Biomedical Research 2016; Special Issue: S1-S9

ISSN 0970-938X
www.biomedres.info

Brain tumor detection from MRI images using histon based segmentation and modified neural network.

V Sheejakumari[1], Sankara Gomathi[2]

[1]Department of Information Technology, Rajas Engineering College, Vadakangulam, India

[2]Department of EIE, National Engineering College, Kovilpatti, India

Abstract

Recently, magnetic resonance imaging has become an efficient tool for medical diagnoses and in research. It has become a very useful medical resource for the detection of brain tumor and provides high tissue information. For getting better accuracy, an efficient technique called histon based method for segmentation is employed in the image. Initially, in the preprocessing stage the noise is removed from the images using median filter. Subsequently, the noise free image is then fed to the feature extraction process. In this step, the feature values like area, mean, correlation and covariance from the images are extracted. The final stage is that the classification of images with the assistance of neural network. The neural network used here is the modified neural network in which the weight values are optimized using Artificial Bee Colony (ABC) optimization algorithm. The method is implemented and the results are analyzed in terms of various statistical performance. Comparative analysis were made with different existing method to prove the efficiency of the proposed method.

Keywords: Magnetic resonance imaging, Brain tumor, Neural network, Optimization algorithm, Segmentation process.

Accepted on April 15, 2016

Introduction

Medical images build essential parts for identifying and work dissimilar body structures and therefore the diseases offensive them [1]. Many form of images area unit generated like ultrasound images, resonance images (MRI), X-rays which may be once more classified in radiographs, X-raying usually termed as CT scan, radiology, diagnostic technique [2]. Arrival of the technology has revolutionized the medical imaging space and has altered the task of research of a range of ailments for drugs practitioner. To produce images of human body for medical purposes it can be very perceptive for the medical process which is trying to analyse the disease Medical imagining is the name given to the field which constitutes of techniques and processes [3].

One of the main smartly analysed fields within the past few decades and builds the primary action within the image inv

estigation and pattern identification is Medical image segmentation. It's a very important and necessary a part of image study and is most tough for image process. It additionally has Associate in nursing additionally immense worth find the last results of the examination. Image segmentation may be a procedure of separating a image into many components such every region is, however the union of 2 adjacent isn't, solid [4]. In handling trendy imaging modalities like Magnetic resonance imaging (MRI) and X-raying (CT), physicians and technicians got to procedure the arising range and size of medical images. Therefore, to get rid of needed data from these giant information sets effective and precise procedure segmentation algorithms is required. Also, sophisticated segmentation algorithms will facilitate the physicians to demarcate higher than anatomical structures conferred within the input images, increase the correctness of diagnosis and facilitate the simplest treatment designing [5].

Biomedical image segmentation is a complex and very particular task. Image segmentation, do a major role in biomedical imaging applications such as the enumeration of tissue volumes diagnosis, confinement of pathology analysis of anatomical structure, treatment planning, partial volume improvement of practical imaging data, and computer incorporated surgery [2]. A foremost goal of image segmentation is to acknowledge structures within the image that area unit expected to correspond to scene objects. The mission of image segmentation is to separate a picture into non-intersecting regions supported intensity or textural data [6]. The artifacts, that have an effect on the brain image, area unit completely different-partial volume impact is additional outstanding in brain whereas within the thorax region it's motion artifact that is additional outstanding. Each imaging system has its own specific margins. as an example, in MR images (MRI) one needs to beware of bias field noise (intensity in-homogeneities within the RF field). Naturally, some procedures area unit additional common as compared to specific algorithms and may be helpful to a wider form of information [7].

The occurrence of brain tumors is mounting quickly, predominantly in the grown-up population weighed against younger population. Brain tumor could be an assortment of abnormal cells that nurture at intervals the brain or round the brain [8]. Tumors will squarely wipe out all work brain cells. It may also obliquely injury sturdy cells by situation additional elements of the brain and transportation regarding inflammation, brain swelling and pressure within the bone [9]. Brain image segmentation from MRI images is sophisticated and difficult however its precise and actual segmentation is important for tumors detection and their classification, edema, hemorrhage detection and death tissues. For early detection of abnormalities in brain elements, MRI imaging is that the most effective imaging technique and stands within the forthcoming analysis limelight in medical imaging arena [10]. The remaining of the paper is organized as follows. Section II makes clear the researches that square measure connected to the prompt methodology. Section III demonstrates the prompt methodology for tomography image classification. Section IV describes the impact of the prompt methodologyology and last Section V concludes the prompt method with suggestions for forthcoming works.

