in the following stages; each contains detailed information of entire process. The following seven phases of the methodology are Collection of MRI images, Pre-processing and Enhancement, Feature extraction, SVM classification and ACCLS based image segmentation. The above phases were executed by following performance effective algorithms. Figure 2 shows the entire process of proposed implementation.

(i) Collection of MRI images

The required MRI images datasets were collected from ANBU Hospitals in Madurai. This research deals with analysis of real world dataset from the patients. Totally 41 MRI slices of patients' images were undertaken, which comprised both normal and abnormal tissues. Among them, abnormal images were discovered to segment and then approximated volume level of tumor [30] was estimated.

Pre-processing The raw MRI input image was first subjected to pre-processing stage which can be utilized for further processes. During pre-processing, the input images were resized to 256 × 256 pixel resolution without losing any image information. The main task of this phase is eliminating unwanted noise in image and also eliminating the patient's artifacts like name, age, sex, date, residential address and other contact details. Next, the RGB color image was converted to gray level, that are represented in quantized bit level as 256 (0–255). It is helpful for increasing visualization of image quality and obtaining optimum signal to noise ratio. After completion of pre-processing phase, image enhancement process was executed.

(ii) Image Enhancement

Numerous image enhancement techniques have been developed in order to enhance the image quality. Histogram equalization (HE) is one of the familiar global methods to make benefitted image. It is the technique of distributing intensity level over the entire range of histogram in the image. The proposed hybrid segmentation system utilizes Brightness Conserves Dynamic Histogram Equalization (BCDHE) with weighted median filter to improve image quality for next phases. The 1D weighted median filters derived are as follows:

Consider the following function,

$$F(\theta) = \sum_{r=0}^{N-1} ar|\theta - xs + r| \tag{1}$$

Where

r image pixel.
N Total pixel size.
a_r It is a weight assigned to each pixel value.

Weighted median filter is estimated by

$$zs = F\left(arg\ min_\theta \ \ \sum_{r=0}^{N-1} ar|\theta - xs + r|\right) \tag{2}$$

Differentiating the Eq. (1), we have

$$\frac{d}{d\theta} F(\theta) = \frac{d}{d\theta} \sum_{r=0}^{N-1} ar|\theta - xs + r| \tag{3}$$

$$= \sum_{r=0}^{N-1} ar(|\theta - xs + r|) \tag{4}$$

$$\frac{d}{d\theta} F(\theta) \triangleq f(\theta) \tag{5}$$

Let 1D weighted median filter as in Eq. (6)

$$F(\theta) = \sum_{k=0}^{N-1} \mathrm{a}(k)|\theta - xs + r| \tag{6}$$

Where k is pixel updating value.

Therefore 1D equation of weighted median filter is derived from combining Eq. (4) and Eq. (6) as

$$\boldsymbol{f(\theta) = \sum_{k=0}^{N-1} a(k)(|\theta - xs + r|)} \tag{7}$$

The above Eq. (7) shows the 1Dimensional weighted median filter. General steps of image enhancement using BCDHE with 1D form of weighted median filter are given below.

Algorithm: Image enhancement by BCDHE with weighted median filter

Step 1: The proposed BCDHE algorithm is uniformly leveled by using 1D weighted median filter.

Step 2: The whole histogram process is divided into sub-histogram that is operated by Equation (8) **as** given in step 3.

Step 3: Assign each sub-divided histogram by following dynamic equation as

$$\boldsymbol{fi = width_i \ X \ log10 \ N} \text{----------------} \ \mathbf{(8)}$$

where, $width_i$ is total width of an image.
N is total number of pixels in an image.

Step 4: Then, equalize all sub-divided histograms separately.

Step 5: Finally, by following Equation (9) the images are reconstructed. Equation (9) is stated as

$$\boldsymbol{g(x,y) = \left(\frac{Ni}{No}\right) f(x,y)} \text{----------------} \ \mathbf{(9)}$$

where Ni denotes average brightness of input image,

$\mathbf{N_o}$ denotes average brightness of output image and

f (x,y) is the original input image.

The above enhancement technique normalizes intensity level of output image by keeping the average intensity value nearer to average intensity level of input image. This will help in proposed hybrid system.

