DOI : https://doi.org/10.56452/6-3-68501
ISSN: 0974-5823 Vol. 6 No. 03 (December, 2021)
International Journal of Mechanical Engineering

Detection and Recognition of Human Brain Tumor based on Automated medical image segmentation techniques

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Abstract: Medical Science in Image processing the brain is central controlling system in human body. Tumor is a Pre-stage of cancer which become a serious problem. Magnetic Resonance Imaging (MRI) scans are widely used to diagnose the brain tumors which provides better accuracy than other Medical Images. In recent years more challenging task to identify the structure, shape and texture of the brain tumor. Hence, this paper proposes various proposed methods used to extract tumor portion, normal images and texture feature extraction from the brain using MRI images. This technique involves different image processing methodologies such as noise removal is performed as the preprocessing step on the brain MRI image. Applying Anisotropic Filter eliminates noise content from MRI and preserves the edges of existing objects and preserving the good visual quality. Next, one of the Artificial Neural Network of Ensemble based classification is used for classifying the images into normal and tumorous brain images. After classification proposed system extracts tumor region from tumorous images using various segmentation techniques. In this paper five widely used standard image segmentation methods (Otsu's, Threshold based Segmentation, K-Means, Fuzzy C_Means and Watershed segmentation) has been tested using MRI dataset to isolate the Tumor region from the rest of the brain MRI and their performance was compared baes on the Segmentation output. K_means showed a better result than four other segmentation methods. Next apply, Morphological extraction. It is performed to sharpen the Tumor Region and separating the affected area from the MRI. Finally, the proposed system to show the Normal and Brain Tumor Portion accurately. This paper tested against the MRI dataset of different patients. The accuracy of this application for tumor detection on brain MRI images and features calculation is much high. More features can be extracted, and the accuracy can be maximized in these proposed methods, which later could be highly helpful for the medical practitioners working in this field. This paper performs efficiently with high PSNR value compare than the existing algorithms.

Key words: *Brain Tumor, Anisotropic Diffusion Filter, Ensemble classification, Segmentation, Morphological Extraction, Texture Feature Extraction.*

Introduction

A brain tumor is a mass or growth of abnormal cells in your brain. Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). Brain tumors can begin in your brain (primary brain tumors), or cancer can begin in other parts of your body and spread to your brain as secondary (metastatic) brain tumors. How quickly a brain tumor grows can vary greatly. The growth rate as well as the location of a brain tumor determines how it will affect the function of your nervous system. Brain tumor treatment options depend on the type of brain tumor you have, as well as its size and location. Tumors can be located at any region of the body. That is tumor can be located in the Brain, Lungs and Breast. Each of these tumors can be segmented based on the region present in the body. For example, tumors in the breast are formed dur to calcium deposits in the breast tissues.

Symptoms of the brain tumor includes New onset or change in pattern of headaches, Headaches that gradually become more frequent and more severe, Unexplained nausea or vomiting, Vision problems, such as blurred vision, double vision or loss of peripheral vision, Gradual loss of sensation or movement in an arm or a leg, Difficulty with balance, Speech difficulties, Feeling very tired, Confusion in everyday matter, Difficulty making decisions, Inability to follow simple commands, Personality or behavior changes, Seizures, especially in someone who doesn't have a history of seizures, Hearing problems.

More than 79,000 new cases of primary brain tumors will be diagnosed this year and also More than of 4,800 children between the ages of 0-19 will be diagnosed with a brain tumor. Brain and central nervous system tumors are the most common cancers among children 0 – 14. Nearly 700,000 people in the U.S. are living with a primary brain or central nervous system tumor. This year, nearly 17,000 people will lose their battle with a brain tumor. More than 100 types of brain tumors exist. A collection of abnormal cells that grows in the brain or central spine canal. One abnormal cell becomes two, two becomes four, four becomes eight, until there is a lump of abnormal cells. Other name for the tumor is Neoplasm, Lesion, Space occupying Mass.

The Main exciting task is to locate and extract the exact tumor region from the image. Due to numerous lighting issues, unnecessary white portions were present in the image which could wrongly be segmented as a Tumor. The unwanted noise and reduced displays several regions from the image that are falsely claimed as a Tumor. Another challenge faced was degraded quality of the MRI image due to several problems that would have occurred during the acquisition stage. Also, extracting texture features also another challenging task.

There are various medical imaging technologies to detect the presence of tumor portion in the brain. Some of them include Ultrasound, CT -Computed Tomography, MRI-Magnetic Resonance Imaging, PET-Positron Emission Tomography and X-Ray.

Brain Tumor extraction and its analysis are challenging task in medical image processing because brain image is complicated. In that MRI has become a useful medical diagnostic tool for the diagnosis of brain and other medical images. The brain is the most important of central nervous system. The main task of the Doctors is to detect the Brain Tumor which is a time consuming for which they heel burden. Brain is an intracranial solid neoplasm. The only optimal solution for this problem is use of this proposed algorithms.

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Paper Organization

This paper is organized as follows; Introduction about the Brain tumor is briefly explained in section 1, Literature review and related work is represented in section 2, details of the proposed methods are described in section 3, Experimental results and discussions in section 4, Conclusion is presented in section 5.

Literature Review

The researches have been proposed by researchers for the MRI brain image segmentation and tumor detection techniques a brief review of some of the recent researches is presented below.

Inan Gule er al [8] have presented image segmentation system automatically segment and label brain MRI to show normal and affected brain tissues using self-organizing map and knowledge based expert systems. The feature vector is used as an input to the self-organizing map. Self-organizing pap is used to over segment images and a knowledge bases expert system is used to join and label the segments

Xu and Song proposed a feature extraction method which is based on a linear separability criterion. This method is based on the Fisher discriminant analysis. This method extracts features from data with a normal or complex distribution. Another feature extraction and selection method is proposed by Mun et al. [5] which is based on enhanced stochastic learning

For MRI brain image segmentation Saha and Bandyopadhyay [17] proposed a technique which is based on fuzzy symmetry based genetic clustering method. In this technique fuzzy variable string length genetic point symmetry is used for clustering and then it is used for segmentation. Instead of Euclidean distance, point symmetry-based distance is used for membership. The aim here is to determine the optimum fuzzy partitioning of the MR image. Maximum value of Fuzzy-index best partitions the data. Genetic algo is used for evolving the number of clusters and evolving appropriate fuzzy clustering of the data. For measuring quality y of cluster fuzzy point symmetry-based cluster validity index is pro-posed in this paper. Experiments are performed on different T1, T2and PD brain images. This technique performs better then FCM and Expectation Maximization algorithm. But this technique does not consider spatial information and sometime does not segment brain image correctly. This technique also does not work properly for the data sets which have same point as a center for different clusters.

