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FUZZY BASED AUTOMATIC DETECTION AND CLASSIFICATION APPROACH FOR MRI-BRAIN TUMOR

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ABSTRACT

The main objective of this study is to detect and classify the brain tumor automatically in MRI images. Here the proposed approach consists of various stages namely Pre-Processing, Detection, Segmentation, Feature Extraction and Classification. The image processing methodologies such as Speckle Noise Removal, Adaptive Histogram Equalization, Fuzzy C-Means clustering and Gabor Feature extractor combined with Fuzzy-KNN methods. It has been developed for detecting and classifying the brain tumor from the MRI images. The classification categorizes and says that the input image is Tumor affected or Normal Image with the severity level. The proposed approach proves its efficiency in terms of detection and classification whereas the proposed approach shows its accuracy is 13.5% more than the existing approach.

Keywords: brain tumor, MRI, image processing, fuzzy clustering, fuzzy-KNN classification.

INTRODUCTION

Brain tumor is defined as the abnormal growth of cells, which will normally grows from brain blood vessels, brain nerves and also the cells emerges from the brain. Brain tumor is also called as changes in brain structure and behavior. There are three types of brain tumors; they are benign tumor, premalignant tumor and malignant tumor. Benign tumor is a slow rising tumor that affects the brain tissues severely. Pre malignant tumor is the tumor which is in carcinogenic condition leads to cancer and it can be cured by proper treatment. Malignant tumor is a complex tumor which leads to a death of a person if there is no proper treatment.

The computerized tomography (CT) and MRI are imaging techniques deeply used to study about the brain and it helps to detect the tumors in the brain tissues. From these methods the CT method has been consider to be the better method to detect the tumors. Because the scanning images shows structural information, which is used to plan the way and the radiotherapy rays are used to target only the tumor tissues leaving other tissues. The skull-stripping method is one of the methods to separates the brain cells from the skull. The tumor cells are separately isolated from the image for applying direct treatment without disturbing other cells in the brain. By this method we can detect the tumor cells very easily. According to CBTRUS there are 64530 cases of malignant and benign (i.e.) primary tumors are diagnosed in the year 2011 throughput the world. Overall about 6 lakhs peoples are currently affecting with this disease.

Overall the world 30% of the people is suffering from brain tumor. Since, brain structure is most complicated the abnormal tissues grows in an uncontrolled manner creates a separate cell division which forms tumor. MRI images help the doctors to analyze brain tumor and its stages. It is motivated to help the doctors, the segmentation of the brain tumor from MRI images taken as a problem to find a solution with various methods in medical imaging field.

The malignant tumors are growing quickly and are cancerous affect the neighbor tissues easily. Detecting and removing the early malignant of brain tumor prolong the human life time for much more years. The main objective of this paper is to segment the abnormal pixels from the normal pixels in MRI images automatically. Main segmentation of brain tumor is based on the pixel intensities and is classified as benign or malignant with the help of the features [1-8].

Image

One of the most essential works is to understand before the basic procedures works with images for to developing on the image segmentation process. The characteristics of the images are different in terms of extension, image format, dimension, size and color. In this section the various kinds of images is discussed. Generally images are categorized into raster images, SAR images, and medical images. Such as MRI, CT, fMRI, DTI, PET, NMRI, and DRFI images.The type of the image is indicated in the image name with extension as .tif, .jpeg, .bmp, .dicom, .png, .pgm and etc. Some more image kinds are still image, moving images, face images and so on. But in this paper MRI images are taken into account as input images.

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Symbols	Description
MRI	Magnetic resonance imaging
NMRI	Nuclear magnetic resonance imaging
MRT	Magnetic resonance tomography
CT	Computed tomography
fMRI	Functional magnetic resonance imaging
DTI	Diffusion tensor imaging
MRS	Magnetic resonance spectroscopy
PET	Positron emission tomography
DRFI	Diabetic retinopathy fundus images
GA-SVM	Genetic algorithm, support vector machine

Background study

Various image processing techniques are applied in the previous researches to do detection and segmenting tumor from MRI images. Some of the research scholars directly applied computer graphics methods, such as cropping, skewing etc. A sequence of image processing steps is applied on MRI images to do tumor segmentation and classification. For example the authors in [1, 25] enhances the tumor pattern in the brain images with the help of common image processing techniques and the author from [2] describes the detection of brain tumor by segmentation. A Hybrid technique GA-SVM is developed and applied to detect the tumor and automatic Bayesian classification method is used for tumor classification [3]. Fuzzy system [4], balloon inflation method [5], wavelet based statistical texture method [6], skill stripping method [7] and FF-OCT [10] are some of the direct methods applied for brain tumor detection and classifications. LDA [8], ANFIS [9] and region with location based retrieval method [11] are some of the methods applied for features and dimensionality reduction based methods to detect and classify brain tumor.

