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Research Article

A NOVEL FUZZY C-MEANS COMBINED FUZZY-KNN METHODOLOGY FOR DETECTING AND CLASSIFYING MRI BRAIN TUMOR

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A R T I C L E I N F O

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A B S T R A C T

This paper discussed about MRI brain tumor, tumor detection and segmentation. A new step wise procedure is proposed 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. The proposed method is experimented using MATLAB software and the results are verified and performance is evaluated by comparing the results with the existing approach results.

INTRODUCTION

Background Study

An uncontrolled growth of cancer cells occur in any part of the human body is called as tumor. There are different types of tumors having different behaviors and needs various kinds of treatment [1]. Primary and metastatic are two types of brain tumors. Initially it begins in the brain and inclines to stay in the brain, and thensecond begin as a cancer elsewhere in the body and spreading to the brain.Generally brain tumor is classified into two types as benign and malignant. One of a grading scheme of the tumor is issued by Word Health Organization [2]. There are four types of grades is used to classify the brain tumor under microscope as I to IV. It can be defined as grade-I, grade-II, grade-III and grade-IV where grade-I and grade-II are called as benign tumors (lower-grade) and grade-III and grade-IV are called as malignant brain tumor (high-grade).

Basically lower grade tumors are not treated, it is considered as deteriorate to high grade brain tumor. In 2012, CBTRUS (Central Brain Tumor Registry of the United States) statistical report presented a statement that brain tumor is the second leading cause of cancer related deaths from children to aged people. The summary is given in Table-1.

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Table 1 CBTRUS Statistical Report

Gender	Age	Disease stage
Children	< 20 yrs	benign
Male	20 to 39 yrs	leukemia
Female	20 to 39 yrs	malignant

The total cases of the report say the number of people affected by brain tumor is given in table-2.

Table 2 CBTRUS Report

Number of People	Disease Stage
69720	Primary brain tumor
24620	Malignant
45100	Non-malignant

Table-1 gives the estimated value according to the age-sex-race-specific incidence rates are given for 2013 CBTRUS statistical report using SEER and NPCR data project (www.abta.org/aboutus/news/brain-tumor-statistics/). Since the brain tumor is an endangering human lives it is essential to discover and treat the tumor to save the human life. Surgery, radiation therapy and chemotherapy are the treatment options applied for brain tumor. Medical imaging and imaging modalities are the important methods used to evaluate patient's brain tumor to take care of the patients. Nowadays, the medical imaging modalities like Ultrasonography, Magneto EncephaloGraphy (MEG), Computed Tomography (CT), XRay, Positron Emission Tomography (PET) and Electro EncephaloGraphy (EEG), Single-Photon Emission Computed Tomography (SPECT) and Magnetic Resonance Imaging (MRI) are used to discover the brain tumor. These images are used to provide completed tumor information which makes the medical experts to provide better treatment. Once clinical doctors suspect the brain tumor, radiologic evaluation is compulsoryto decide the location, the extent of the tumor, and its association to the neighboring structures. It is more essential and difficult to decide among various forms of therapy like surgery, chemotherapy and radiation therapy. The assessment of brain tumors by imaging modals is one of the key issues in radiology departments.

MRI is one of the soft tissue contrasts imaging modality; it gives the details about the tumor like shape, size and location of brain tumor without any disturbing the patient [3]. Most of the clinical experts said that the MRI can be used for accurate diagnosis to detect MRI tumor [4]. In general a sequence of MRI images are employed to diagnose and examine the tumor compartments. These image sequences comprises of

- T1-weighted MRI (T1w)
- T1-weighted MRI with contrast enhancement (T1wc)
- T2-weighted MRI (T2w)
- Proton Density-weighted MRI (PDw)
- FLuid-Attenuated Inversion Recovery (FLAIR).

A standard sequences for a type of brain tumor of a patient is shown in Figure-1 [5]. It is under type of glioblastoma. Main segmentation of brain tumor is based on the pixel intensities and is classified as benign or malignant with the help of the features [6-13].