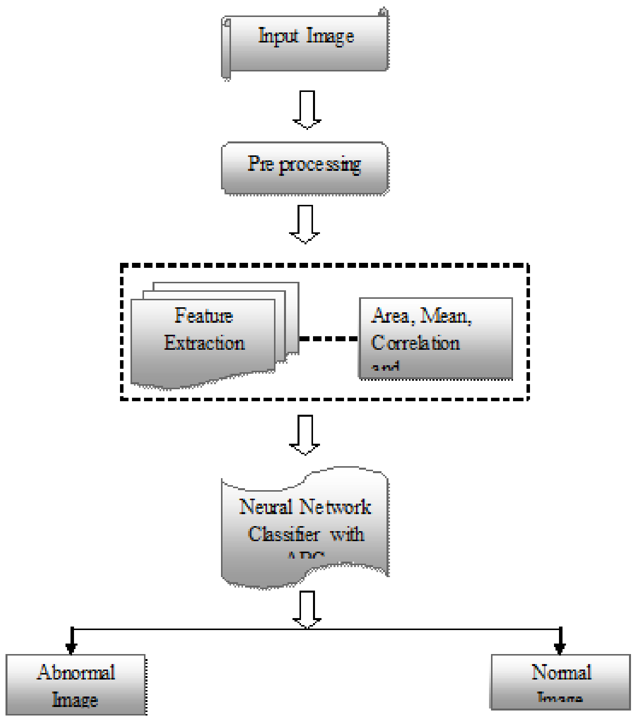

Figure 1. Block diagram of our proposed method.

Existing Methods and New Idea

Literature presents a handful of researches for classification of MRI images for tumor detection and has been a hot topic due to its significant applications. Here, present a brief review of some of the techniques presented in the literature for medical image classification. Song et al. [11] developed a simulation technique for choosing imaging parameters supported diminution of errors in signal intensity versus time and physiological parameters derived from tracer kinetic analysis for time-resolved acquisitions with k-space under sampling. Optimization was performed for time-resolved angiography with stochastic trajectories (TWIST) rule applied to contrast-enhanced adult male Renography. a sensible 4D phantom comprised of arteria and 2 kidneys, one healthy and one pathologic, was created with ideal tissue time-enhancement pattern generated employing a three-compartment model with mounted parameters, together with Glomerular Filtration Rate (GFR) and Renal Plasma Flow (RPF). TWIST acquisitions with totally different combos of sampled central and peripheral k-space parts were applied to the present phantom. Acquisition performance was assessed by the distinction between simulated Signal Intensity (SI) and calculated GFR and RPF and their ideal values.

Qin and Clausi [12] bestowed Andre Markoff Random Feld (MRF) based mostly variable segmentation formula referred to as "multivariate reiterative region growing victimization semantics" (MIRGS). In MIRGS, the impact of intraclass variation and machine price were reduced victimization the MRF abstraction context model incorporated with accommodative edge penalty and applied to regions. linguistics region growing ranging from watershed over-segmentation and performed instead with segmentation step by step reduces the answer house size, that improves segmentation effectiveness. Chunming Li et al. [13] bestowed region-based methodology for image segmentation that was ready to affect intensity inhomogeneities within the segmentation. First, supported the model of images with intensity inhomogeneities, they derived an area intensity agglomeration property of the image intensities, and defined an area agglomeration criterion operate for the image intensities in an exceedingly neighborhood of every purpose. This native agglomeration criterion operate was then integrated with reference to the neighborhood center to offer a world criterion of image segmentation in an exceedingly level set formulation, this criterion defined Associate in Nursing energy in terms of the extent set functions that described a partition of the image domain and a bias field that accounted for the intensity irregularity of the image.

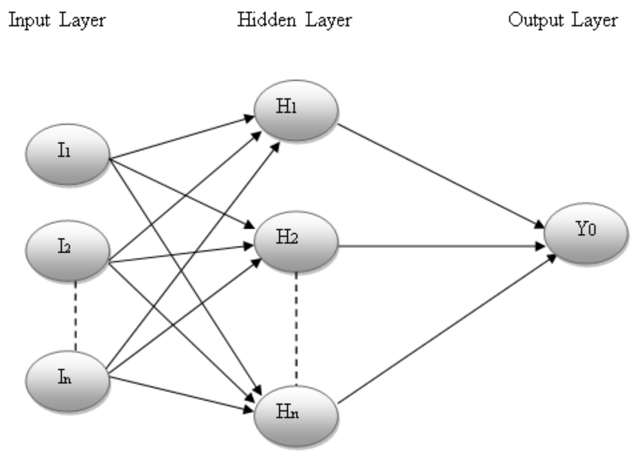

Figure 2. General feed forward neural network architecture.

AlZubi bestowed a paper that geared toward the event of AN automatic image segmentation system for classifying Region of Interest (ROI) in medical images that were obtained from completely different medical scanners like PET, CT, or MRI. Multiresolution Analysis (MRA) victimization moving ridge, ridgelet, and curvelet transforms has been utilized in the projected segmentation system. Curvelet remodel is AN extension of moving ridge and ridgelet transforms that aimed to take care of fascinating phenomena occurring on curves. Genus et al. [14] bestowed a generalized multiple-kernel Fuzzy C-M. Genus et al. [14] bestowed a generalized multiple-kernel fuzzy C-means (FCM) (MKFCM) methodology as a framework for image-segmentation issues. Within the framework, other than the very fact that the composite kernels were utilized in the kernel FCM (KFCM), a linear combination of multiple kernels was projected and also the change rules for the linear coefficients of the composite kernel were derived similarly. The projected MKFCM formula provided a versatile vehicle to fuse completely different component data in image-segmentation issues.

