Global Journal of Pure and Applied Mathematics.
ISSN 0973-1768 Volume 13, Number 7 (2017), pp. 3919-3935

http://www.ripublication.com

Classification of Brain Tumor by DEA-ANN with DTCWT Based Features and Mixture Model Based Brain MRI Segmentation

Deepa[1]* and Sam Emmanuel[2]

[1] Loyola Institute of Technology and Science, Anna University, Tamil Nadu, India
[2] Nesamony Memorial Christian College, Manonmaniam Sundaranar University, Tamil Nadu, India.
**Corresponding author [1]E-mail: deepaamuth@gmail.com*
[2]E-mail: sam_emmanuel@yahoo.com

Abstract

Segmentation of medical images is crucial in computer vision issues. Classification is especially for variation from abnormality identification in magnetic resonance (MR) brain images. In the proposed DTCWT based DEA-ANN methodology, initially the brain MRI is divided into white matter (WM), grey matter (GM), Cerebrospinal liquid (CSF) and outliers by ordering of observations. Then outliers comprises of tumor cells in which Dual Tree Complex Wavelet Transform (DTCWT) based Features along with extra eight type of features Contrast, Correlation, Homogeneity, Energy, Entropy, Standard deviation, Skewness, and Kurtosis are extracted. Finally, the extracted components are trained by Dolphin Echolocation Algorithm (DEA) - Artificial Neural Network (ANN) to analyze those features to judge whether brain tumor is available in the given image or not. Our proposed method has obtained a classification accuracy of 98.99% compared with other classifier. This leads to better classification accuracy and made promising method for brain tumor identification.

Keywords: Tumor detection, Dual tree complex wavelet transform, Dolphin echolocation algorithm, Artificial neural network, Brain MRI image.

1. INTRODUCTION

Image segmentation is a standout amongst the most boundless intends to arrange effectively the pixels of an image in a decision situated applications. Image segmentation is a method that segments an image into uniform and non-overlapping

regions taking into account on some similarity measure [1]. This method has an assortment of application, including PC vision, picture examination, restorative medical handling, remote sensing and geological data framework [2]. Image segmentation depends on two essential properties of image one is intensity values, including intermittent that alludes to sudden or unexpected changes in intensity as edges and the other one is similar that alludes to partitioning a computerized image into regions as indicated by some pre-characterized resemblance standard [3]. Be that as it may, it is still a challenging issue for images are regularly bounded by complex noise and intensity inhomogeneity [4].

One of the essential stages in the medical image investigation is segmentation of objects or identification of their contours. Medical images are moderately difficult to segment because of a few undesirable properties, for example, low signal to-noise and contrast-to-noise proportions, and broken edges [5]. The segmentation of some of the medical images is a troublesome task because of its little size, low contrast, and apparent brokenness of the edges [6]. In this connection, diversity of segmentation strategies has been tested in the literature, including Histogram Thresholding [7], Edge Detection [8], Region Growing [9], Watershed Transformation [10], Clustering and Soft Computing methods. Soft Computing procedures include image segmentation utilizing Genetic algorithms [11, 12] Fuzzy Logic strategies [13] and Neural Network based methodologies [14, 15].

Feature extraction is one of the most important methods for capturing visual content of an image. This approach combines the intensity-, texture-, and shape based features and classifies the tumor as white matter, gray matter, CSF, and abnormal and normal areas. The various methods such as multi-texton histogram (MTH), principal component analysis (PCA), texton co-occurrence matrix (TCM), and linear discriminant analysis (LDA) are used for reducing the number of features [16–19].

In this proposed methodology, we have used Dual Tree Complex Wavelet Transform (DTCWT) based features along with additional eight features to accurately obtain the information present in the brain image along with in order to improve the classification performance and to overcome the drawback of existing Artificial Neural Network (ANN) here we design new optimized Dolphin Echolocation Algorithm (DEA) based ANN classifier.

The organization of the paper is summarized as follows. The proposed methodology is explained in section 2 followed by experimental results and their results are discussed in section 3. Finally the conclusion is explained in section 4.

2. RELATED WORKS

Havaei M *et al.* [20] have presented a fully automatic brain tumor segmentation method on basis of Deep Neural Networks (DNNs). Demirhan A *et al.* [21] have presented a new tissue segmentation algorithm to segmented brain MR images utilizing self-organizing map that was trained with unsupervised learning algorithm and fine-tuned with learning vector quantization (LVQ). Vishnuvarthanan G *et al.* [22] have proposed

Novel SOM based FKM algorithm for tissue segmentation and tumor identification in magnetic resonance brain images. Pereira S *et al.* [23] have proposed an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3 ×3 kernels. Yang G *et al.* [24] have proposed a novel wavelet-energy based approach for automated classification of MR brain images as normal or abnormal.