The author in [12] utilized different direct segmentation methods for segmenting tumor from MRI images. Using unsupervised automatic method [13], fishes-kolmogorow model [14], symmetric information [15], and mathematical models [16] automatic brain tumor detection is obtained. Some of the research people explained about detecting and extracting the brain tumor using chemotaxis mode designing [17], SOM [18], Clustering and morphological [19, 21], modified probabilistic neural network [20, 22] methods automatically. In [23] the Mahalanobis distance method is used to analyze the pixels and detect brain tumor and segmentation SOM is used. In [24] maxima transformation method is applied to fetch the tumor portion in the MRI image. Even though various methods has been introduced and explained in the early researches, it is necessary to provide a fully automatic detection, segmentation, extraction and classification for brain tumor in MRI images. In this paper the contribution of the proposed work and flow of the work is shown in Figure-1.

METHODOLOGY

Image segmentation utilizes various key features and form a system model with steps to implement. All these steps are combined and provide an outlook on the techniques necessitates and executing the system model effectively. The segmentation process given clearly in the below sections and a system model showing the comprehensive phases of MRI image segmentation and is visualized in Figure-1. MRI image segmentation code is written and executed to compare the efficacies of the different methods entailed at each phases of the segmentation process and the system model is described in the following sections.

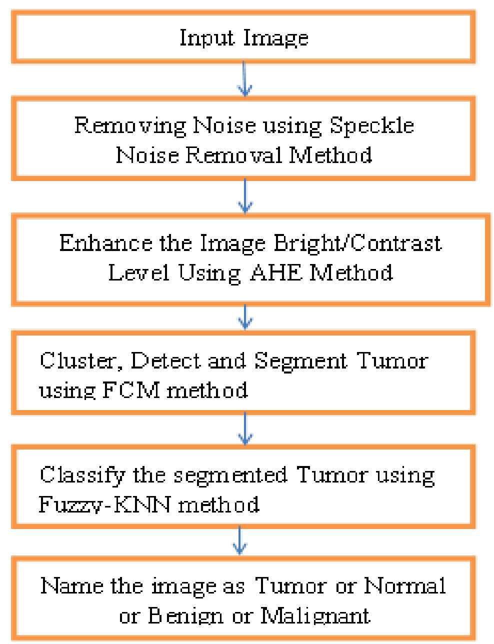

Figure-1. System model for proposed approach

The phases of the system model exploiting the various aspects of the image segmentation process. In the input image some noise occurs on the image due to the sources, and it can be removed to clean the image. In this scenario various noises are calculated and filtered using various filters [median filter, ideal filter etc.] integrated together in speckle noise removal method. After that image contrast and brightness levels are enhanced to highlight the tumor from the background, foreground of the image.

Our contribution of this paper is

- Preprocessing
- Segmentation
- Feature Extraction
- Tumor Classification

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Specific techniques are applied in the above step by step process and deliver the classification result as the given input image is “Normal”, “Benign” or “Malignant”.

Speckle noise removal

One of the main challenging tasks in medical image processing is noise reduction. Various approaches were discussed in the earlier studies for noise reduction. Commonly speckle noise is basically found in medical images. In this study multiple filtering methods are proposed for removing speckle noise from the MRI images. MRI imaging technique is typically used as an analytical tool for present medicine. MRI is used to do visualizing internal organs, size, structure of nerves and injuries. In MRI imaging, speckle noise indicates its occurrence at the time of visualization process. Speckle noise is the negative impact on the MRI images. The common model of the speckle noise can be represented as:

$$g(n,m) = f(n,m) * u(n,m) + \xi(n,m) \tag{1}$$

Where $g(n,m)$ the input image observed from MRI, $u(n,m)$ is the multiplicative and $\xi(n,m)$ is the additive component of the speckle noise. n, m denotes the both axis of the image samples. Noise can be removed by ignoring the additive component of the noise and can be written as:

$$g(n,m) = f(n,m) * u(n,m) + \xi(n,m) - \xi(n,m) \tag{2}$$

$$g(n,m) = f(n,m) * u(n,m) \tag{3}$$

(3) is the noise removed image. After noise reduction, the image is enhanced using AHE method.