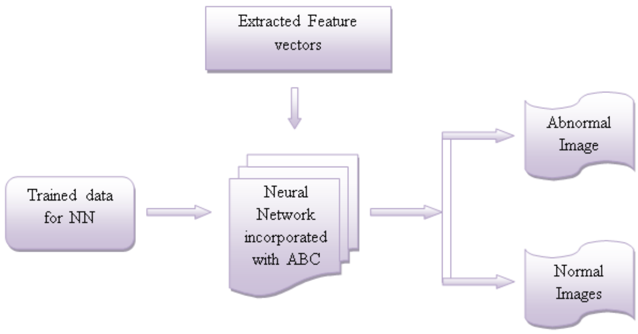

Figure 3. *Classification process in the proposed method.*

Liu et al. [15] bestowed fast interactive image segmentation methodology. Because it was projected for itinerant however it absolutely was conjointly perceptive in medical imagining instead of victimization world improvement, there algorithm began with imaginative over-segmentation victimization the mean shift formula and adopted this by judicial bunch and native anesthetic neighborhood classification. This procedure obtained higher quality results than previous ways that used graph cuts on over segmental region. Corso et al. [16] have bestowed a technique for automatic segmentation of heterogeneous image information that takes a step toward bridging the gap between bottom-up affinity-based segmentation ways and top-down generative model primarily based approaches. They enclosed Bayesian formulation for incorporating soft model assignments into the calculation of affinities, that square measure conventionally model free. They integrated the ensuing model-aware affinities into the construction segmentation by weighted aggregation formula, and apply the technique to the task of detective work and segmenting brain tumour and hydrops in multichannel MR Volumes. The computationally economical methodology runs orders of magnitude quicker than current state-of the-art techniques giving comparable or improved results. AlZubi et al. presented a paper which aimed at the development of an automatic image segmentation system for classifying Region of Interest (ROI) in medical images which were obtained from different medical scanners such as PET, CT, or MRI. Multiresolution Analysis (MRA) using wavelet, ridgelet, and curvelet transforms has been used in the proposed segmentation system. Curvelet transform is an extension of wavelet and ridgelet transforms which aimed to deal with interesting phenomena occurring along curves.

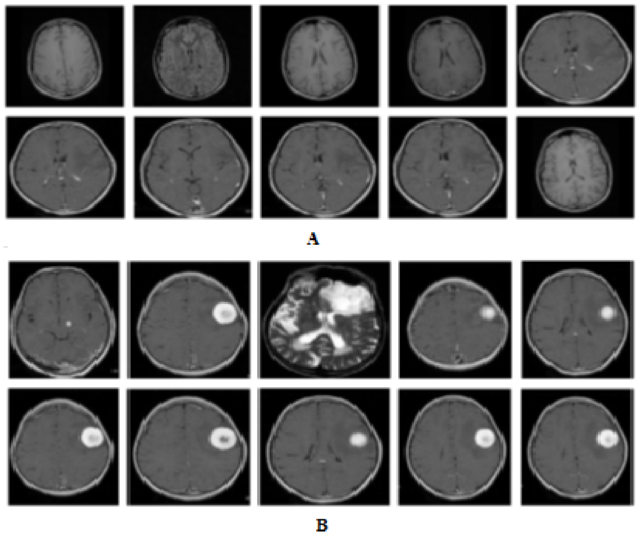

Figure 4. *MRI image dataset, A. MRI images without tumor; B. MRI tumor images.*

Proposed Method

Brain tumor detection from the MRI image has become an efficient and mostly followed method in the field of medical diagnosis. Various techniques have been developed in order to detect the tumor more efficiently. In this section, the proposed technique is described in detail about brain tumor detection. The proposed technique is carried out in four modules, namely pre-processing, segmentation, feature extraction module and classification module. The input MRI brain image is initially pre-processed using RGB to Grey Converter and median filter. The pre-processing makes the image fit for further processing. Subsequently, the image is segmented using Histogram based segmentation method in the segmentation module. From the segmented image, various features like area, mean, correlation and covariance from the images are extracted in the feature extraction module. Finally, the classification is carried out using Neural Network in the classification module to detect brain tumor. The neural network is modified using ABC where weight optimization is done. The block diagram of the proposed technique is given in Figure 1.

Preprocessing

The first step in our method is the image preprocessing. In order to reduce the imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, preprocessing steps are applied. In this, the input images are converted into grey image for better segmentation. A data set is created with the brain MRI images which are manually segmented in order to compare the segmented output for better result. After the conversion, the images are filtered to remove the noise which is present in the output. The noise removal is done with the application of filter and utilized the median filter for the noise removal which is explained in detail in the below section.