Zhang et al. [17] proposed a Hidden Markov Random Field Model and the Expectation-Maximization algorithm for segmentation of brain MR images. This is a fully automatic technique for brain MR images segmentation. This method is based on estimation of threshold that is heuristic in nature. Thus most of the time, this method does not produce accurate results. Method in [27] is also computationally very expensive.

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Proposed Methodology

These proposed methods involved applying preprocessing techniques, the ADF filter to remove the noise, to classify the tumor images by using Artificial Neural Network based Ensemble classification, apply five different Segmentation methods and Morphological operations are then applied to extract the Tumor Regions. Calculate the performance measures. The proposed method flow chart shown in figure 1.

Algorithms:

STEP 1: Read the MRI Brain Images from the dataset.

STEP 2: Apply ADF filter to remove noise from the original image.

STEP 3: Apply Artificial neural network technique like Ensemble based classification to classify the Normal and Tumorous image.

STEP 4: To extract the tumor portion by Applying Five Segmentation Otsu's, Threshold Based Segmentation**,** Fuzzy C_Means, K_means, Watershed Segmentation, the K-Means is the prominent one compare than other four segmentation

STEP 5: Apply Morphological extraction to sharpen the Tumor Region and separating the affected area from the MRI

STEP 6: Calculate various Textural feature extraction they are Contrast, Dissimilarity measures, Energy, Entropy, Homogeneity, STD, MSE, PSNR, Number of iterations, Maximum Probability, SNR, Inverse Difference moment normalized.

STEP 7: Display the output of filtered image, Otsu's segmentation, Fuzzy C-Means, Adaptive K_means, Watershed, K_means, bounding box, tumor alone the output images are shown in figure 3,4,5.

STEP 8: The Table 1 shows the performance measures

ADF Filtering For Noise Removal

The key purpose of preprocessing is to remove the noises from the MRI image and make it more useful for the rest stages of the whole process. Different kind of filters like Average Filter, Median Filter, Mean Filter, Winer Filter High pass filter have been applied in this regard. Among them the Anisotropic filter showed the better performance than others, and these are used for the rest of the processing steps. ADF is a non-linear filtering technique to eliminate in flat regions to great extent while preserving edges by lowering the diffusion at images edges [8]. ADF techniques is advantageous in terms of noise reduction and edge preservation, and holds better place in terms of computationally efficient filters. So, it is adopting for brain MR images.

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The ADF is used to restore MR image intensities. ADF is able of process the image while conserving the main edges of existing objects. In mathematical form, ADF can be represented by the below Eq (1)

$$\frac{\partial x}{\partial t} = div(c(m,n,t)\nabla I) = \nabla c.\nabla x + c(m,n,t)\nabla x \qquad (1)$$

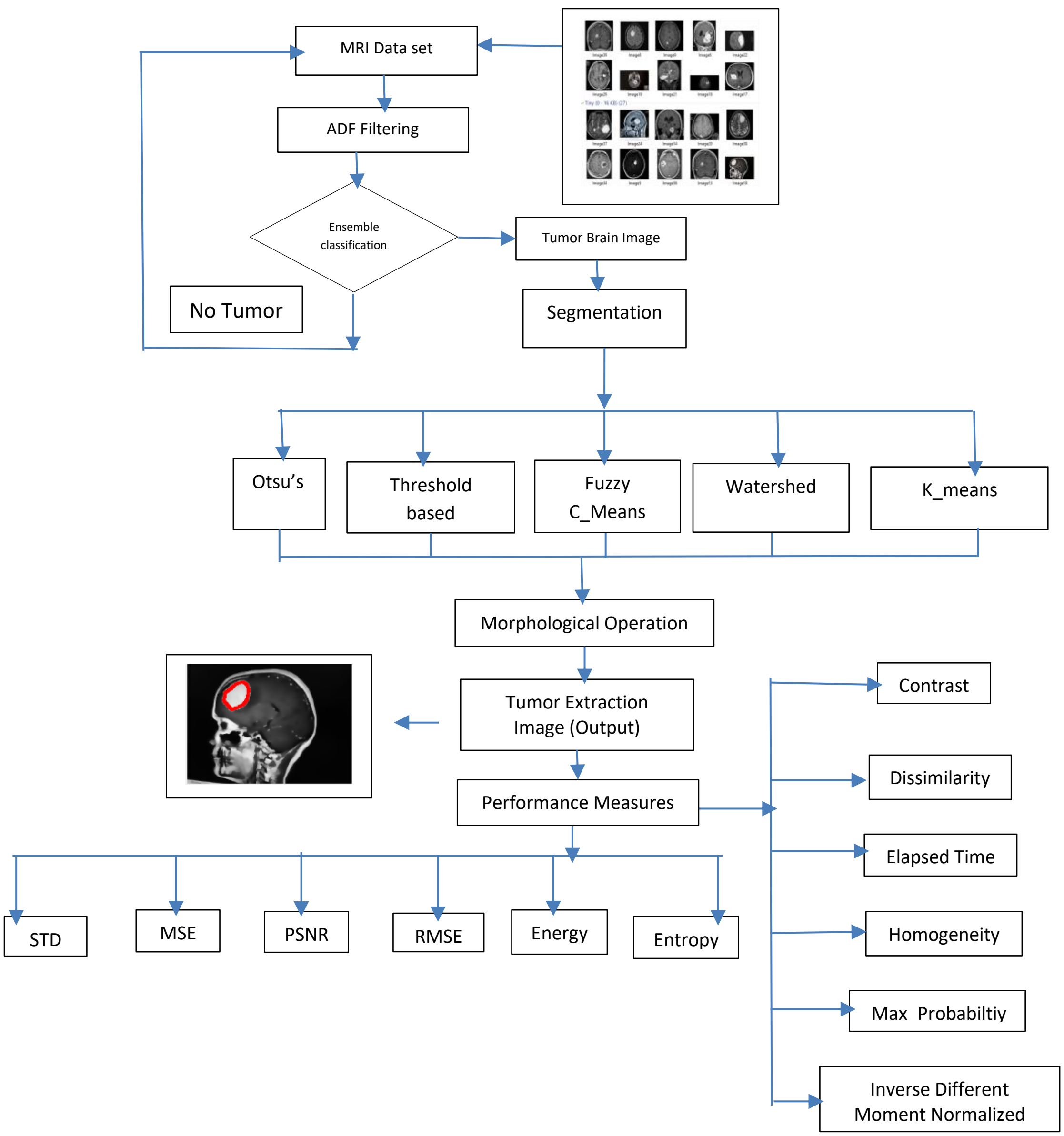

Figure 1. Proposed method Flow chart for detecting the Brain Tumor using MRI images