Adaptive histogram equalization method

AHE is used to improve the contrast levels in the MRI images. In contrast to normal histogram equalization method AHE redistributes the lightness values of the different sections in the image. Because of this AHE is suitable for increasing the local contrast of the MRI image and bringing out more detail. This step enhances the image’s contrast level to improve the visual appearance of an image. In the initial phase the color image is converted into gray scale image. Some degradation process happens on the output image, so that the image should be enhanced.

Fuzzy C-Means method

FCM is one of a clustering technique used for soft segmentation methodology. Various deserving families of fuzzy based clustering techniques are proposed [1, 5].Clustering methods used to group similar pixels [objects] to discover the different pattern in a set of data. FCM utilizes the fuzzy clustering method in real world applications. In general, clustering is a function which groups the feature vectors as a class in self-organized mode. Example {X(q): q = 1, 2, 3, . . . , Q} be a Q feature vectors consists of N vectors and it can be written as x(q) = (x1(q), x2(q), . . . , xn(q)) is N components. The entire process of clustering is assigning Q feature vectors into K number of clusters {c(k): k=1, . . ., K}, obtained using minimum similarity distance. A centroid will be chosen among the entire data and then within a distance the similarity among the data is computed. The data are grouped into single cluster should have minimum distance. Different values based group formation among a large set of data using logic is fuzzy logic. It forms the group using approximate values instead of exact and fixed values, where the logic values are 0 or 1. For example if X is a set of data points, and A is considered as a fuzzy set, the X is grouped using a function f(x) = $\mu A(x)$. F(x) is associated with every point in X lies in the interval [0, 1]. The mathematical representation of FCM is:

n is th enumber of data points
v_j denotes the cluster center
m is the fuzzyness index $m \in [1, \infty]$
c denotes the center of the celuster.
μ_{ij} denotes the membership of the data to cluster center
d_{ij} denotes the euclidean distance among i^{th} and j^{th} data and cluster center.

The main motto of the FCM is to reduce:

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (\mu_{ij})^m \|xi \quad vj\|^2 \tag{4}$$

Where $\|xi - vj\|$.
is the euclidean distance among data at i, j th cluster center.

Algorithm_FCM

{
$X = \{x_1, x_2, \ldots, x_n\}$ set of data points [taken from Image I]
$V = \{v1, v2, \ldots, vx\}$ set of centers.
choose c as the cluster center randomly
compute fuzzy membership function μ_{ij} using

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

compute the fuzzy centers v_j using I
$V_j = (\sum_{(i=1)}^{n} (\mu_{ij})^m xi) \div (\sum_{(i=1)}^{n} (\mu_{ij})^m) \forall j = 1, 2, 3, \ldots, c.$
Repeat steps 4 and 5 until get the j as minimum and achieved for
$\|Uk+1 - Uk\| < \beta$ where
}.

k is th enumber of iteration
β is the termination criterion among [0, 1]
$U = (\mu_{ij}) + c$ is the fuzzy membership matrix
J is the objective function

Gabor feature extraction

Gabor filters are used to extract the features from segmented tumor in MRI images. Because this filter can

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filter the abnormal cells [pixels] correctly by considering the characteristics of the pixels. Also Gabor filter can localize the optimum location of the cells in spatial and frequency domain and it is appropriately applicable for texture based segmentation applications. Gabor filters applied already in various applications like texture segmentation, target detection, edge detection, retina identification and etc. Gabor filter in spatial can be written as:

$$h(x,y) = s(x,y)g(x,y) \tag{5}$$

where $s(x,y)$ is the carrier

$g(x,y)$ is 2D Gaussian shape function [envelop]

Also $s(x,y)$ can be represented as:

$$s(x,y) = e^{-j2\pi(u_0x+v_0y)} \tag{6}$$

And $g(x,y)$ can be written as:

$$g(x,y) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)} \tag{7}$$

So $h(x,y)$

$$h(x,y) = e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)} e^{-j2\pi(u_0x+v_0y)} \tag{8}$$

$$= g(x,y)e^{-j2\pi(u_0x+v_0y)} \tag{9}$$

In same way the frequency domain based features [orientation of the pixels]. The feature values of an image ((u_10, v_10 , σ_1x, σ_1y) are computed on spatial frequency point (u_10, v_10) . Thus the features of the segmented tumor are extracted using Gabor Filter. According to these feature values the abnormality is classified using Fuzzy-KNN classifier.