(iii) Clustering formation by KMFCM

The enhanced images are fed into KMFCM technique by setting cluster numbers N, maximum iterations and termination parameters. The cluster centers (C_{center}) are calculated by using Eq. (10).

$$C_{center} = \frac{\{1, N\}m}{\{N+1\}} \tag{10}$$

Where, C_{center} is the initial condition for calculating out of each cluster. And m is defined as.

$$m = max\{MRI\ image\} + 1 \tag{11}$$

Figure 3 describes the clustering formation using KMFCM algorithm.

The initial centers of clusters are not selected randomly, thus conditional looping reduces less number of iterations, which becomes better than random selection. The clustered points were re-clustered out of membership values. The clustering formation uses both hard and soft technique; hard thresholding puts only each point belonging to the nearest cluster whereas soft clustering provides each point based on degree of membership value.

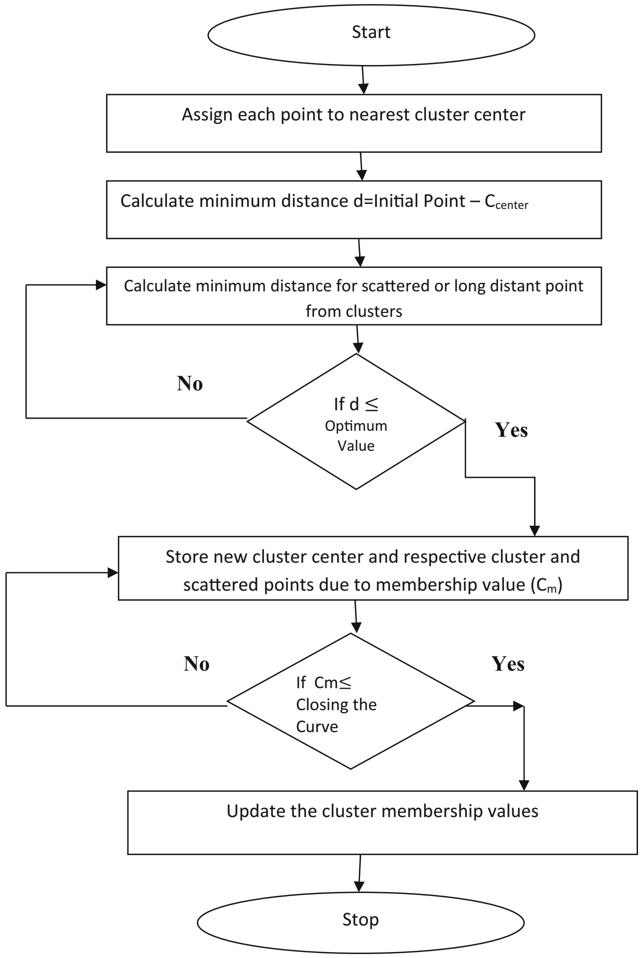


Fig. 3 Clustering formation using KMFCM algorithm

Then each clustered image features is extracted by applying AGLCM method.

(iv) Feature Extraction

Feature extraction is defined as the method of extracting quantitative information which is collected from an input image. The feature includes image color, texture, shape and contrast. The proposed system follows adaptive gray level co-occurrence matrix (AGLCM) for statistical analysis. In histogram technique, image intensity or region describes texture characteristics. The co-occurrence matrix is a superior statistical method that furnishes valuable information about exact location of neighborhood pixels. The following statistical features are extracted from the given original input images:

(i) Mean or Average (M)

The average/ mean value of an image is estimated as ratio sum of adding individual pixels and total number of pixels in an image.

$$\boldsymbol{M} = \left(\frac{\mathbf{1}}{\boldsymbol{m\ x\ n}}\right)\sum_{x=1}^{m}\sum_{y=1}^{n}\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) \tag{12}$$

(ii) Standard deviation (SD)

It is defined as the second central moment which describes probability distribution of observed population and it is a measure of homogeneity characteristics of an image. A high value represents better intensity level whereas low value indicates small intensity level.

$$\boldsymbol{SD} = \sqrt{\left(\frac{1}{m\ x\ n}\right)\sum_{x=1}^{m}\sum_{y=1}^{n}(\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})-\boldsymbol{N})\mathbf{2}} \tag{13}$$

(iii) Entropy (E)