3. BRAIN TUMOR CLASSIFICATION BY DEA-ANN WITH DTCWT BASED FEATURES

In this proposed methodology, we present a novel method for identification of tumor in brain MRI through the detection of outliers. Identification of tumor in brain MRI is one of the complex task, the detection through outlier will enhance the detection accuracy. The proposed method consider three types of brain MRI (T1W, T2W and FLAIR) acquisition, then classify the samples into three basic components of white matter (WM), gray matter (GM) and Cerebrospinal fluid (CSF) using confidence level of ordering. Then the remaining unclassified samples are considered as outliers. These outliers are trimmed from the samples and the mixture parameters used for the further analysis of mixture model of brain MRI which is obtained by Log-likelihood maximization using Expectation Maximization (EM) algorithm. Then DTCWT based features along with eight additional features are extracted from outliers. Finally, these features are used to identify the tumor cell by using Dolphin Echolocation Algorithm (DEA) -Artificial Neural Network (ANN) classifier. The process flow of the proposed method is shown in Fig. 1.

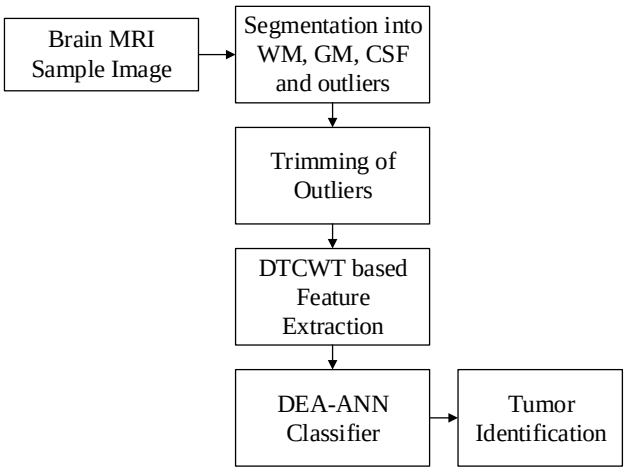


Figure. 1 Process flow of proposed method

3.1 Segmentation

3.1.1 Maximum Likelihood Estimators

Let $Y = \{y_1, y_2, ..., y_N\}, y_j \in R^d$ denotes the random sample of N independent and identically distributed (i.i.d.) observations trained from unobservable d-variate

multimodal distribution $\tilde{\psi}$. By supposing $\tilde{\psi}$ has K different modes, each belonging to family of parametric unimodal distribution models, distribution $\tilde{\psi}$ can be denoted as a K-component mixture.

$$\tilde{\psi} \approx \psi(y \mid \Theta) = \sum_{k=1}^{K} \pi_k \, p(y \mid \theta_k) \tag{1}$$

Where $\Theta = \{\pi_k, \theta_k\}_{k=1}^{K}$ represents a set of indefinite mixture parameters, with mixing weights π_k that act upon $\pi_k > 0, \forall k$ and $\sum_{k=1}^{K} \pi_k = 1$, and parameters $\theta_k \subset R^d$ of d-variate distribution model $p(y \mid \theta_k)$ of the kth component. In standard mixtures, the parameters θ_k denote the place μ_k and scale Σ_k of the kth component. The indefinite mixture parameters Θ can be found by maximizing the likelihood function $l(\Theta \mid Y) = \prod_{y \in Y} \psi(y \mid \Theta)$ of sample Y or by maximizing the equivalent log-likelihood function.

$$L(\Theta \mid Y) = \sum_{y \in Y} \log(\psi(y \mid \Theta)) \tag{2}$$

If sample Y is contaminated by outliers, maximizing the log-likelihood (2) leads to biased approximations of Θ. An unbiased estimator is attained by trimming the outliers such that the log-likelihood is calculated on a subsample Y_H, i.e, $L(\Theta \mid Y_H)$, which does not comprise any outliers. Subsample Y_H of size $H = [N(1-\alpha)]$ is acquired by trimming fraction α of all the observations, where α have to be set higher or equal to the predictable outlier fraction h $(\alpha \geq h)$. Selection of these H observations is a serious step that needs a specific ordering of observations, based on which inlying observations are possible to be selected into subsample Y_H than the outliers.