Fuzzy-KNN classification

The set of all Gabor feature values are retrieved from the enhanced image I and input to Fuzzy-KNN classifier. Fuzzy-KNN (33) method consists of KNN (33) and Fuzzy. KNN classification method is one of the supervised learning methods and it has predefined classes before start clustering. Clustering processed on top of elements and the elements in a class may differ. But the elements in the class are closest neighbors. The K-Nearest neighbour is represented in mathematical form is:

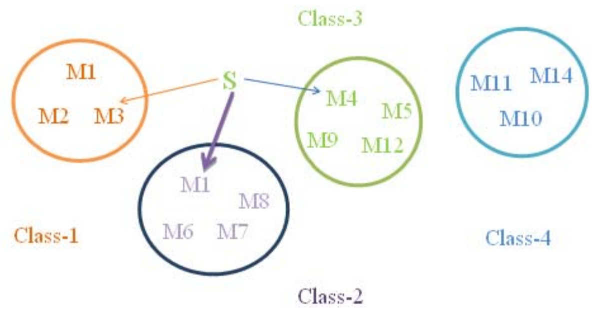

Figure-2. KNN [three neighbors, and S is closest to patter W4 in Class-3].

K-Nearest neighbor

Example M = {M1, M2, ... Mt} is a set of data which are labeled #
Every Mi is having L number of attributes as Mi = (Mi.1, Mi.2, . . . , Mi.l) #
An input X is not – classified element #
K Number of closest neighbor is in space for X #
R is the set of K nearest neighbors (NN) #
t is a set of classes to be identified for appropriate classes #
C be a set of classes #
M contains the t elements #
Each cluster is defined by a subset of elements from M #

The distance among the X and Mi is computed, if the distance is very less then add Mi as neighbour and delete the farthest neighbour and include X as an element in C and neighbour for Mi . If X is close to all the Mi in Ci then X is neighbour to all Mi in Ci . Else find the minimum and maximum distance among X and Mi in Ci , remove the elements having maximum distance and add them to other closest Ci .

Fuzzy-KNN = KNN + Fuzzy Set theory

Fuzzy KNN (33)

The main idea behind fuzzy-KNN is to allocate the members as a process of the objects' distance from their k-nearest neighbours and members in the possible classes.

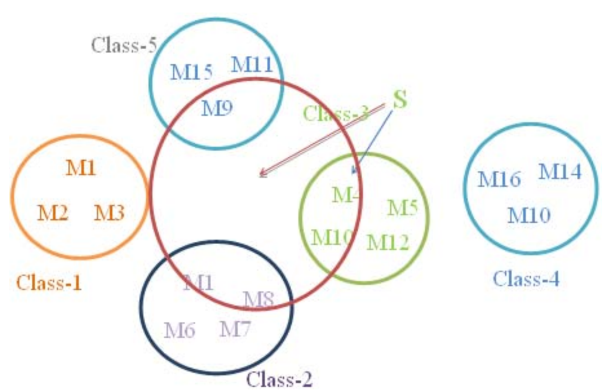

Figure-3. Fuzzy-KNN.

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Consider $M = \{M1, M2, \ldots, ML\}$ is a set of t labeled data – objects #
Mi is defined by L characteristics $Mi = (ML1, ML2, \ldots, MLi)$. #
X is not classified element #
K neighbour of X are closer #
$\mu_i(X)$ is the members of X in class i #
μ_{ij} is a member in ith class of jth vector of the labeled set [labeled Mj in class i]. #
$\mu_i(X)$ is representing class member in various ways. It is a complete member in one class and non-member in other classes. The membership is assigned using mean distance among the elements in a class and X. The idea behind the Fuzzy KNN is a two layer clustering algorithm. First centroid is computed using KNN, second fuzzy based membership is computed. The proposed approach Fuzzy-KNN algorithm is presented here for any one can implement this algorithm and verify the results of the proposed approach.