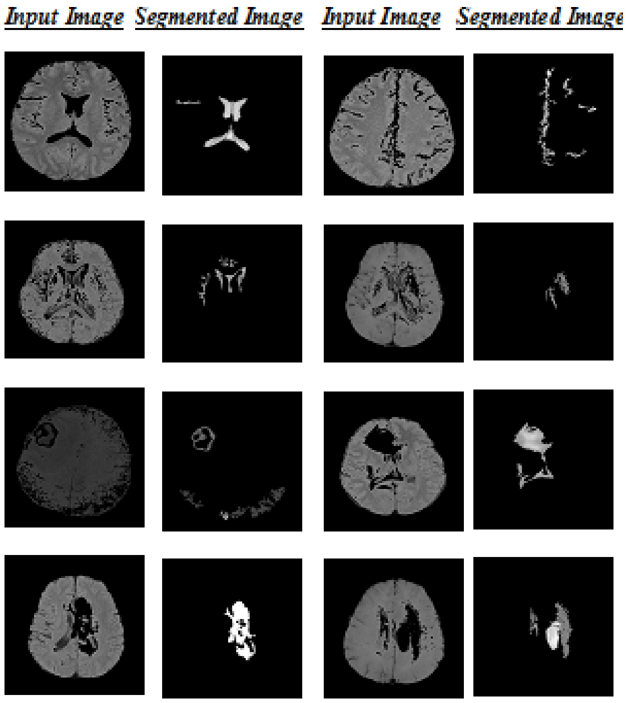

Figure 5. *Input MRI images and segmented results.*

Noise removal using Median filter: Noise suppression or noise removal is a very important task in image process. In the projected technique we tend to utilize median filter for the noise removal. The median filter is commonly applied to grey scale image as a result of its property of edge protective smoothing. Within the median filtering operation, the constituent values within the neighborhood window area unit stratified in line with intensity, and also the median becomes the output scale for the constituent underneath analysis. Therefore following steps were wont to take away the noise from images, in median filtering, the neighboring constituents area unit stratified in line with brightness and also the median becomes the new value for the central pixel. Median filters will do a wonderful job of rejecting sure forms of noise, especially, "shot" or impulse noise within which some individual pixels have extreme values. The final expression for the median filter is given as per the below equation

$$M_f(a_1, a_2 \ldots\ldots a_N) = MIN\left(\sum_{i=1}^{N} \left\|a_1 - a_i\right\|, \ldots\ldots \sum_{i=1}^{N} \left\|a_N - a_i\right\|\right)$$

$\rightarrow (1)$

Using Equation 1, the median filtering is performed to remove the noise from the acquired image. The output image from the median filter is blurred image and these images are subtracted from the black and white image obtained in the preprocessing stage to obtain the output image. These images are then processed for feature extraction.

Segmentation

In the proposed method, employed a histon based segmentation which is more effective in terms of segmentation accuracy. Histon is generally a contour which is represented based on the existing histograms of the primary image in such a manner that the group of all points with the similar intensity sphere of the predefined radius, called expanse, belong to one single value. For every intensity value in histogram, the number of pixels encapsulated in the similar intensity sphere is evaluated. This count is then added to the value of the histogram at that particular intensity value. This computation is carried out for all the intensity values that lead to the formation of histon. Histon can provide an additional asset to the histogram by improving the depiction of spatial properties of an image. The specific application of histon is in the domain of segmentation of images showing slow gradual variations in the intensity value with respect to space. In order to initialize the centroid, histon is used. The various process followed in the histon based segmentation process are explained below,

Construction of histogram: Consider an input image I of size P x Q. The histogram for the corresponding image is computed using the below equation,

$$H(S) = \sum_{p=1}^{P} \sum_{q=1}^{Q} \eta(I(p,q) - S \;\; for \;\; 0 \leq S \leq K-1 \rightarrow (2)$$

where η is the dirac impulse function and K is the total number of intensity levels in the image. The value of each bin is the number of image pixels having intensity S.

Construction of histon: Consider a X × Y neighborhood around the pixel I (p, q), the total distance of all the pixels in the neighborhood and that of I(p,q) is given by,

$$D(p,q) = \sqrt{\sum_{x \in X} \sum_{y \in Y} (I(p,q) - I(p,q))^2} \rightarrow (3)$$

where η is the dirac impulse function and K is the total number of intensity levels in the image. The value of each bin is the number of image pixels having intensity S. Then define a matrix M with M(p,q) which is given by,

$$M(p,q) = \begin{cases} 1 & D(p,q) < \text{expanse} \\ -1 & otherwise \end{cases} \rightarrow (4)$$

The expanse in the proposed method is given by

$$\text{expanse} = \frac{1}{\text{PxQ}} \sum_{p=1}^{P} \sum_{q=1}^{Q} D(p,q) \rightarrow (5)$$

The histon can be given by the expression,

$$H_a(S) = \sum_{p=1}^{P} \sum_{q=1}^{Q} (1 + G(p,q))\eta(I(p,q) - S \;\; for \;\; 0 \leq S$$

$$\leq K - 1 \rightarrow (6)$$

Where η is the dirac impulse function and K is the total number of intensity levels in the image. The value of each bin is the number of image pixels having intensity S.