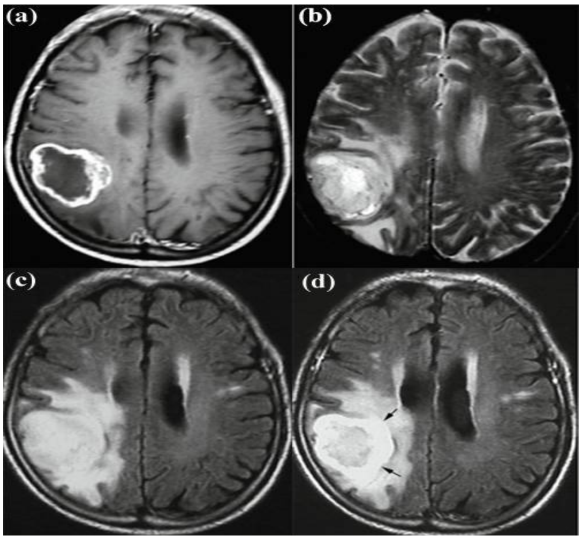


Figure 1 Four imaging modalities: (a) T1-weighted MRI; (b)T2-weighted MRI; (c) FLAIR; and (d) FLAIR with contrastenhancement [5] .

Where T1w shows the healthy tissues and it has become the most commonly used sequence images for analysing the structure of the brain. Figure-1 comprises of four imaging modalities

(a) T1-weighted MRI;
(b)T2-weighted MRI;
(c) FLAIR; and
(d) FLAIR with contrastenhancement.

In recent years, medical imaging and softcomputing have made significant advancements inthe field of brain tumor segmentation. In general, most of abnormal brain tumor tissues may be easily detected by brain tumor segmentation methods. But accurate and reproducible segmentation results andrepresentation of abnormalities have not been solvedall the way. Since brain tumor segmentation has greatimpact on diagnosis, monitoring, treatment planningfor patients, and clinical trials, this paper focuses onMRI-based brain tumor segmentation and presents arelatively detailed overview for the current existingmethods of MRI-based brain tumor segmentation.In this paper it is motivated to design and develop a novel method for MRI brain tumor segmentation from MRI images. A sequence of medical image processing methods is used to segment the brain tumor in MRI images.

METHODOLOGY

Image segmentation utilizes various key features and forms 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-2. 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.

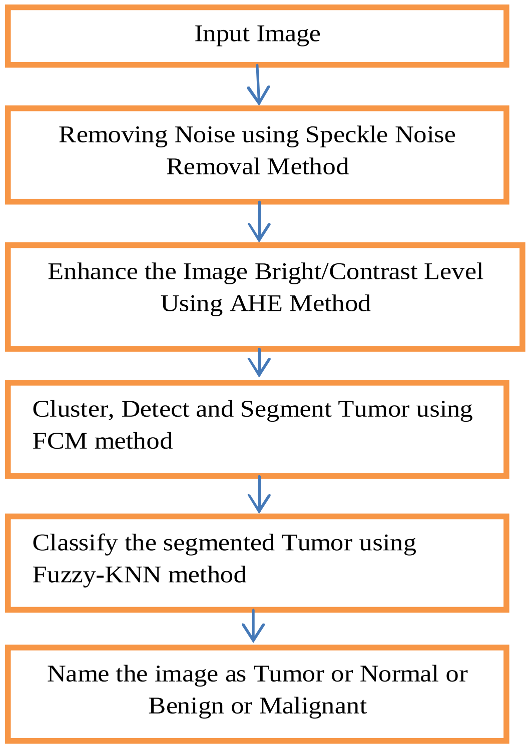


Figure 2 System Model for Proposed Approach

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

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:

$$g(n,m) = f(n,m) * u(n,m) + \xi(n,m) \quad (1)$$

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,mdenotes the both axis of the image samples. Noise can be removed by ignoring the additive component of the noise and can be written as:

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

$$g(n,m) = f(n,m) * u(n,m) \quad (3)$$

(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:

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

Where $\|xi - vj\|$,

is the euclidean distance among data at i, j th cluster center.