2.1.2 Ordering of Observations

The confidence level ordering is used to obtain robust estimates of the parameters of unbalanced mixtures and unbalanced scales, here the ordering of observations $\tilde{v}(Y \mid \Theta) = (\tilde{v}_1, ..., \tilde{v}_N)$ based on monotonically growing component wise confidence levels of observations.

$$\int_{\Omega(y_{\tilde{v}_1})} p(w \mid \theta_{z_{\tilde{v}_1}}) dw \leq ... \leq \int_{\Omega(y_{\tilde{v}_N})} p(w \mid \theta_{z_{\tilde{v}_N}}) dw \tag{3}$$

Where $\Omega(y_j) = \{w \in \Omega : p(w \mid \theta_{z_j}) \geq p(y_j \mid \theta_{z_j})\}$ are equivalent confidence regions, $\Omega \subseteq R^d$ is the sample space, and $z_j \in \{1, ..., K\}$ is a grouping of observations to one of K components. If EM algorithm is utilized to estimate the mixture parameter Θ, observations $y_j \in Y$ can be categorized based on maximum posterior probability as,

$$z_j = \arg\max_{k=1,..,K} \tau\left(y_j \mid \theta_k\right) \tag{4}$$

Where $\tau\left(y_j \mid \theta_k\right) = \pi_k p\left(y_j \mid \theta_k\right) \Big/ \sum_{l=1}^{K} \pi_l p\left(y_j \mid \theta_l\right)$. In normal type of the mixtures, each observation $y_j \in Y$ can be categorized based on component wise Mahalanobis distances $d_{\Sigma}^2\left(y_j \mid \mu_k, \Sigma_k\right) = \left(y_j - \mu_k\right)\Sigma_k^{-1}\left(y_j - \mu_k\right)^T$ as

$$z_j = \arg\min_{k=1,..,K} d_{\Sigma}^2\left(y_j \mid \mu_k, \Sigma_k\right) \tag{5}$$

The confidence levels essential for the ordering (3) can be calculated from the Mahalanobis distances $d_{\Sigma}^2\left(y_j \mid \mu_{z_j}, \Sigma_{z_j}\right)_{j=1,...,N}$ as value of cumulative density function of χ_d^2 distribution.

2.1.3 Trimming of observations

The algorithm for likelihood maximization based on confidence level ordering is given here.

Input: Trimming fraction α, initial parameters $\Theta^{(0)} = \left\{\pi_1^{(0)},...,\pi_K^{(0)},\theta_1^{(0)},...,\theta_K^{(0)}\right\}$, and log likelihood termination threshold ϵ.

Confidence level ordering (3), conserves the inlying observations of all the mixture constituents even for samples of highly unbalanced mixtures and constituents of heterogeneous scales.

2.2 Feature Extraction

In the feature extraction process, we need to extract the features from the outliers in order to identify the tumor in the brain MRI images. The proposed method, extracts dual tree complex wavelet transform based feature extract along with additional eight types of features. They are texture features and intensity based features like contrast, correlation, homogeneity, energy, entropy, standard deviation, skewness and kurtosis. Before feature extraction we need to identify the shape of the tumor this can be identified by using Region of Interest (ROI).

2.2.1 Region of Interest

Initially pixel having higher intensity value in the image is chosen, then it is compared with nearby pixels. The process goes till there is variation in the intensity level of pixel value. All the pixels having the same intensity form the Region of Interests (ROI). Then from these Regions the features are extracted for classification purpose.

2.2.2 Dual Tree Complex Wavelet Transform (DTCWT)

In dual-tree, two real wavelet trees are utilized, each proficient of perfect reconstruction (PR). One tree produces the real part of the transform while the additional is utilized in producing complex part. As exposed, {R_0 (k), R_1(k)} is a Quadrature Mirror Filter (QMF) pair in the real-coefficient analysis branch. For the complex part, {J_0(k), J_1(k)} is another QMF pair in the analysis branch.