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Where, ∇x denotes image gradiant and $c(m,n,t)$ denotes the diffusion coefficient. The following notation shows a discretized approximation by the forward and backward differences.

$$I_{i,j}^{t+1} = I_{i,j}^{t+1} + dt \sum_{(k,l)\in N_4} g\left(I_{k,I-}^{t} I_{i,j}^{t}\right).\left(I_{k,I-}^{t} I_{i,j}^{t}\right) \quad (2)$$

$$h(I_{k,I-}^{t} I_{i,j}^{t}) = \frac{c_{k,I}^{t} + c_{i,j}^{t}}{2} \quad (3)$$

where, $N_{4=}\{(i-I,j),(i+I,j),(i,j-I),(i,j+I)\}$ denotes the 4-neighbourhood of the central pixel $I_{i,j}^{t}$. From Eq (3). The noise pixel has strong diffusion action and signal pixel has weak diffusion action. Thus, noise can be removed and signal will be kept. There are many diffusion models to adopt the constant step size for each iteration or whole iterative process of the image. Here a better iteration step is proposed in the Eq (4).

$$dt = \frac{1}{4}c \quad (4)$$

Where, ¼ is used to promise the convergence of the Eq (2). Final output phase image is obtained by iterative process. For iteration process, iteration error (IE) is used for controlling the iterative number and its formula is in Eq (5).

$$IE = \frac{\| I^{n} - I^{n-1} \|}{\| I^{n} \|} \leq T_{ie} \quad (5)$$

When IE is less than or equal to tolerance T_{ie}, the iterative process is stopped.

Ensemble Base Classification:

The rule for the ensemble classifier requires successful diversity. The classifier sometimes makes different mistakes. To avoid such mistakes, train the base learners. Ensemble base classifier is used for classification. The number of classifiers are generated and aggregate together using algebraic combination rules

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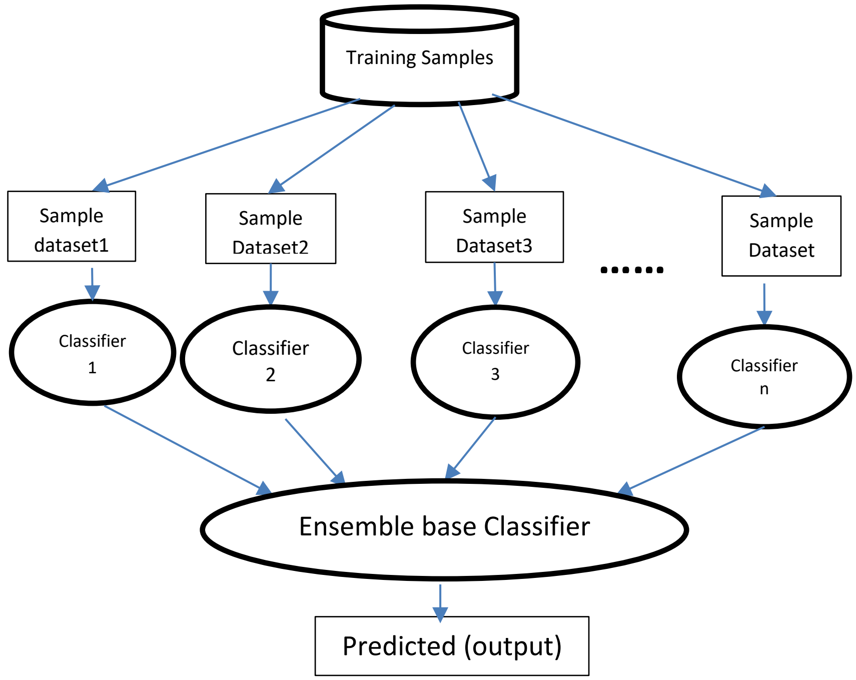

Figure 2. Artificial Neural Network-based Ensemble base Classification

Weighted Average or weighted majority Voting strategy is implemented for combining classifiers result. The voting methods are classified into two types one is Soft Voting and Hard Voting. For soft voting method the even number of classifiers are used to produce the exact predicted output (i.e., max probability value fix as output). But the hard voting use odd number of classifiers are used, here binary values are fixed for each classifier based on the 0's and 1's value the predicted output will be produce. Then how to fix the value of weight, either fix the weight value manually (based on the accuracy fix the weighted average) or otherwise automatically by using ANN machine learning [9]. For machine learning stacking is the good choice to fix the weight. Then fix the value of Gate function. The gate function also used the machine learning technique. The gating function is the co-efficient of individual members depend on the input data set. Train the gating function by using validation or authentication set. Then calculate (Weight multiply Gate function produce the predicted output). Each classifiers gives binary results. Cross authentication is used for evaluating the performance of the complete classifier. Here the dataset arbitrarily into Training set and Testing set.

Pseudocode: Combining classifiers and voting

- Sklearn.ensemble. voting classifier (estimators, *, voting='hard', weights=None, n_jobs=None, flatten_transform =True, verbose=False)
- Voting {'hard', 'soft'}, default ='hard'
- If 'hard' voting uses predicted class labels for majority rule voting.