Algorithm proposed approach

Read Image I
a) I1= Speckle-Noise-Removal(I)
b) I2 = AHE(I1)
c) I3 =FCM-Algorithm(I2)
d) Feature[ ] = Gabor-Filter(I3)
e) Abnormal-type = Fuzzy-KNN (Feature[ ])
f) Print "Abnormal-type"

Algorithm for KNN Approach

Set K #
Computing the Nearest Neighbours #
For i = 1 to t #
Compute the distance among y to Xi #
If i <= k Then #
add xi to E #
Else – if xi is closer to y than any existing NN then #
Eliminate the farthest NN and add xi in the set E #
endif #
Check the more – number class represented in E and add y in this class #
If there is a draw then #
Compute the total distance from y to all neighbours in all the class #
in the draw #
If the sums are different then #
Add xi to class with smallest sum #
Else #
Add xi to class where last minimum is found. #
End if #
End if #

Next i

Algorithm for Fuzzy-KNN

Set K #
Computing the Nearest Neighbours #
For i = 1 to t #
Compute the distance among y to Xi
If i <= k Then #
add xi to E #
Else – if xi is closer to y than any existing NN then #
Eliminate the farthest NN and add xi in the set E #
endif #
Compute $\mu_i(y)$ with the help of #
For i = 1 to c // number of classes#

$$\mu_i(y) = \frac{\sum_{j=1}^{k} \mu_{ij} \left(\frac{1}{\|y - x_j\|^{\frac{2}{m-1}}} \right)}{\sum_{j=1}^{k} \left(\frac{1}{\|y - x_j\|^{\frac{2}{m-1}}} \right)} \quad \#$$

Next i#

The above algorithms FCM, Fuzzy-KNN are implemented using MATLAB 2012a software and the results were investigated.

Experimental results

Totally 200 images were taken for experiment and verify the performance of the proposed approach. Also the performance is evaluated by comparing the obtained results with the existing approach based results. From the total 150 images are abnormal and 50 images are normal in the database and the number of benign and malignant is shown in the following Table-1.

Images collected from various resources [internet, Brain Imaging Resources [34] for experimenting the proposed approach. All the image processing methods given in Figure-1 are implemented in a sequence manner and the results obtained in each stage for a normal, benign and malignant images is shown in Figures 5, 6 and in Figure-7 respectively. The Fuzzy-KNN learning rate for malignant is greater than 0.5 and benign is lesser than 0.5. And the learning rate is 0 for normal images. According to the detection and classification number is given in Table-1 and Figure-4.