The filters utilized for DTCWT are designated to be linear-phase sustaining the Perfect Reconstruction (PR) condition and are combined so that the final result of the transform is around analytic.

$$\Psi(t) = \Psi_R(t) + j\Psi_J(t) \tag{6}$$

where $\Psi_R(t), \Psi_J(t)$ are the wavelet made by two DWTs. In addition, both low-pass filters R_0(k) andJ_0(k) have to be intended to possess a property so as the corresponding wavelets to form an rough Hilbert transform pair.

$$\Psi_J(t) \approx H\{\Psi_R(t)\} \tag{7}$$

where

$$\Psi_R(t) = \sqrt{2}\sum_k R_1(k)\Phi_R(t) \tag{8}$$

$$\Phi_R(t) = \sqrt{2}\sum_k R_0(k)\Phi_R(t) \tag{9}$$

For this goal one of the two low pass filters has to be approximately half-sample shift to the other

$$J_0(k) \approx R_0(k-0.5) \Rightarrow \Psi_J(t) \approx H\{\Psi_R(t)\} \tag{10}$$

This half-sample delay principals to approximately shift invariant wavelet transform. Also one-dimensional application, DTCWT may be utilized for two dimensional tasks over 2-D DT CWT relying on the M-D dual-tree wavelets possessions to be around analytic and oriented.

2.2.3 Texture Features Based Spatial Gray Level Dependence Matrix method (SGLDM)

Spatial Gray Level Dependence Matrix technique (SGLDM) is utilized in each ROI to extract second order measurable texture features for the analysis. This system is in light of the estimation of second order joint conditional likelihood density functions $[P(i, j/d, \theta)]$. The calculated value for these likelihood density function is given by

$$\phi(d,\theta) = [P(i, j/d, \theta)], 0 < i, j < N_g \tag{11}$$

Where N_g is maximum grey level. $\theta = 0,45,90, and\, 135$ degrees. Each $P(i, j \mid d, \theta)$ is the likelihood grid of two pixels which are placed with a inter test distance d and

direction θ having a gray level i to j. In this technique, four gray level co-occurrence matrixes for four different directions are acquired for a given distance and the following five statistical texture features are computed for each gray level co-occurrence matrix.

Contrast: It is a measure of local variants of gray levels exhibit in an image. Images with huge adjacent gray level differences are related with high contrast. Contrast of the image is given by

$$\text{Contrast} = \sum_{i,j} (i-j)^2 g(i,j) \tag{12}$$

Where g (i, j) relates to the elements of co-occurrence matrix, i.e the likelihood of moving from pixel with gray level i to j.

Correlation: It is a measure of uniformity of grayscale distribution of pixels. A texture on high correlation has a uniform distribution, whereas a texture on low correlation is non-uniform. The correlation is given by

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu)(j-\mu)g(i,j)}{\sigma^2} \tag{13}$$

Where $\mu = \sum_{i,j} ig(i,j)$ and $\sigma = \sum_{i,j} (i-\mu)^2 g(i,j)$.

Homogeneity (*Inverse Difference Moment)*: It is a measure of the local homogeneity of an image. Homogeneity is given by

$$\text{Homogeneity} = \sum_{i,j} \frac{1}{1+(i-j)^2} g(i,j) \tag{14}$$

Energy: It is a measure of image homogeneity, it replicates pixel pair replications. Identical images have very rare gray tone changes, which result into higher energy. Energy is given by

$$\text{Energy} = \sum_{i,j} (g(i,j))^2 \tag{15}$$

Entropy: Entropy is a measure of non-uniformity of the image or region of interest. It is calculated by using

$$\text{Entropy} = -\sum_{i,j} g(i,j) \log(g(i,j)) \tag{16}$$

2.2.3 Intensity Based Features

Here we extract three types of intensity based features like standard deviation, skewness and kurtosis.

Standard deviation: Standard deviation gives the variation or distribution exists from average value. The low value specifies that data points tend to be very near to mean, whereas high value specifies that data point spread out above big range of values. The standard deviation is given by

$$SD = \sqrt{\frac{1}{N^2}\sum_{i,j=1}^{N}\left(p(i,j) - \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j)\right)^2} \tag{17}$$

Where p (i, j) = transformed value of estimation sub band matrix of size N*N.

Skewness: Skewness is the measure of the asymmetry of the probability distribution of a real valued random variable. Skewness SK is calculated by using,

$$SK = \frac{1}{SD^3}\sum_{i,j=1}^{N}\left(p(i,j) - \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j)\right)^3 \tag{18}$$

Kurtosis: Kurtosis is a measure of the shape of the probability distribution of a real valued random variable. Kurtosis KU is calculated by

$$KU = \frac{1}{SD^4}\sum_{i,j=1}^{N}\left(p(i,j) - \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j)\right)^4 \tag{19}$$

Totally eight type of features are extracted for the image along with DTCWT based features are given to classification stage to identify the tumor cell in the MRI brain images.