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- Else if 'Soft' predicts the class label based on the **argmax ()** of the sums of the predicted probabilities which is recommended for an ensemble of well standardized classifiers.
- Vc = Vot.C (m1, m2,m3 ……………mn)
- Voting {'hard', 'Soft'}, default = 'hard'
- Voting {'hard', 'Soft'}, default = 'soft'
- Vc.fit (Xtrain.Ytrain)

Training Data and Testing Data

For classification **e**ither use trained data or training the data by using the below way

Training data:

- **Combined Training Data**

Vc = Vot .C1(m1,m2,m3……………….mn)

Vc.fit (Xtrain, Ytrain)

m1 =c1 [ ]

m2 = c2 [ ]

m3 =c3 [ ]

- **Individual Training Data**

Vc = Vot .C1(m1,m2,m3……………….mn)

Vc.fit (Xtrain, Ytrain)

m1 =c1 [ ]

m1. fit ()

m2 = c2[ ]

m2.fit ()

m3 =c3[ ]

m3.fit ( )

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Testing Data:

After completion of training model, should test each model get the predicted output.

Y prediction =m1 . predict (X test)

Y prediction =m2 . predict (X test)

Y prediction =m3 . predict (X test)

Predict_prob ( )

Image Segmentation

After denoising the images and classification to extract the tumor portion from the MRI images five major segmentation methods are applied they are all Otsu's, K-Means, Fuzzy C_Means, Threshold Based Segmentation, Watershed Segmentation. This segmentation methods are explained below briefly.

Otsu's Thresholding:

Otsu's thresholding is a clustering-oriented segmentation method which converts the gray scale image to binary image by assuming that the image only has two types of pixels, one is foreground pixels and another is background pixels. Threshold values were selected for specific images, and that were used to covert the images to binary images. The morphological operation was done which operated the morphological opening then the output was subtracted from the original image. Image enhancement was done and others small objects were removed to show the segmented tumor[1]. This method is sometimes unable to detect the tumors accurately, sometimes a portion of tumor or the skull portion is also misinterpreted as the brain tumor, as well as the displayed regions are dependent on threshold values.

K-Means Clustering:

K-means clustering is an unsupervised learning. Another name is partitioning based clustering Technology. The process of grouping data objects into clusters based on the similarities. The initial set of clusters (K) need to be defined since the segmentation process is dependent on the value of K or number of clusters. The value of K is selected as 4, since the human brain images with tumor can be clustered into 4 clusters, where the targeted tumor belongs is also one of the clusters. At first, the image was converted to linear space, and then the K-Means algorithm was applied, which generated a set of clusters and cluster centroids. The linear space image is then reconverted to the spatial domain. After that, the tumor was extracted from the cluster 3 by applying morphological operations.

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Algorithm:

STEP 1: Initialize the number of clusters.

STEP 2: Randomly choose 'K' objects from the dataset (D) and assign it as cluster centers or cluster centroids for each cluster.

STEP 3: Assign or reassign the data points to the clusters using similarity distance measures.

STEP 4: Find new cluster centers updates the cluster centers by taking mean of all data points in a cluster

STEP 5: Repeat step 3 and 4 till stopping the criteria or convergence.

Watershed Segmentation:

Watershed segmentation techniques is highly useful when the targeted objects are in touching position. At first, necessary steps are followed like preprocessing, morphological operations, image enhancements, image binarization and erosion using a specific disk-shaped structural element. The complement of the eroded image has been taken, and the distance transform was applied after which the bright catchment basins were determined by taking the negative of the distance transform [6]. The watershed algorithm was applied which returned a labeled matrix comprises of positive values along the catchment basins. After that to get the ultimate segmented output, the labeled matrix was converted to an RGB image.

Algorithm:

STEP 1: The notation minimum and maximum will be used to denote the min and max values of $g(x, y)$

STEP 2: Finally let $T(n)$ represent the set of co-ordinates (s, f) for which $g(s, t) < n$

STEP 3: That is $T[n] = \{\frac{s,t}{g(s,t)} < n$

STEP 4: Geometrically, $T(n)$ is the set of co-ordinates of points in $g(x, y)$ lying below the plane $g(x, y) = n$

Fuzzy C-Means Segmentation:

To extract the region of interest from the brain. Initially the MRI image is converted to gray scale and noise removal techniques are applied to remove the noise from the image. Thresholding is then applied in order to convert the gray scale to a binary image. Sobel Edge detector is then used to detect the edges after which Fuzzy C mean segmentation [8] techniques is use to extract the tumor from the image. The entire algorithm of Fuzzy C means implemented where C is the number of clusters that will be formed. Though this methodology gives accurate prediction of tumor cells which are not predicted by K-means but this technique is comparatively slower than the K-means clustering algorithm.

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ISSN: 0974-5823 Vol. 6 No. 03 (December, 2021)

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Algorithm:

Let $X = \{x_1, x_2, x_3 \dots \dots x_n\}$ be the set of data points and $V = \{v_1, v_2, v_3 \dots \dots v_c\}$ be the set of centers.

STEP 1: Randomly select 'C" cluster centers.

STEP 2: Calculate the fuzzy membership μ_{ij} using

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ji}}{d_{ik}}\right)^{\left(\frac{2}{m-1}\right)}} \tag{6}$$

STEP 3: Compute the fuzzy centers v_j using

$$v_j = \frac{\left(\sum_{i=1}^{n} (\mu_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n} (\mu_{ij})^m\right)} \tag{7}$$

$$v_j = 1,2,3 \dots \dots \dots \dots \dots \dots c$$

STEP 4: Repeat step 2 and 3 until the minimum 'j' value is achieved

$$\left\| U^{(k+l)} - U^{(k)} \right\| < \beta \tag{8}$$

Threshold Based Segmentation:

Thresholding is the modest segmentation method. The pixels are partitioned depending on their intensity value. Global thresholding, using an appropriate threshold T. Threshold-based segmentation is observed as the most forthright image segmentation technique which separated the image directly into segments based on the intensity values [11]. Segmentation of an image which has more than two types of regions consistent to numerous types of objects known as local thresholding method. In case of intensity images, light objects over the dark background are segmented by using a specific threshold value. The pixels which are above the specific threshold values are denoted as 1, and on the other the pixels which are less than this value is denoted as 0. So, for any image f (x, y) the segmented image g (x, y) is

$$g(x,y) = \begin{cases} 0, & if\ f(x,y) \leq T \\ 1, & if\ f(x,y) > T \end{cases} \tag{9}$$

Variable thresholding, if the threshold T can change over the image. Local or regional thresholding, if T depends on a neighbourhood of (x, y). Adaptive thresholding, if T is a function of (x, y). 1 valued pixel are representing the region of interest (ROI), and the value 0 are used for background.