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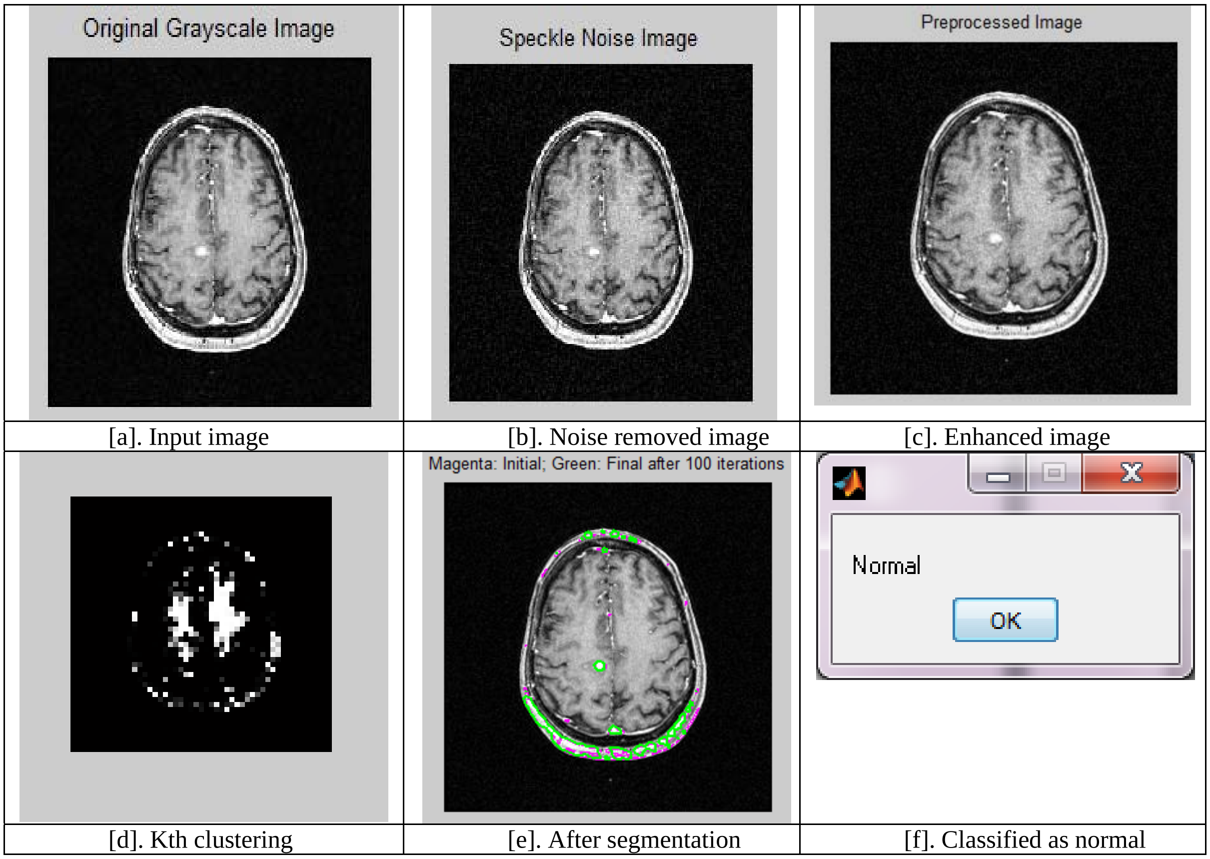
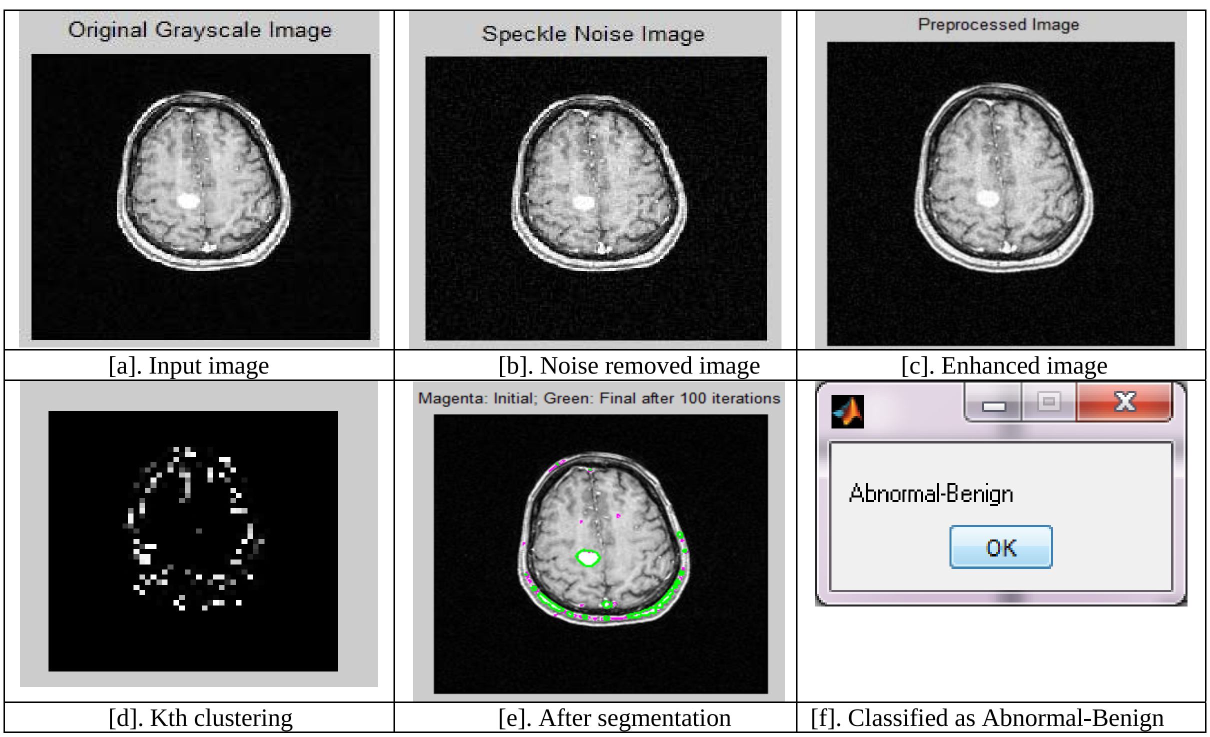


[a]. Input image | [b]. Noise removed image | [c]. Enhanced image
[d]. Kth clustering | [e]. After segmentation | [f]. Classified as normal

Figure-4. Detecting, segmenting and classifying normal MRI image.