Calculating the maxima and minima of histon: Once getting the histon, calculate the maxima and minima. For the discreteness of histon, find that there are many maxima and minima and the corresponding fitting curve is very hard to locate the initialization. To further reduce the number of maxima and minima, we calculate the maximum values again based on the first calculation.

Curve fitting with the reduction maximum values: Take the first c modes with largest number of pixels as the initialization. Once the segmentation is completed the feature extraction process is carried out which is then further utilized for the classification of tumor images from MRI database.

Feature extraction

Area: The simple form descriptor employed in the planned methodology is that the space the world of a selected image is calculated exploitation the expression,

$$Area,\ A \ = \frac{I_h}{I_w} \rightarrow (7)$$

Where, I_h - Image height; I_w- Image width.

Mean: is the mean of pixel in the image. The n^{th} moment of mean is

$$\mu_0 \ = \sum_{i\,=\,0}^{L\,-\,1} (z_i - m)^n p(z_i) \rightarrow (8)$$

where

z is the gray level value

m is the mean value of z.

Covariance: Covariance is a measure of how much two variables change together. The covariance between two real-valued random variables X and Y with finite second moments is given by:

$$Cov(X,Y)=E[(X-E(X))(Y-E(Y))]\rightarrow(9)$$

Where E(X) is the expected value of X .The sample covariance of the K sets of N observations on the variables is the K × K matrix with $Q=[q_{jk}]$ the entries given by

$$q_{jk} = \frac{1}{N-1}\sum_{j\,=\,1}^{N} (x_{ij} - x_j)(x_{ik} - x_k) \rightarrow (10)$$

Correlation: Correlation refers to any of a broad class of statistical relationships involving dependence. Here, correlation of the image is given as the covariance divided by the standard deviation.

$$\rho_{X,Y} = q_{jk}/\sigma_X\sigma_Y\rightarrow(11)$$

Where $\rho_{X,Y}$ is the correlation and σ is the standard deviation. After extracting the features of the each of the regions, the details are fed into the neural network for training.

Classification using neural network

Once the options extraction is formed the feature square measure recognized by examining the feature vector of the input image with the bottom image. The extracted feature values square measure accustomed the neural network. Unremarkably the neural networks square measure trained such the input needs to send a specific output. The neural network has superior compatibility with the classification procedure. Within the steered technique, the Feed Forward Neural Network is employed for coaching. The feature values square measure compared with the info offered to the neural network whereas coaching. There are square measure 3 layers particularly input layer, hidden layer and output layer during a neural network. The Figure 2 shows the basic diagram for feed forward neural network. Here enclosed an improvement formula i.e. ABC within the steered technique for the distribution of weights for the dissimilar nodes within the neural network so as to settle on comparative weights.

Planned artificial bee colony for improvement of weights in neural network: The aim of bees within the ABC model is to get the simplest resolution, the position of a food supply signifies a possible resolution to the improvement drawback and therefore the nectar quantity of a food supply corresponds to the standard (fitness) of the connected resolution [16]. Each utilized bee goes to the food supply space visited by her at the sooner cycle when sharing their data with onlookers as a result of that food supply lives in her memory, and so selects a completely unique food supply by suggests that of visual data within the neighborhood of the one in her memory and assesses its nectar quantity [17].

Employee bee phase: The colony of artificial bees encloses 3 teams of bees: utilized bees, onlookers and scouts. A bee waiting on the dance space for creating call to pick out a food supply is named onlooker a bee aiming to the food supply visited by it erstwhile is called an utilized bee. A bee effecting whimsical search is named a scout. Half of the colony contains utilized artificial bees and therefore the last half includes the onlookers. For each food supply, there's only one utilized bee. The quantity of utilized bees is a twin of the quantity of food sources round the hive in alternative words.

A set of food source positions are arbitrarily chosen by the employed bees at the initialization stage and their nectar amounts are found out. After that, these bees come into the hive and share the nectar information of the sources with the onlooker bees waiting on the dance area inside the hive. At first, ABC produces an arbitrarily distributed initial population signified by ρ having n solutions where each solution is the food source position and S_p is the population size. Each solution is represented by h_i, Where $1 \leq i \leq n$ is a N-dimensional vector, where N is the number of optimization parameters taken into consideration. After initialization, the population of the positions is subjected to replicate cycles of the search processes of the employed bees, the onlooker bees, and scout bees.

Onlooker bee phase: In this stage, choice of the food sources by the onlookers once receiving the knowledge of utilized bees and generation of novel resolution is performed. The looker-on bee wishes a food supply space betting on the nectar data allotted by the utilized bees on the dance space. Because the nectar quantity of a food supply enhances, the chance with that that food supply is chosen by onlooker will increase, too. Therefore, the dance of utilized bees carrying higher nectar recruits the onlookers for the food supply areas with higher nectar quantity.