The Entropy (E) value of an image is calculated as randomness of textural characteristics, as given below:

$$\boldsymbol{E} = -\sum_{x=1}^{m}\sum_{y=1}^{n}\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})\boldsymbol{log2}\ (\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})) \tag{14}$$

(iv) Skewness (S_k)

It is a measure of symmetry property of an image. Let random variable is considered as X then, skewness S_k (X) is calculated as.

$$\boldsymbol{Sk}(\boldsymbol{X}) = \left(\frac{\mathbf{1}}{\boldsymbol{m\ x\ n}}\right)\frac{\sum(\boldsymbol{x},\boldsymbol{y})-\boldsymbol{N}\big)\mathbf{3}}{\boldsymbol{SD}\mathbf{4}} \tag{15}$$

(v) Kurtosis (K)

This parameter is used to describe shape characteristics of an image in a probabilistic manner. The kurtosis is defined with random variable X which is given by.

$$\boldsymbol{K}(\boldsymbol{X}) = \left(\frac{\mathbf{1}}{\boldsymbol{m\ x\ n}}\right)\frac{\sum(\boldsymbol{x},\boldsymbol{y})-\boldsymbol{N}\big)\mathbf{4}}{\boldsymbol{SD}\mathbf{4}} \tag{16}$$

(vi) Energy (EN)

Energy is defined as the number of pair pixels which are repeated in a quantifiable manner. It is often called as angular second moment which measures image similarity and stated as,

$$\boldsymbol{EN} == \sqrt{\sum_{x=1}^{m}\sum_{y=1}^{n}\boldsymbol{f}\mathbf{2}(\boldsymbol{x},\boldsymbol{y})} \tag{17}$$

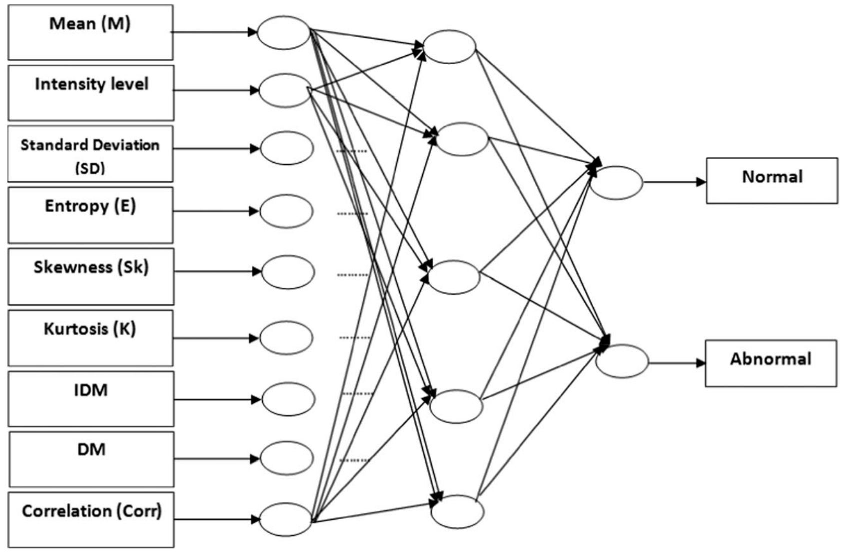


Fig. 4 SVM classifier

(vii) Contrast(Con)

It is used to measure intensity level of both pixels and neighborhood pixels and it is given as,

$$Con = \sum_{x=1}^{m}(x-y)2f(x,y) \tag{18}$$

(viii) Inverse Directional Moment (IDM)

It is also called as homogeneity. It is a measure of local homogeneity property of an image. It may have either single or range of values so as to determine whether image is textured or not.

$$IDM = \sum_{x=1}^{m}\sum_{y=1}^{n}\frac{1}{1+(x-y)2}f(x,y) \tag{19}$$

(ix) Directional Moment (DM)

It is a texture property of an image by measuring alignment of an image in terms of angle and it is given by.

$$DM = \sum_{x=1}^{m}\sum_{y=1}^{n}f(x,y)|x-y| \tag{20}$$

(x) Correlation (Corr)

It describes the spatial feature of dependencies among pixels and neighborhood pixels and it is given by.