Algorithm_FCM ( )

{

$X = \{x_1, x_2, \dots, x_n\}$set of data points[taken from Image I]

$V = \{v1, v2, \dots, vx\}$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 :

$$V_j = \left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^{m} xi \right) \div \left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^{m}\right) \forall\, j = 1,2,3,\dots,c.$$

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]

$U = \left(\mu_{ij}\right) + c$ 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 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:

$$h(x,y) = s(x,y)g(x,y) \quad (5)$$

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

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

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

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

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

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

So $h(x,y)$

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

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

In same way the frequency domain based features [orientation of the pixels]. The feature values of an image $((u_0, v_0, \sigma_x, \sigma_y)$are computed on spatial frequency point (u_0, v_0). 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:

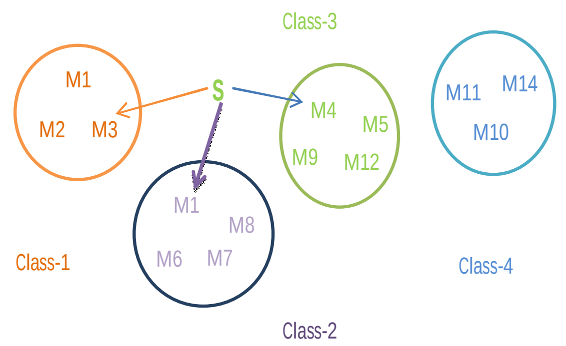


Figure 3 KNN [three neighbors, and S is closest to patter W4 in Class-3]

K-Nearest Neighbor

Example $M =$
$\{M1, M2, \ldots Mt\}$ is a set of data which are labeled.
Every Mi is having L number of attributes as Mi
$= (ML1, ML2, \ldots, MLi)$
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 Miin 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.

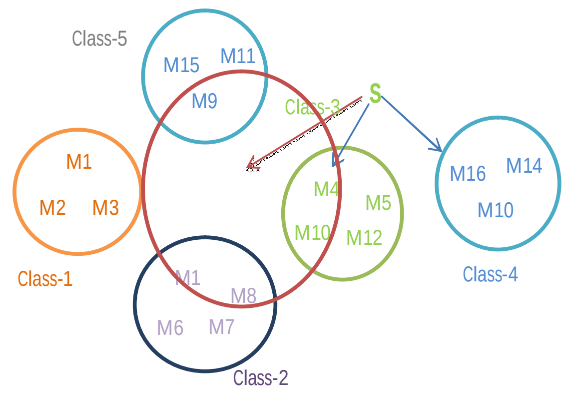


Figure 4 Fuzzy-KNN

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_i is a member in ith class of jth vector of the labeled set [labeled Mj in class i].

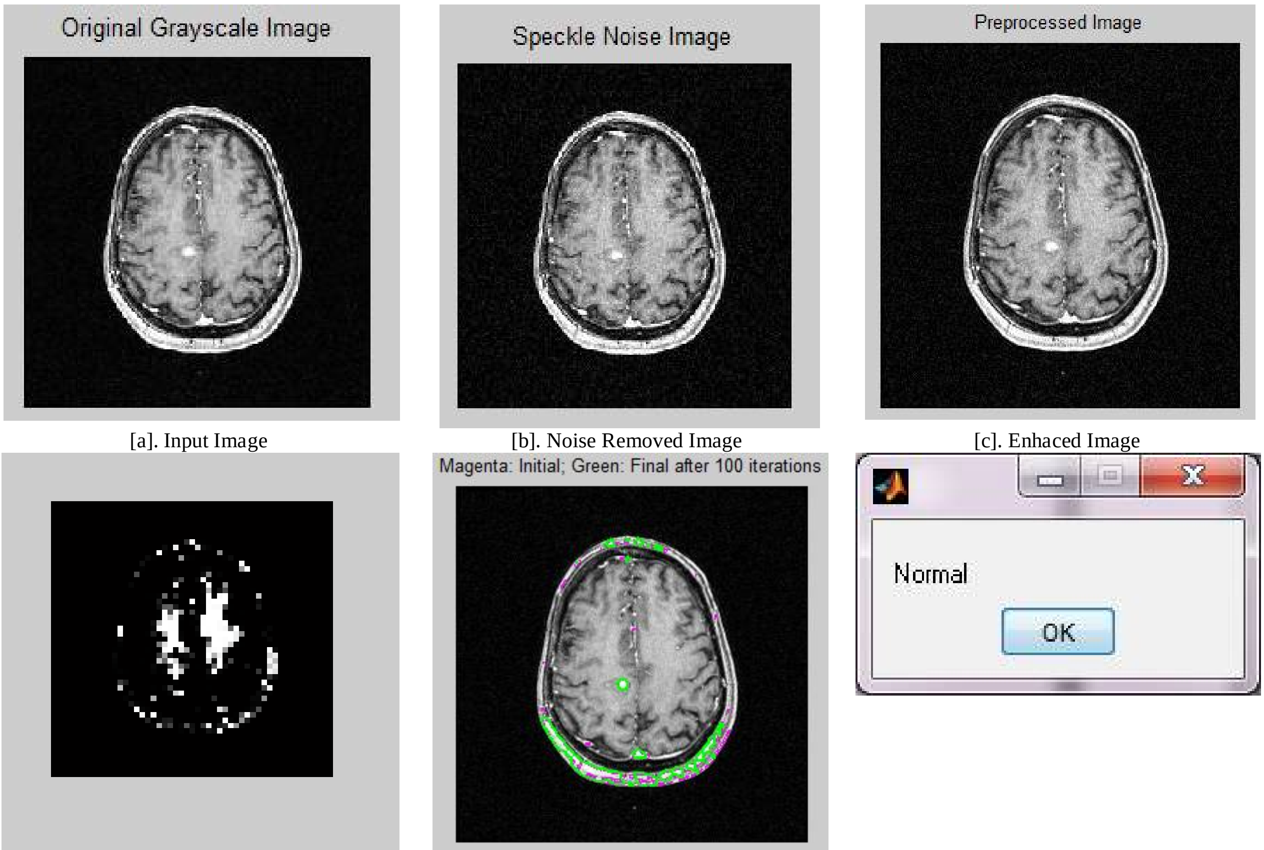
$\mu_i(X)$is representing class member in various ways. It is a complete member in one class and non-member in other classes. The membership is assigned using mean distance among the elements in a class and X. The idea behind the Fuzzy KNN is a two layer clustering algorithm. First centroid is computed 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