An onlooker bee selects a food source depending on the possibility value related with that food source (P_i) specified by the expression:

$$P_i = \frac{f_i}{\sum_{a=1}^{n} f_a} \rightarrow (12)$$

Where,

f_i is the fitness value of the solution

n is the number of food sources which is equal to the number of employed bees.

After incoming at the chosen space, spectator selects a unique food supply within the neighborhood of the one within the memory looking on visual info. Visual info relies on the link of food supply positions. Once the nectar of a food supply is discarded by the bees, a unique food supply is randomly known by a scout bee and substituted with the discarded one. Associate in nursing artificial spectator bee probabilistically generates a modification on the position (solution) in her memory for locating a unique food supply and checks the nectar quantity (fitness value) of the novel supply (new solution).

Let the old position be represented by $x_{i,a}$ and the new position is represented by $q_{i,a}$, which is defined by the equation,

$X_{i,a} = q_{i,a} + \sigma_{i,a}(q_{i,a} - q_{j,a}),\ i \neq j \rightarrow (13)$

$j=\{1,2,\ldots,n\}$

$a=\{1,2,\ldots,n\}$

$\sigma_{i,a}$ is a random number in the range[-1, 1].

The position update equation shows that as the difference between the parameters of the $q_{i,a}$ and $q_{j,a}$ decreases, the perturbation on the position $q_{i,a}$ also decreases, too. Thus, as the search approaches to the optimum solution in the search space, the step length is adaptively reduced.

Rearranging the position updating step, we have:

$x_{i,a}-q_{i,a}=\sigma_{i,a}(q_{i,a}-q_{j,a}) \rightarrow (14)$

As $x_{i,a}$ is the position update from $q_{i,a}$ in the previous step, representing in the time domain, then $q_{i,a}$ as Z_T when $x_{i,a}$ is taken as Z_{T+1} . Hence:

$Z_{T+1}-Z_T=\sigma_{i,a}(q_{i,a}-q_{j,a}) \rightarrow (15)$

The left side $Z_{i+1}-Z_t$ is the discrete version of the derivative of order α=1. Therefore :

$W_\alpha[z_{T+1}]=\sigma_{i,a}(q_{i,a}-q_{j,a}) \rightarrow (16)$

Scout bee phase: The used bee whose food supply is tired out by the used and watcher bees turns into a scout and it carries out impulsive search. The food supply whose nectar is discarded by the bees is substituted with a unique food supply by the scouts. This is often replicated by at random manufacturing a grip and commutation it with the discarded one. Now, if a grip will never be increased more through a planned range of cycles referred to as limit at the moment that food supply is meant to be discarded. Within the classic ABC rule a scout explores the locality of the hive in associate impulsive means. This looking feature of scout is useful within the initial iterations; although execution of a completely impulsive movement within the final iterations might not be economical. Therefore during this strategy, a scout appearance at the search area globally within the initial iterations and domestically within the closing iterations. As within the final iterations, improvement of the simplest food supply might not occur, thus it's going to be chosen as a scout and far from the population. As a result the ABC assists to find the correct weight factors for each node in the neural network thus enhancing the classification process shown in Figure 3.

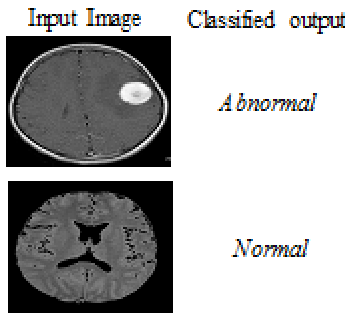

Figure 6. *Classified tumor and non tumor images.*

Results and Discussions

This section describes the experimental results of the proposed Segmentation technique using brain MRI images with and without tumors. The proposed approach is implemented in MATLAB. Here, the proposed technique is tested by using medical images taken from the publicly available sources. The performance of the proposed technique is compared with the modified region growing algorithm to evaluate the sensitivity, specificity and accuracy. Also Area, mean, covariance and correlation creates variables that are linear combinations of the original variables. The new variables have the property that the variables are all orthogonal. These components can be used to find clusters in a set of data. These components are mentioned as a variance-focused approach seeking to reproduce the total variable variance, in which components reflect both common and unique variance of the variable. These are generally preferred for the purposes of data reduction [18-19].

MRI image dataset description

The MRI image dataset utilized in the proposed image segmentation technique is taken from the publicly available sources. This image dataset contains brain images with tumor and without tumor. The Figure 4 shows some of the sample MRI images with tumor images and non-tumor images.

The experimental results obtained for the proposed technique are given in this section. The Figure 5 shows some of the input MRI images and segmented output obtained in each case. The final classification of brain tumor as normal image or abnormal image is shown in the below Figure 6. The proposed method evolved to be better in terms of classification with higher accuracy.