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ISSN: 0974-5823 Vol. 6 No. 03 (December, 2021)

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Peaks and valleys of the image histogram can help in choosing the suitable value for the threshold(s). Some factors affect the suitability of the histogram for guiding the choice of the threshold, the separation between peaks, the noise content in the image, the relative size of objects and background, the uniformity of the illumination, and the uniformity of the reflectance.

The merits of threshold technique are it is useful for image linearization which is vital for any segmentation. Though some groups described thresholding using Otsu's method is more suitable for segmenting brain tumours from MRI images. The demerits of this method are not suitable for all types of MRI images, which arises due to the vast variation of image intensity on background and foreground of an image.

Morphological Operation

Morphology is an instrument to extract image features useful in the legation and recital of region shape such as boundaries, skeletons and convex hulls. For morphological operation structuring element (kernel) is required. Morphological image processing is a non-linear process, based on exploring an image using a small template called structuring element (SE). SE is used to quantify the image by placing it in all locations in the image and comparing the pixels in its neighborhood. With the use of some operations, it is determined whether the SE 'fits' into the neighborhood or 'hits' into the neighborhood, as shown in Fig. 4. The SE is considered to be fit in the image, if the corresponding image pixels is also 1 for each of its pixels set to 1. A SE is said to hit the image, or intersect an image if at least one of its pixels set to 1 corresponds to a matching image pixel. The locations at which it fits in, the information related to size and shape of SE is derived. This image processing technique has four basic operations: erosion, dilation, opening and closing which are applicable for binary images [11]. Erosion involves filtering on inside and removes pixels on object boundaries. Erosion can split apart the joined objects or augment the distance between them or remove some redundant pixels. Erosion of set A by a structuring element B, given by the expression:

$$\mathrm{A} \ominus \mathrm{B} = \{\mathrm{x} : \mathrm{B_x} \subset \mathrm{A}\} \tag{10}$$

where $\subset$ signifies the subset relation, and $\mathrm{B_x} = \{b + x; b \in B\}$ (11)

Dilation is dual operator for erosion. It involves filtering on outside. Dilation increases the pixels on both the inner and outer edges of objects. This technique performs object growth, hole filling, and then joining the disconnected objects. The size and shape of the structuring element determines the number of pixels added to the objects in an image. The expression for dilation of set A by a structuring element B is given by:

$$A \oplus \mathrm{B} = (\mathrm{A^C} \ominus \mathrm{B})^{\mathrm{c}} \tag{12}$$

where $\mathrm{A^C}$ signifies the complement of A, and $\hat{B} = \{-b : b \in B\}$ is a 180◦ rotation of B about the origin.

As dilation has an expanding effect and erosion has a shrinking effect, they can be used to determine image borders.

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To remove small objects morphological opening is applied to the image. It is combination of two process and can be described as an erosion process followed by a dilation process, given by the expression:

$$A \circ B = \cup \{Bx : Bx \subset A\} \qquad (13)$$

$$A \circ B = (A \ominus B) \oplus B \qquad (14)$$

Dual version of opening is called closing, given by the expression: $A * B = (A^C \circ B)^C$

$$A * B = (A \oplus B) \ominus B \qquad (15)$$

Morphological closing is also a combination of two process and can be defined as a dilation process followed by an erosion process.

Performance Measures

Various measures are used to evaluate the preprocessing and tumor segmentation approaches including, texture features and execution time.

Feature extraction

The transformation of an image into its set of features is known as feature extraction. Useful features of the image are extracted from the image for classification purpose. It is a challenging task to extract good feature set for classification [13]. In this paper the texture feature is using as a proposed system.

Texture features

A number of image features are evaluated to provide statistical and textural information which help analyze the segmented image. The functional definition of these features is explained below.

1. **Mean:** It is mathematical average of given numbers and is calculated by dividing the sum of given numbers by the total numbers.

$$\text{Mean: } \mu = \sum_{I=0}^{G-1} ip(i) \qquad (16)$$

2. **Entropy:** It is used to measure the randomness of an image.

$$\text{Entropy: } H = -\sum_{I=0}^{G-1} p(i) log_2 [p(i)] \qquad (17)$$

3. **Variance:** Variance tells the intensity variation around the mean.

$$\sigma^2 = \sum_{I=0}^{G-1} (i-\mu)^2 p(i) \qquad (18)$$

4. **Skewness:** Skewness is used to measures the symmetriness of the histogram around the mean.

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$$\mu_3 = \sigma^{-3} \sum_{I=0}^{G-1} (i-\mu)^3 P(i) \tag{19}$$

5. **Kurtosis:** Kurtosis is the flatness of the histogram

$$\mu_4 = \sigma^{-4} \sum_{I=0}^{G_{-1}} (i-\mu)^4 P(i) - 3 \tag{20}$$

6. **Energy:** Energy known as uniformity of energy; it is the sum of squared elements.

$$E = \sum_{I=0}^{G-1} [P(i)]^2 \tag{21}$$

7. **RMSE:** The Root Mean Square error that can be defied as

$$x_{rms} = \sqrt{\sum_{i,j}^{M,N} \frac{(x(i,j))^2}{M*N}} \tag{22}$$

8. **PSNR:** Peak Signal to Noise Ratio is used to calculate the peak value of signal power with respect to noise power. The larges the PSNR the good segmentation effect and less noise in the output image. PSNR is evaluates using the below equation.

$$x_{Psnr} = 20 * \log \frac{256}{x_{rmse}} \tag{23}$$

$$x_{rmse} = \sqrt{\sum_{i,j}^{M,N} \frac{[(x(i,j) - x_m]^2}{M*N}} \tag{24}$$

9. **Contrast:** Contrast is created by the difference in luminance reflected from two adjacent surfaces.

$$\boldsymbol{x_{con}} = \sum_{\boldsymbol{i,j}}^{\boldsymbol{M,N}} |\boldsymbol{i}-\boldsymbol{j}|^2 \boldsymbol{P(i,j)} \tag{25}$$