$$\frac{Corr = \sum_{x=1}^{m}(x-y)f(x,y)-NxNy}{\sigma x\sigma y} \tag{21}$$

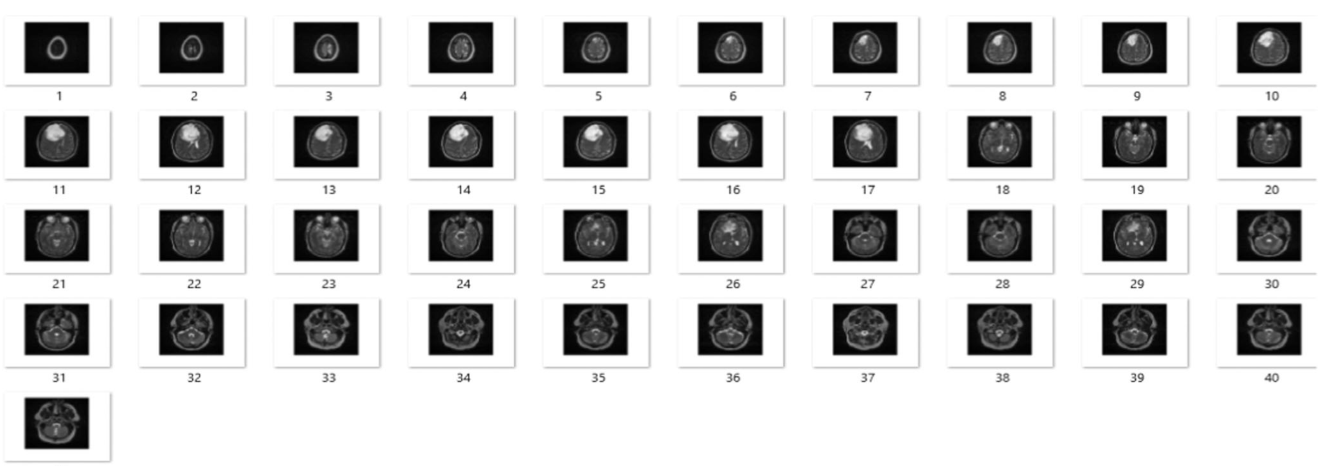


Fig. 5 MRI images dataset

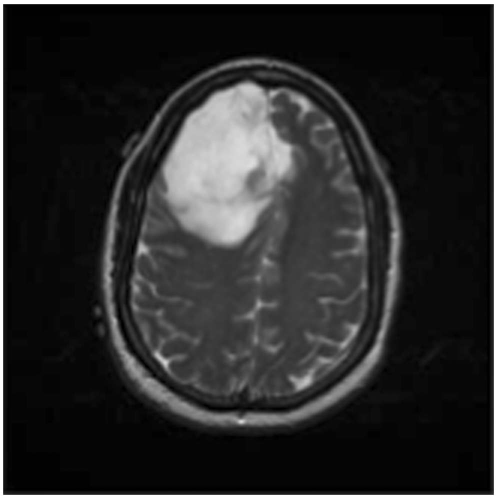


Fig. 6 Abnormal image

After Extraction of important features from an input image, SVM classification is performed. The extracted image features are fed to the Support Vector Machine (SVM).

(v) Classification

In this phase, an efficient classifier called Support Vector Machine (SVM) with linear kernel is the most accurate utilized to categorize whether the image is normal or abnormal. Several classification methods are designed for an effective brain tumor classification like Support Vector Machines with linear kernel, auto-scale, GRB and box constrained. The proposed methodology follows Support Vector Machine (SVM) with linear kernel to classify an image. SVM with linear kernel is one of the supervised techniques which are widely used for classification purposes. SVM requires the input of crucial extracted features of an input image, after feature extraction. Figure 4 shows the block functional diagram of Support Vector Machine (SVM) classifier.