1. Read Image I
2. I1= Speckle-Noise-Removal(I)
3. I2 = AHE(I1)
4. I3 =FCM-Algorithm(I2)
5. Feature[ ] = Gabor-Filter(I3)
6. Abnormal-type = Fuzzy-KNN (Feature[ ])
7. Print "Abnormal-type"

Algorithm for KNN Approach

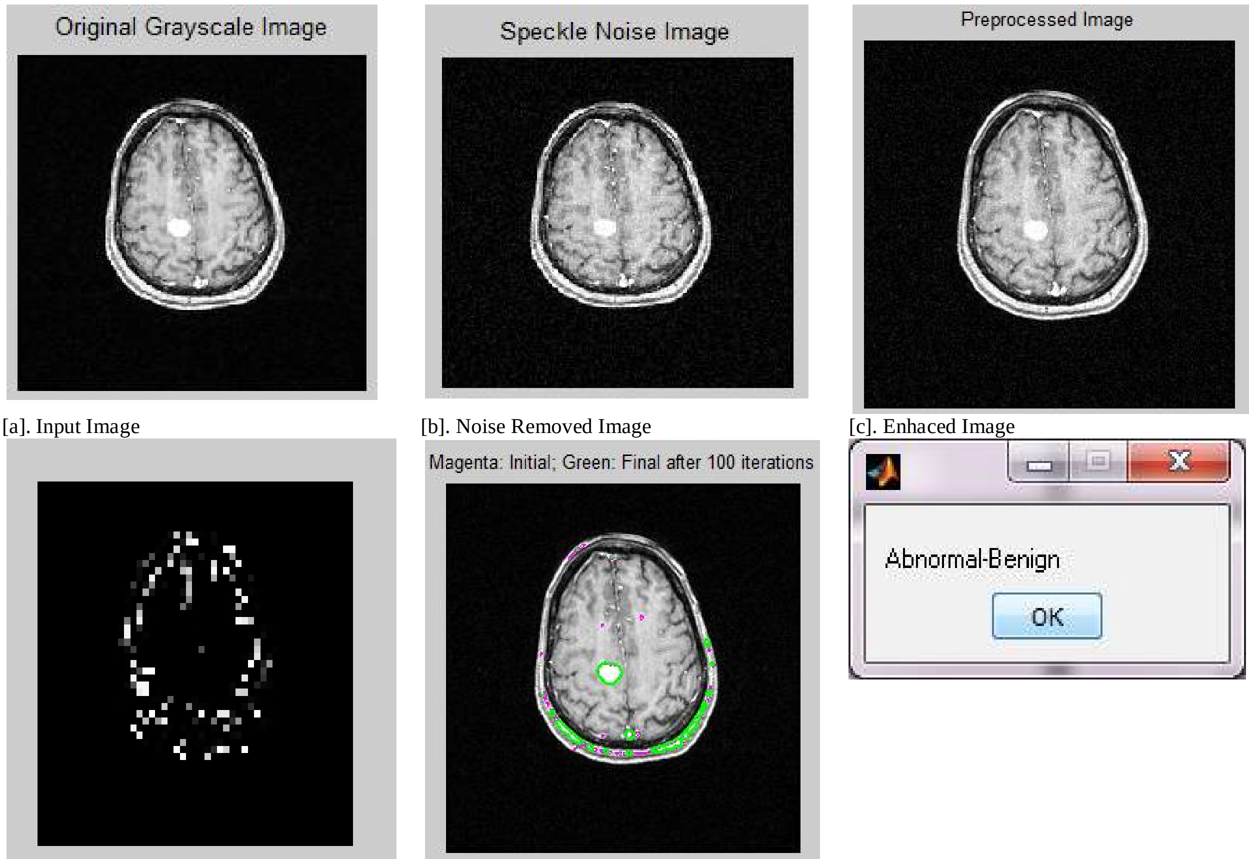
Set K
Computing the Nearest Neighbours
For i = 1 to t
  Compute the distance among y to Xi
  If i <= *k Then*
    add xi to E
  Else – if xi is closer to y than any existing NN then
    Eliminate the farthest NN and add xi in the set E
endif Check the more – number class represented in E and add y in 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.