10. **HOMOGENITY**: Homogeneity is a measure of intensity contrasty between a pixel and its neighbors

$$\boldsymbol{x_{hom}} = \sum_{\boldsymbol{i,j}}^{\boldsymbol{M,N}} \frac{\boldsymbol{P(i,j)}}{\boldsymbol{1+|i-j|}} \tag{26}$$

11. **Maximum Probability:** This is performed by fitting a normal distribution to a neighborhood of values in the likelihood function around the location of the maximum.

$$\max_{i,j} \; p(i,j) \tag{27}$$

12. **STD:** The standard deviation (σ) provides a measure of the dispersion of image gray level intensities

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \tag{28}$$

13. MSE: The MSE represents the cumulative squared error between the compressed and the original image.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2 \tag{29}$$

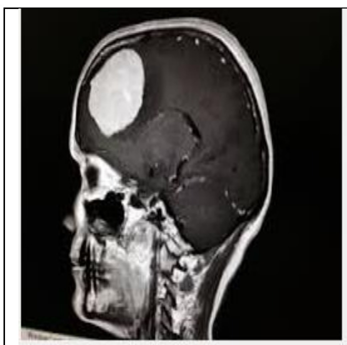
Where N is the number of data points, f_i the value returned by the model and y_i the actual value for data point i.

14. **Dissimilarity Measures**: Dissimilarity measure. is a numerical measure of how different two data objects are lower when objects are more alike

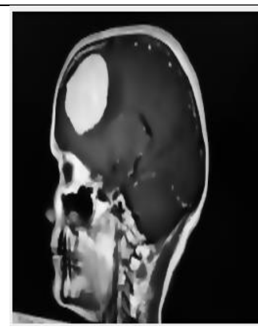
$$d_{i,j} = \frac{\sum_{k=1}^{a} \omega_{ijk}\, d_{ijk}}{\sum_{k=1}^{a} w_{ijk}} \tag{30}$$

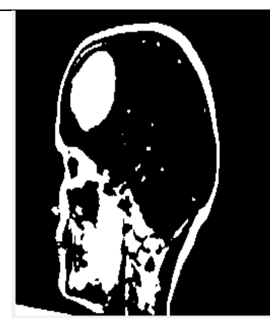
Experimental Results And Discussions

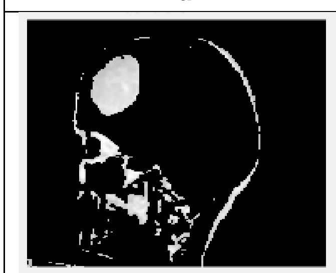
Tumor detection has been implemented by using MATLAB (2020) on Dual core 2 Duo, processor speed 1.6 GHZ. The MRI images has been collected from different online sources and all of the used images are 2D images. It has also been tested on dataset of real brain MRI consisting of Normal and Tumorous Brain Images.


a

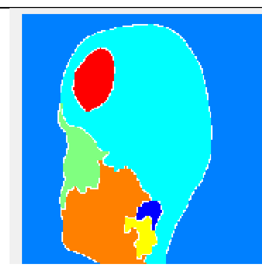

b

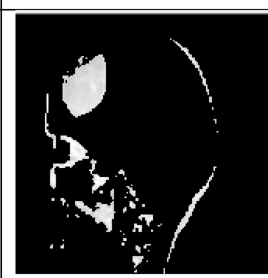

c


d


e


f


g


h

DOI : https://doi.org/10.56452/6-3-68501
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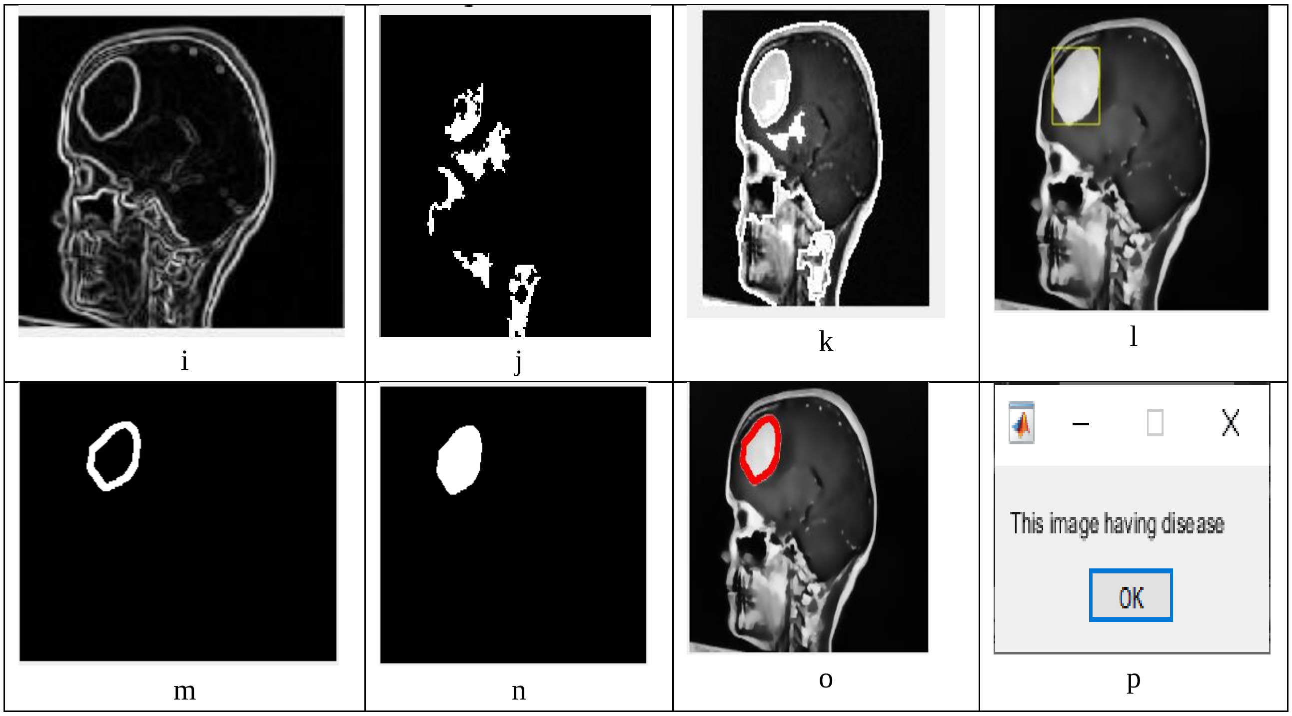
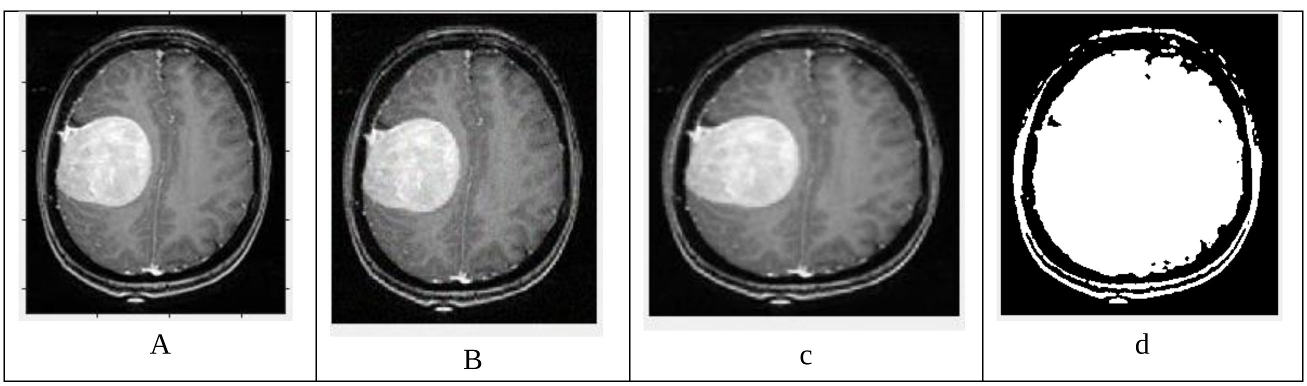