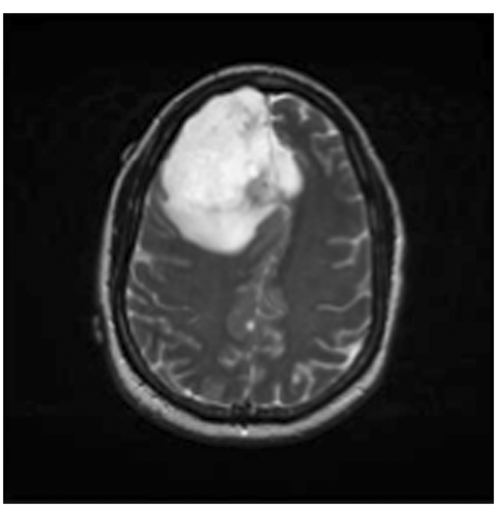


Fig. 7 Pre-processed and enhanced image

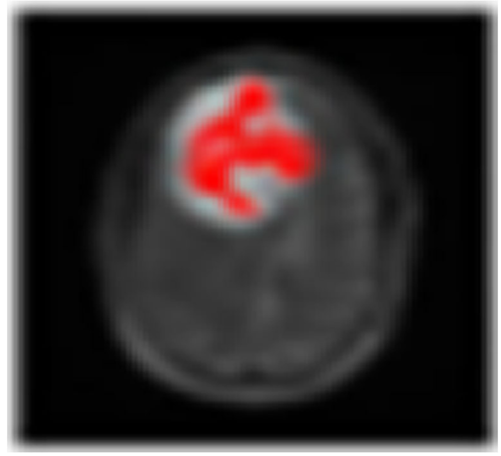


Fig. 8 Detected tumor

(vi) Active contour by level set (ACLS)

The proposed active contour method was used for image segmentation and boundary tracking. The boundary shapes were represented as a closed curve called contours and were modified iteratively by performing shrink/expansion operation, based on constraints. The proposed active contour with level set method has robust segmentation capabilities compared to traditional method. The traditional edge detectors based on threshold or local filtering result in discontinuous boundaries. The main advantage of active contour technique is partitioning the whole image into sub-regions with continuous boundaries. There are various image properties used by active contour for segmentation like image edges, statistics and texture. Thresholding or binarization process is intensity based segmentation, which is used to extract the desired object from an image background. It has small storage space, fast processing and ease of manipulation. After thresholding, the

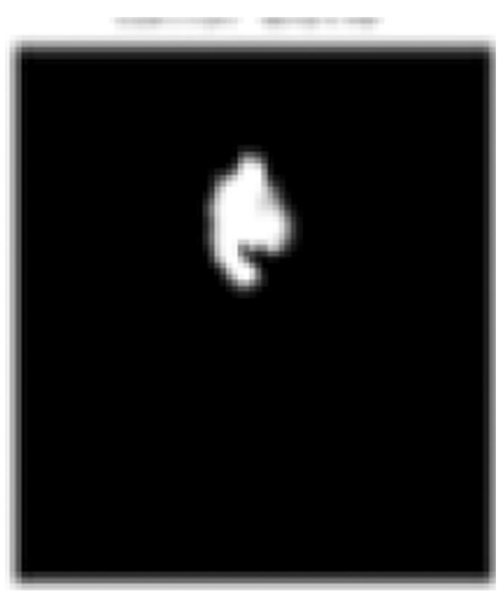


Fig. 9 Segmented tumor

Table 2 Comparison of tumor volume rate analysis of proposed method with existing [24]

Abnormal Images	Estimated Value (EV)	Actual tumor value (AV)	Difference=AV-EV	Error (%)	Accuracy rate (%) (Proposed)	OTSU's Method [24]	Watershed method [25]
Image6	23,958 mm^3	23,638 mm^3	320 mm^3	1.3	98.9	98.7	98.3
Image7	14,796 mm^3	14,586 mm^3	210 mm^3	1.44	98.99	98.66	98.4
Image8	24,299 mm^3	24,001 mm^3	298 mm^3	1.24	99.1	98.76	98.56
Image9	13,524 mm^3	13,361 mm^3	163 mm^3	1.22	99.7	99	99.2
Image10	33,314 mm^3	32,987 mm^3	327 mm^3	1	89	85	81
Image11	621 mm^3	540 mm^3	81 mm^3	15	98.5	97.5	97.2
Image12	7998 mm^3	7811 mm^3	187 mm^3	2.5	95.8	98.83	98.92
Image13	14,824 mm^3	14,652 mm^3	172 mm^3	1.17	95.6	94.2	93.4
Image14	1373 mm^3	1298 mm^3	75 mm^3	5.8	99.2	98.3	97.9
Image15	6792 mm^3	6677 mm^3	115 mm^3	1.7	99.3	98.8	98.5
Image16	21,177 mm^3	20,923 mm^3	254 mm^3	1.2	99.43	98.38	98.12
Image17	7202 mm^3	7084 mm^3	118 mm^3	1.62	99.25	98.18	97.92

lighting tumor cluster was fed into the level set approach. The level set contours the tumor area of thresholding image on original MRI image. Hence, original noise free image with contouring tumor area has been obtained. Then, tumor area can be calculated by measuring number of white pixels from total number of pixels in an image.