[a]. Input image | [b]. Noise removed image | [c]. Enhanced image
[d]. Kth clustering | [e]. After segmentation | [f]. Classified as Abnormal-Benign

Figure-5. Detecting, segmenting and classifying benign MRI image.

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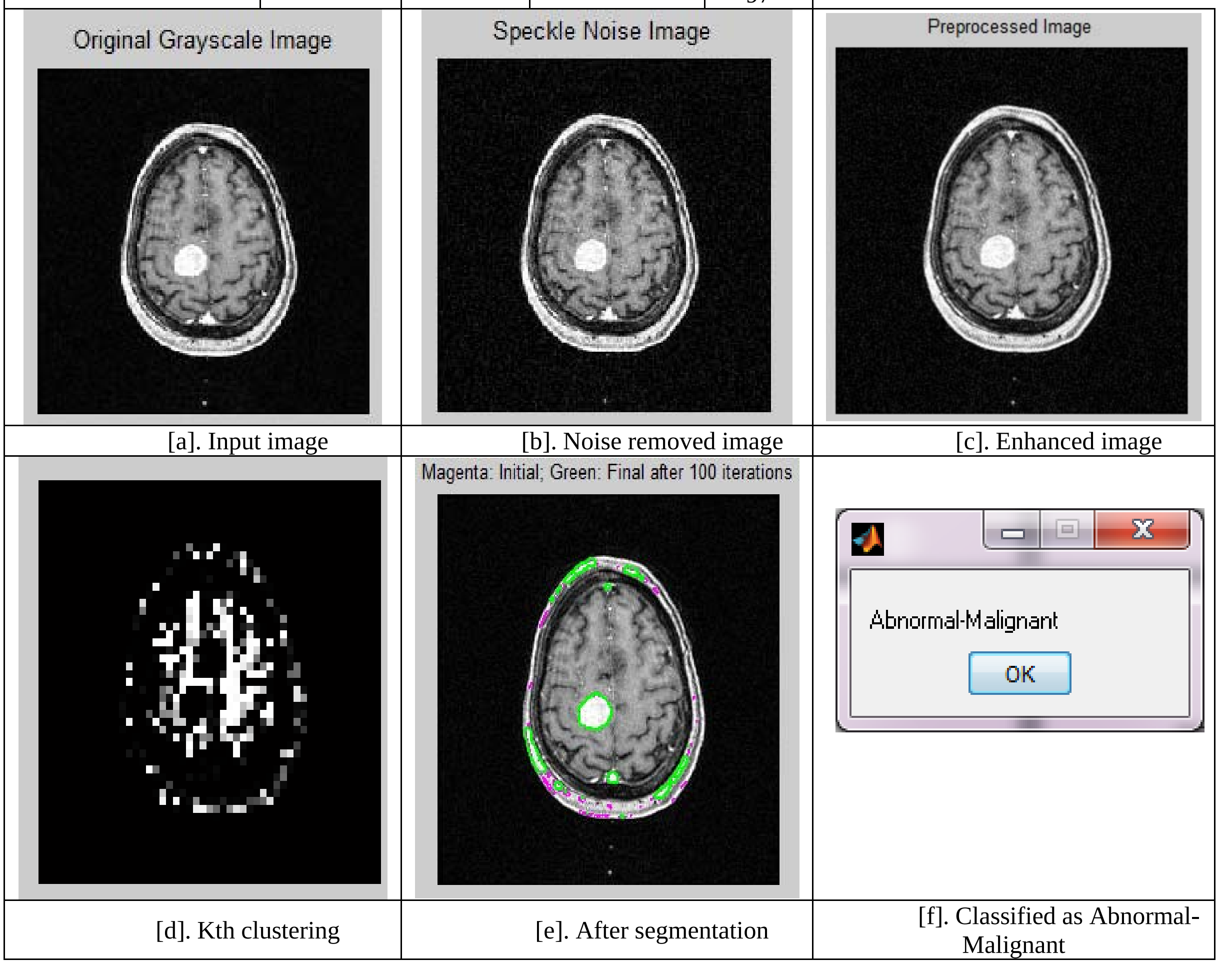
Table-1. Proposed approach detection and classification rate.

Methods	Normal	Benign	Malignant	Total
Available images	50	75	75	200
Proposed results	49	74	74	97



[a]. Input image | [b]. Noise removed image | [c]. Enhanced image

[d]. Kth clustering | [e]. After segmentation | [f]. Classified as Abnormal-Malignant

Figure-6. Detecting, segmenting and classifying malignant MRI image.