Figure 3. Sample Image A: Outputs for proposed method to detect accurate tumor portion a). Input image b)Noisy Image c) ADF filtered image d) Otsu segmentation e) Threshold based segmentaion f) Fuzzy C-means g) Watershed segmentaion h) K_means i) Sobel opeartor j) Region maximum k) Bounding extraction l) Bounding Box m) Tumor outline n) Tumor alone o) Tumor detected portion p) Tumor Positive



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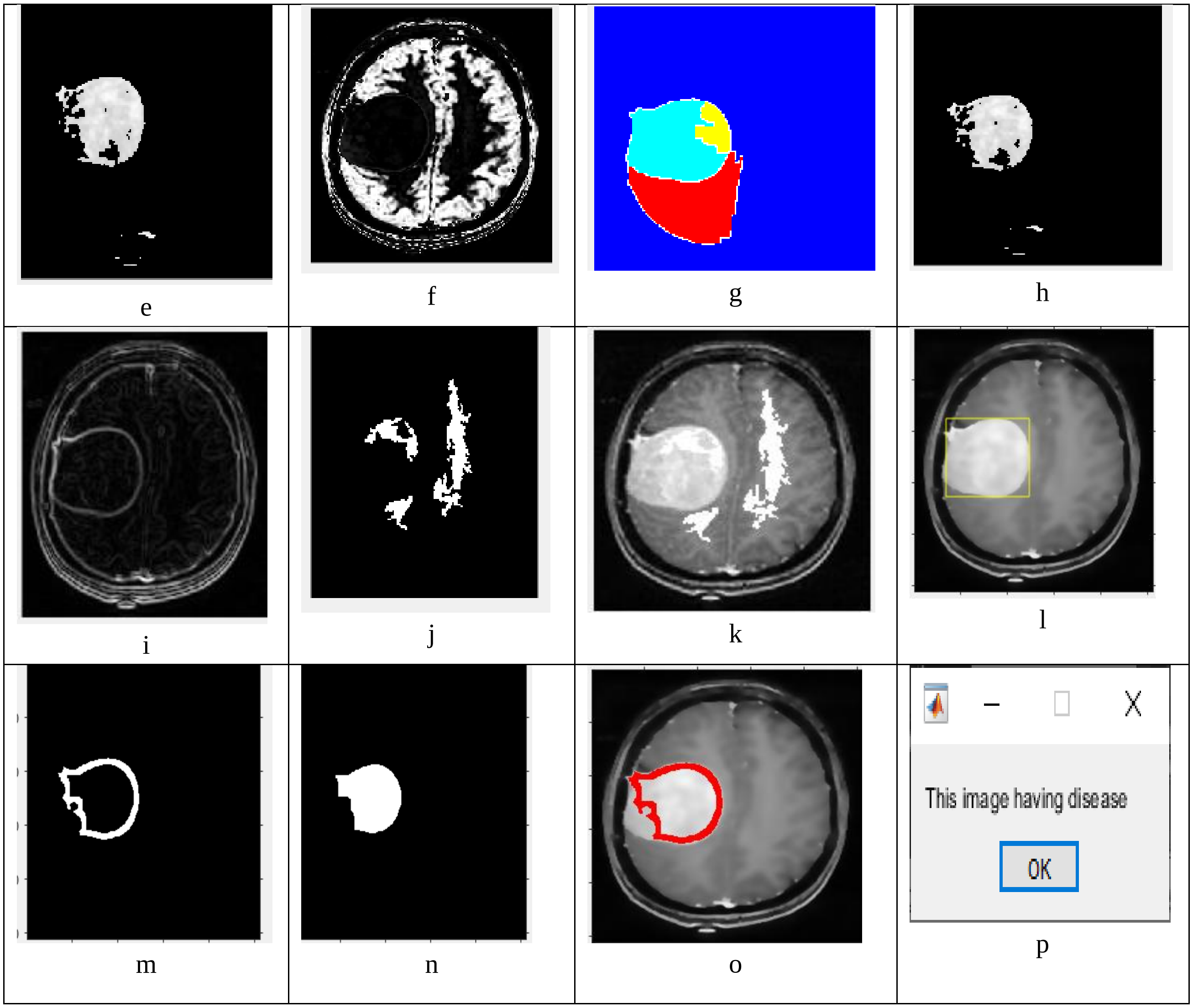

Figure 4. Sample Image B: Outputs for proposed method to detect accurate tumor portion a). Input image b)Noisy Image c) ADF filtered image d) Otsu segmentation e) Threshold based segmentaion f) Fuzzy C-means g) Watershed segmentaion h) K_means i) Sobel opeartor j) Region maximum k) Bounding extraction l) Bounding Box m) Tumor outline n) Tumor alone o) Tumor detected portion p) Tumor Positive

These proposed methods are tested more than of 100 real Brain Images. This paper implemented and tested to show the results and performance measures below by using various proposed methodologies like ADF for noise removal, SVM for classification, compared five well-Known Segmentation techniques for brain tumor detection, Morphological operation for separating the affected area from the MRI. Then finally, calculate the Textural feature extraction for the output images.