Table 1. *Evaluation metrics values.*

Images	TP	FP	TN	FN	Sensitivity	Specificity	Accuracy	PPV	NPV	FDR
1	1	1	1	0	1	0.5	0.83	50	100	50
2	1	1	2	0	1	0.67	0.91	50	100	50
3	1	1	3	0	1	0.75	0.94	50	100	50

Table 2. *Performance of the HGNN classification method from different brain MRI images.*

Images	TP	FP	TN	FN	Sensitivity	Accuracy	Specificity	PPV	NPV	FDR
1	1	0	3	1	50	80	100	100	75	0
2	1	0	4	0	100	85	100	100	100	0
3	1	0	4	0	100	90	100	100	100	0

Table 3. *Performance of the IPSONN classification method from different brain MRI images.*

Images	TP	FP	TN	FN	Sensitivity	ACC	Specificity	PPV	NPV	FDR
1	0	1	4	0	90	80	80	0	100	100
2	1	0	4	0	100	87	100	100	100	0
3	1	0	4	0	100	91	100	100	100	0

Performance evaluation

The evaluation metrics used to evaluate the proposed technique consists of sensitivity, specificity and accuracy. In order to find these metrics, we first compute some of the terms of True positive (TP), True negative (TN), False negative (FN) and False positive (FP). Sensitivity is the proportion of true positives that are correctly identified by a diagnostic test. It shows how good the test is at detecting a disease (Table 1).

Table 4. *Evaluation metrics in proposed and existing method.*

Methods	Sensitivity	Specificity	Accuracy
Proposed method	100	60.5	87.5
HGNN	83	100	85
IPSONN	96	93.3	86

Sensitivity=TP/(TP+FN)

Specificity is the proportion of the true negatives correctly identified by a diagnostic test. It suggests how good the test is at identifying normal (negative) condition.

Specificity=TN/(TN+FP)

Accuracy is the proportion of true results, either true positive or true negative, in a population. It measures the degree of veracity of a diagnostic test on a condition.

Accuracy=(TN+TP)/(TN+TP+FN+FP)

Comparative analysis

In order to evaluate the effectiveness of the proposed method we have compared our technique with that of other methods likes HGNN and IPSONN. The Table 2 shows the values obtained in the existing method where HGNN is used. The values shows that our proposed delivered better results in terms of accuracy, specificity and sensitivity. The Table 3 shows the statistical values that are obtained in the existing method where IPSONN is used. The values reveal that our proposed method is more efficient in terms of accuracy and other measures. The Table 4 shows the comparative averages of the proposed method along with the other existing works like HGNN and IPSONN. The average values shows that our proposed method delivers better results in terms of accuracy, specificity and sensitivity. The graphical representation of the various evaluation metrics in proposed and existing methods are , The Figure 7 shows the graphical representation of the sensitivity value for proposed and existing methods like HGNN and

IPSONN. The value shows that the proposed method delivers better results.

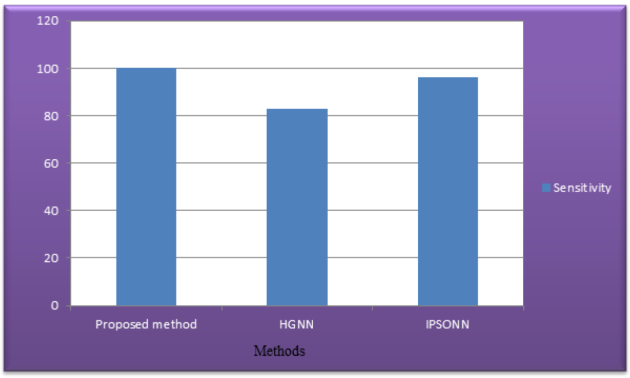

***Figure** 7. Graphical representation for sensitivity in proposed and existing method.*

The Figure 8 shows the graphical representation of the specificity value for proposed and existing methods like HGNN and IPSONN. The value shows that the proposed method delivers better results.

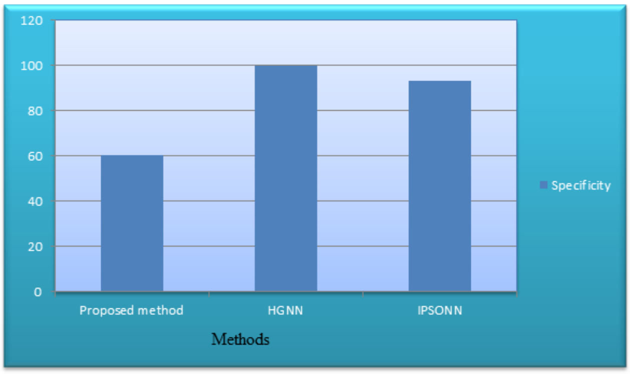

***Figure** 8. Graphical representation for specificity in proposed and existing method.*

The Figure 9 shows the graphical representation of the Accuracy value for proposed and existing methods like HGNN and IPSONN. The value shows that the proposed method delivers better results.