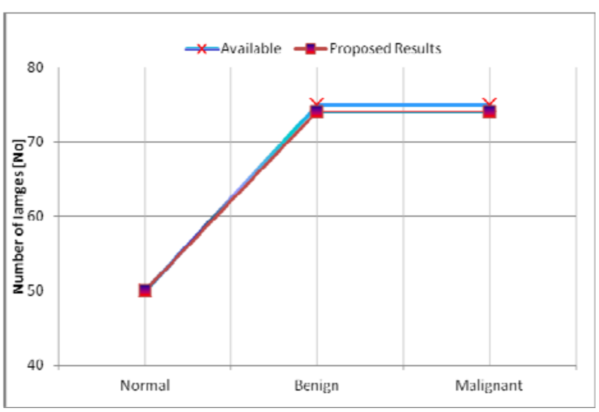


Figure-7. Classification performance of proposed approach.

From Table-1, it is clear that the number of database images is 200, whereas 50 images are normal and 75 images benign and 75 images are malignant. The results of the proposed approach are shown in Figure-1 in such a way the image processing techniques applied, and it produced the accurate results. The proposed approach classifies 49 images are normal and 74 images are benign and 74 images are malignant.

The performance of the proposed approach is evaluated using the following metrics such as sensitivity, specificity and accuracy of the detection and classification of normal and abnormality in MRI images. The equations of the performance metrics is as:

$$\text{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100\%$$

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$$\text{Specificity}(\%) = \frac{TN}{TN+FP} \times 100\%$$

$$\text{Accuracy}(\%) = \frac{TP+TN}{N} \times 100\%$$

Where

$TP \rightarrow$ True Positive; $TN \rightarrow$ True Negative; $FP \rightarrow$ False Positive; $FN \rightarrow$ False Negative; $N \rightarrow$ is the total Number of images

. And are calculated using:

$$TPR = \frac{\text{Number of classification correctly obtained}}{\text{Total number of images to be classified}}$$

$$TNR = \frac{\text{Number of Normal images identified}}{\text{Total Number of normal images}}$$

$$FPR = \frac{\text{number of classification wrongly obtained}}{\text{Total Number of images to be classified}}$$

$$FNR = \frac{\text{number of abnormal images incorrectly identified as Normal}}{\text{Total Number of abnormal images}}$$

Using the above equations the performance evaluation metrics are calculated and given in the following Table-2 and in Figure-8.

Table-2. Performance evaluation of proposed approach comparing with existing systems.

Methods	Sensitivity	Specificity	Accuracy
BBN [reff-34]	76.19	82.3	8 8.3
RBNN [ref-34]	85	72	8 4
SMO [ref-34]	92	90	8 9
MLPNN [ref-35]	80.4	78.3	8 1.7
SVM [ref-35]	84.3	81.8	8 4.5
Proposed Approach	99	98.9 7	9 9

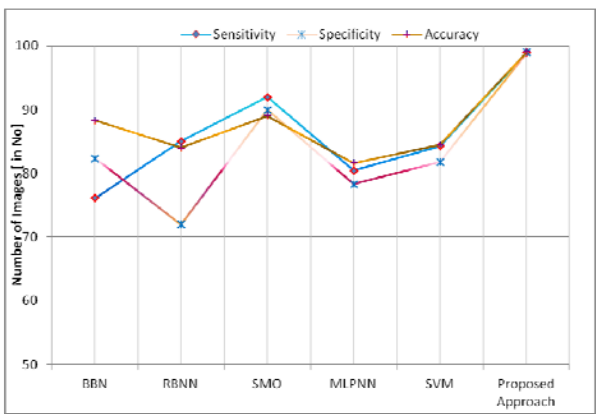

Figure-9. Performance evaluation of proposed approach comparing with existing systems.

CONCLUSIONS

In this paper, it is proposed a new step wise procedure to detect and classify the brain tumor in MRI images. The main motto is to introduce a best approach to bring up the efficiency of a new system to be developed. Further improvements can be obtained by applying optimization approaches. The Fuzzy-KNN classifier classifies the images as normal or abnormal and presents the location of the tumor using FCM clustering. From Figures 5, 6, 7 and Figure-8, it is proved that the efficiency of the proposed approach is better than the existing approaches. And the accuracy obtained from the proposed approach is 99% for 200 images. It also improved by experimenting on real-time hospital images, benchmark database image and on ground-truth images.

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