[a]. Input Image [b]. Noise Removed Image [c]. Enhaced Image

[d]. Kth clustering [e]. After Segmentation [f]. Classified as Normal

Figure 5 Detecting, Segmenting and Classifying Normal MRI Image

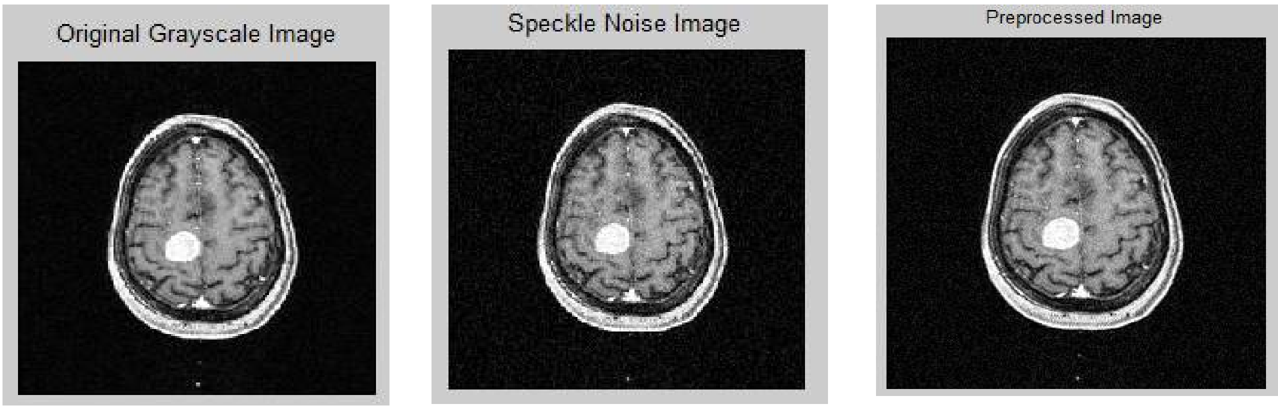


[a]. Input Image [b]. Noise Removed Image [c]. Enhaced Image

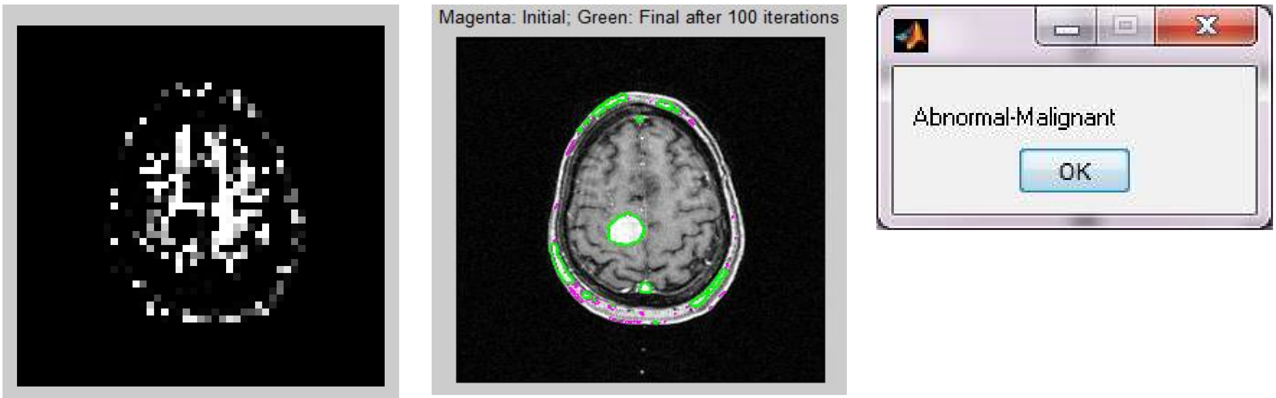
[d]. Kth clustering [e]. After Segmentation [f]. Classified as Abnormal-Benign

Figure 6 Detecting, Segmenting and Classifying Benign MRI Image

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



[a]. Input Image [b]. Noise Removed Image [c]. Enhaced Image



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

Figure 7 Detecting, Segmenting and Classifying Malignant MRI Image

Table3 Proposed Approach Detection and Classification Rate

Methods	Normal	Benign	Malignant	Total
Available Images	50	75	75	200
Proposed Results	49	74	74	197

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
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 Fig.1 are implemented in a sequence manner and the results obtained in each stage for a normal, benign and malignant images is shown in Fig.5, 6 and in Fig.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 Fig.4.