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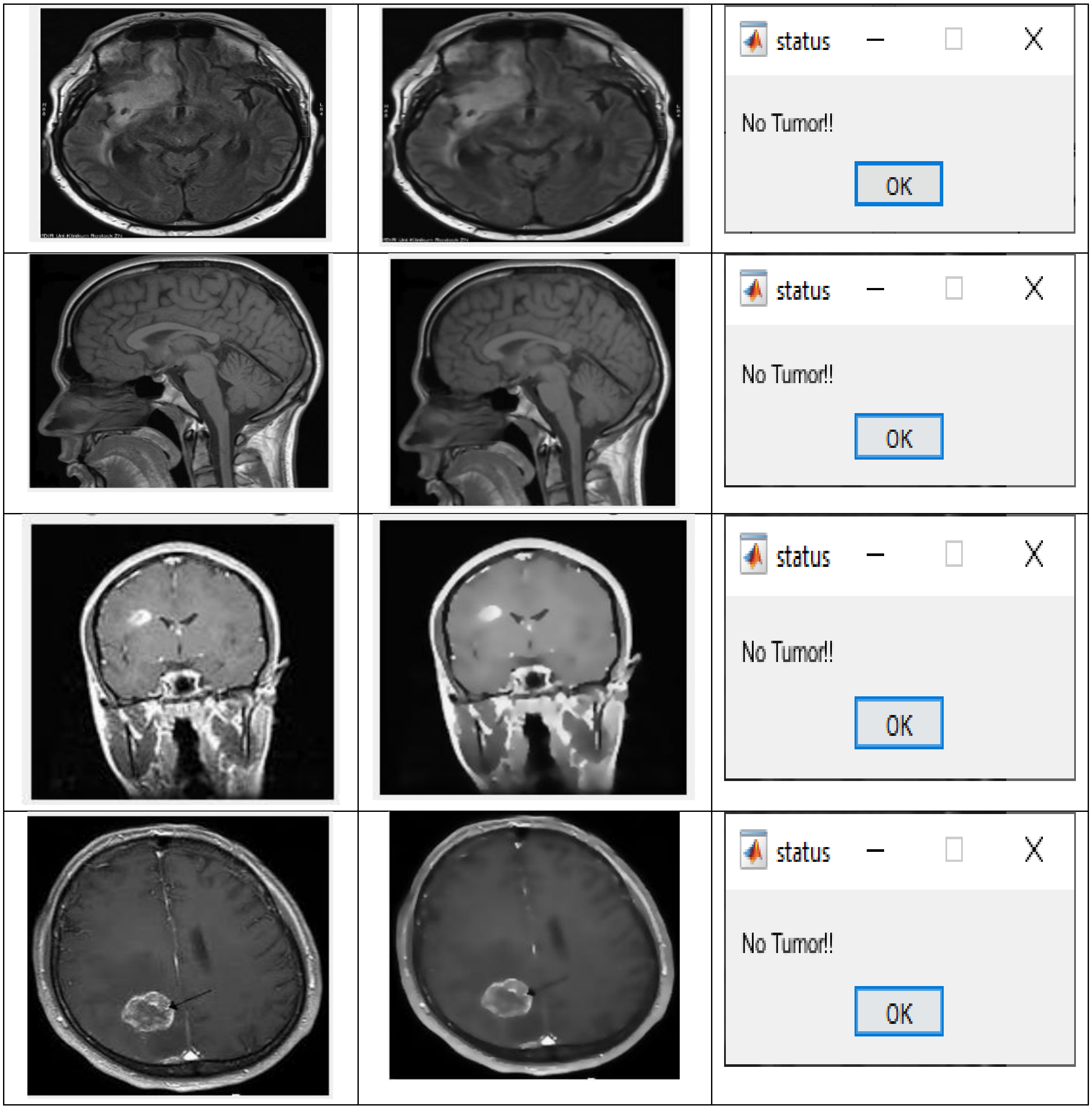

Figure 5. Outputs for proposed method to detect No Tumor portion (Tumor Negative)

Images	Contrast	Dissi-milarity	Energy	Entropy	Homo-geneity	STD	MSE	PSNR	No. of iterations	Max_Prob	SNR	Inverse Difference moment normalized
A	1.3187 2.1582	0.1884 0.3083	0.8003 0.7844	0.4250 0.4714	0.9765 0.9615	67.2549	28.22 01	28.854 90	26	0.8906 0.8820	19.117093	0.9883 0.9809
B	0.3692 0.2758	0.0527 0.0394	0.8281 0.8300	0.3435 0.3350	0.9934 0.9951	69.3444	28.22 01	30.271 43	16	0.9059 0.9068	22.392488	0.9967 0.9976

Table 1. Performance measures for Tumor Detection images.

Conclusion

The proposed system is developing for the diagnosis of brain tumor from MRI Images of the brain. The system makes the diagnosis in several phases. First preprocessing step for noises removal and preserve edges using ADF is performed on brain MRI images. In second step is classification phase proposed system used Ensemble based Classifier and weighted majority voting for combining purpose. Once the image is determined as Tumor these are further processed for Tumor extraction from them. Third phase segmentation that extracts the tumor region using five various segmentation methods are applied and implemented their performance was compared. In this paper K-Means Clustering performed better than other four segmentation methods. Fourth phase Morphological operation are used to extract the tumor from the segmented region. This proposed system finally detect the tumor portion accurately. Fifth phase various image textural features are evaluated to show the quality of segmented tumor image which can be useful in identifying the Tumor type whether affected the tumor or no tumor. This paper proposes better in terms of various performance measures.

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