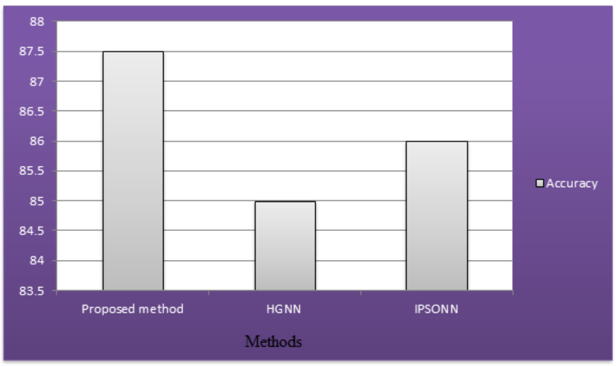

***Figure** 9. Graphical representation for accuracy in proposed and existing method.*

Conclusion

In this paper, an effective technique for classification of brain tumor is presented. The proposed technique consists of pre-processing, segmentation, feature extraction of the region and finally classification. The MRI image dataset that utilized in the proposed image segmentation technique is taken from the publicly available sources. The performance of the proposed technique is evaluated by considering the existing algorithm and the proposed method in terms of the evaluation metrics. The obtained results for the tumor detection area unit evaluated through analysis metrics specifically, sensitivity, specificity and accuracy. So as to seek out these metrics, it is tend to initial cipher a number of the terms like, True positive, True negative, false negative and false positive. From the analysis metrics, we will see that our technique achieved higher results for sensitivity, specificity and accuracy that tested the effectiveness of the planned technique.

References

1. Zuo W, Wang K, Zhang D, Zhang H. Combination of Polar Edge Detection and Active Contour Model for Automated Tongue Segmentation. In Proceedings of the Third International Conference on Image and Graphics, 2004.
2. Sharma N, Aggarwal LM. Automated medical image segmentation techniques. J Med Physics 2010; 35: 3-14.
3. http://www.fda.gov/Radiation-EmittingProducts/default.htm
4. Cheng HD, Jiang XH, Sun Y, Wang J. Colour image segmentation: advances and prospects. Pattern Recognition 2001; 34: 2259-2281.
5. Ma Z, Manuel J, Tavares RS, Jorge RN. Segmentation of Structures in 2d Medical Images. In proceedings of 5th European Congress on Computational Methods in Applied Sciences and Engineering. 2008.
6. Zijdenbos A, Forghani R, Evans A. Automatic pipeline analysis of 3D MRI data for clinical trials: application to multiple sclerosis. IEEE Transact Med Imaging 2002; 21: 1280-1291.
7. Jabbar NI, Mehrotra M. Application of Fuzzy Neural Network for Image Tumor Description. Proceedings World Academy Sci Eng Technol. 2008; 2: 8.
8. Iscan Z, Dokur Z, Ölmez T. Tumor detection by using Zernike moments on segmented magnetic resonance brain images. Expert Systems with Applications 2010; 37: 2540-2549.
9. Jaya J, Thanushkodi K, Karnan M. Tracking Algorithm for De-Noising of MR Brain Images. IJCSNS Int J Comput Sci Network Security 2009; 9: 11.
10. Song T, Laine AF, Chen Q, Rusinek H, Bokacheva L, Lim RP, Laub G, Kroeker R, Lee VS. Optimal k-space sampling for dynamic contrast-enhanced MRI with an application to MR renography. Magnetic Resonance Med 2009; 61: 1242-1248.

11. Qin AK, Clausi DA. A Multiple-Kernel Fuzzy C-Means Algorithm for Image Segmentation. IEEE Transact Image Process 2010; 19: 2157-2169.
12. Li C, Huang R, Ding Z, Gatenby JC, Metaxas DN. A Level Set Method for Image Segmentation in the Presence of Intensity Inhomogeneities With Application to MRI. IEEE Transact Image Process 2011; 20: 545-556.
13. Chen L, Chen CLP, Lu M. A Multiple-Kernel Fuzzy C-Means Algorithm for Image Segmentation. IEEE Transact Systems Cybernetics 2011.
14. Liu D, Pulli K, Shapiro L, Xiong Y. Fast interactive image segmentation by discriminative clustering. Proceedings of ACM Multimedia 2010.
15. Corso JJ, Sharon E, Dube S, El-Saden S, Sinha U, Yuille A. Efficient Multilevel Brain Tumor Segmentation with Integrated Bayesian Model Classification. IEEE Transact Med Imaging 207: 629-640.
16. Karaboga D, Ozturk C. Fuzzy clustering with artificial bee colony algorithm. J Sci Res Essays 2010; 5: 1899-1902.
17. Ali SM, Abood LK, Abdoon RS. Brain Tumor Extraction in MRI images using Clustering and Morphological Operations Techniques. Int J Geographical Info System Appl Remote Sensing. 2013.
18. Sheejakumari V, Gomathi S. Healthy and pathological tissues classification in MRI Brain Images using Hybrid Genetic Algorithm-Neural Network (HGANNA) Approach. European J Sci Res 2012; 87: 212-226.
19. Sheejakumari V, Gomathi S. MRI Brain Images healthy and pathological tissue classification with aid of Improved Particle Swarm Optimization and Neural Network (IPSONN). Comput Math Methods Med. 2015; 2015: 1-12.

[*]Correspondence to:

V Sheejakumari

Department of Information Technology

Rajas Engineering College

India