$$\textbf{Tumor area, A} = \frac{\textbf{Number of White pixels}}{\textbf{Total Number of pixels}}$$

(vii) Intensity level adjustment

The proposed work utilizes novel intensity adjustment for MRI tumor segmentation. It is one of the image enhancement techniques that maps intensity values of an image to a new range. Through this method low contrast image has was modified to high contrast image. This can be done by removing and subtracting the image portion which is not needed. Thus, processing speed increases and required time reduces for overall processing.

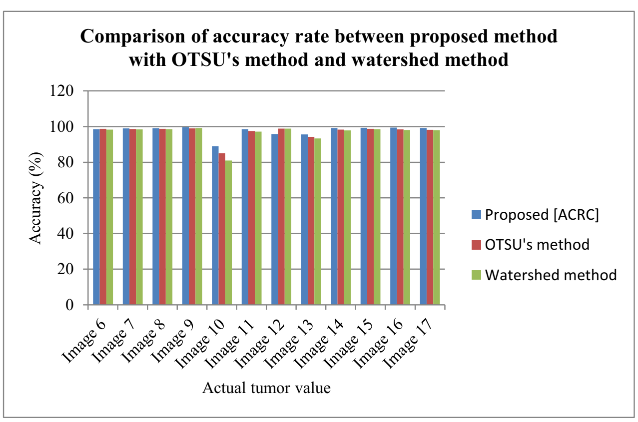


Fig. 10 Comparison of volume accuracy rate of the proposed approach with the existing method [24]

(viii) Volume estimation

The proposed work follows a new approach for volume calculation called manual land marking that has higher performance than others. In manual land marking, mouse can be utilized to select an affected part of tumor area continuously. The mouse can start an operation starting point of area to the end without loss of pixels information. The estimated amount of pixels is represented in xy-coordinates for measurement. The number of pixels in a dragged area is same as tumor volume.

Simulation results

Datasets

The performance of the proposed approach utilizes a set of MRI datasets, collected from patients in ANBU hospital Madurai. The collected MRI datasets were taken for consideration as shown in Fig. 5. This MRI dataset contains both male and female sliced image as well as it both low and high contrast image. The entire proposed work was implemented in MATLAB simulation environment. The collected MRI images were clustered by using KMFCM algorithm.

From the dataset, MRI slices 6 to 17 were detected as abnormal images which were classified from SVM classifier. Let consider a single MRI slices (Abnormal) for full process from the total input images. It is shown in Fig. 6.

After image pre-processing and enhancement the above image is represented as below (Fig. 7).

After classifying the image by support vector machine (SVM), detected tumor is shown in Fig. 8.

Then, detected tumor can be segmented by using Active contour by level set (ACLS) as illustrated in Fig. 9.

After segmentation process, volume of the tumor can be calculated and compared with existing method [24] as described in the Table 2.

Figure 10 illustrates the comparison between the proposed and the existing method:

Conclusion

Image segmentation executes a most important role in medical imaging field. Among various imaging techniques MRI is an effective image model for examination of tumor. Also, MRI scan is better than CT scan for tumor diagnosis. Fuzzy C-means algorithm is faster than K-means algorithm in effective tumor detection. Hence, in this research work K-means clustering integrated with Fuzzy C-means (KMFCM) is used. The proposed approach consists of several stages as explained in the above sections. From the experimental result it is confirmed that the proposed approach has better segmentation compared to other approaches. The main advantage of the proposed method is reduction in the execution time strategy thereby improving the quality of experimentation. In addition, intensity adjustment process will improve segmentation accuracy.

Compliance with Ethical Standards

Disclosure of Potential Conflicts of Interest No conflicts of interest: Author 1 & 2 declares that they have no conflict of interest.

Research Involving Human Participants and/or Animals All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2008″.

Informed Consent Informed consent was obtained from all patients for being included in the study.

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