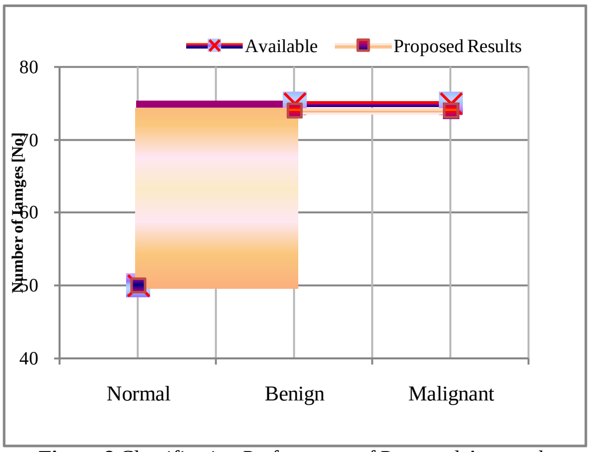


Figure 8 Classification Performance of Proposed Approach

From Table-3, 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-2 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:

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

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

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

Where TP → True Positive; TN → True Negative; FP → False Positive;
FN → False Negative; N → 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-4 and in Fig.9.

Table 4 Performance Evaluation of Proposed Approach Comparing with Existing Systems

Methods	Sensitivity	Specificity	Accuracy
BBN [reff-34]	76.19	82.3	88.3
RBNN [ref-34]	85	72	84
SMO [ref-34]	92	90	89
MLPNN [ref-35]	80.4	78.3	81.7
SVM [ref-35]	84.3	81.8	84.5
Proposed Approach	99	98.97	99

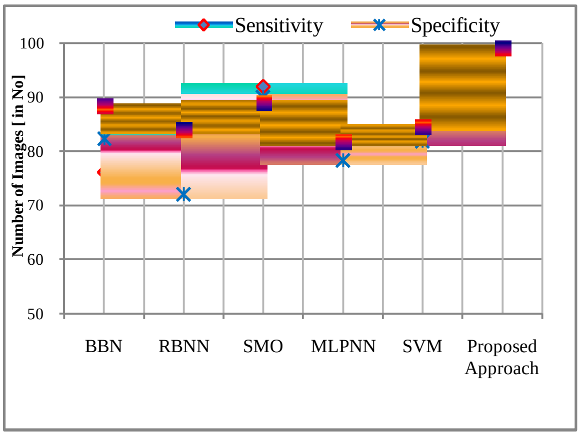


Figure 9 Performance Evaluation of Proposed Approach Comparing with Existing Systems

CONCLUSION

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 Fig.5, 6, 7 and Fig.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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