2.3 Classification using DEA based ANN

A classification method uses Artificial Neural Network classifier (ANN) for classifying the reviews and opinions.

Dolphins primarily investigate all around the search space to discover the prey. The moment a dolphin approaches the target, the animal confine its search, and incrementally increases its clicks in order to concentrate on the location. The method simulates dolphin echolocation by restraining its exploration relative to the distance from the target. Prior to starting, search space should be sorted out by using the following regulation.

Search space order: For every variable to be optimized during the procedure, sort alternatives of the search space in an uphill or downhill order. If alternatives take account of more than one characteristic, then carry out ordering according to the most significant one. Using this technique, for variable j, vector A_j of length LA_j is shaped which contains all probable alternatives for the j^{th} variable putting these vectors subsequently to each other, as the columns of a matrix, the Matrix Alternatives$_{MA+NV}$ is produced, in which MA is $\max(LA_j)_{j=1:NV}$, with NV being the number of variables.

Furthermore, a curve according to which the convergence factor must change during the optimization procedure should be assigned. Here, the change of convergence *(CF)* is considered as

$$PP(Loop_i) = PP_i + (1 - PP_1)\frac{Loop_i^{power} - 1}{(LoopsNumber)^{power} - 1} \quad (20)$$

PP is the predefined probability, PP_1 the convergence factor of the first loop in which the answers are selected randomly, $Loop_i$ the number of the current loop.

The detailed procedure of dolphin echolocation algorithm (DEA) as follows,

1. Start *NL* locations for a dolphin arbitrarily. This step enclose creating L_{NL+NV} matrix, in which *NL* is the number of locations and *NV* is the number of variables.
2. Compute the *PP* of the loop using Equation (20).
3. Calculate the fitness of each location.
4. Calculate the accumulative fitness according to dolphin rules as follows.
   - for i = 1 to the number of locations
   - for j = 1 to the number of variables
   - find the position of *L(i,j)* in j^{th} column of the Alternatives matrix andname it as *A*. for $k = -R_e$to R_e

$$AF_{(A+K)j} = \frac{1}{R_e} * (R_e - |k|)Fitness\ i + AF_{(A+K)j} \quad (21)$$

Where $AF_{(A+k)j}$ is the accumulative fitness of the $(A + k)^{th}$ alternative to be chosen for the j^{th} variable, R_e is the effective radius in which accumulative fitness of the alternative *A*'s neighbours are affected from its fitness. *Fitness(i)* is the fitness of location *i*. It should be added that for alternatives close to edges (where $A + k$ is not a valid; $A + k < 0$ or $A + k > LAj$), the *AF* is calculated using a reflective characteristic.

In order to hand out the option much evenly in the search space, a small value of ε is added to all the arrays as $AF = AF + \varepsilon$. Here, *e* should be selected according to the method the fitness is defined. It is superior to be less than the minimum value achieved for the fitness.

Find the top location of this loop and name it "The best Location". Find the alternatives allocated to the variables of the top location, and let their *AF* be equal to zero. And it can be defined as follows

- for *j=1*: Number of variables
- for *i = 1*: Number of alternatives
- if *i* = The best location*(j)*

$$AF_{ij}=0 \quad (22)$$

5. For variable $j_{(j=1toNV)}$, compute the probability of choosing alternative $i_{(i=1toALj)}$, according to the following relationship:

$$P_{ij} = \frac{AF_{ij}}{\sum_{i=1}^{LA_j} AF_{ij}} \tag{23}$$

6. Allocate a probability equal to *PP* to all alternatives chosen for all variables of the best location and dedicate rest of the probability to the other alternatives according to the following formula:

- for $j = 1:$ Number of variables
- for $i = 1:$ Number of alternatives
- if i = The best location(j)

$$P_{ij} = PP \tag{24}$$

Else

$$P_{ij} = (1 - PP)P_{ij} \tag{25}$$

Compute the subsequently step locations according to the probabilities assigned toeach alternative. Replicate Steps 2–6 as many times as the Loops Number.

The process is repeated until the back propagation error gets minimized. i.e. If the minimum value is obtained, then the FFBNN is well trained for performing the testing phase. Accordingly, ANN classifier is well trained and the features are tested. In the testing phase, a query image is given by performing all the initial process mentioned and the tumor image associate to the query image are classified.

4. EXPERIMENTAL RESULTS & DISCUSSIONS

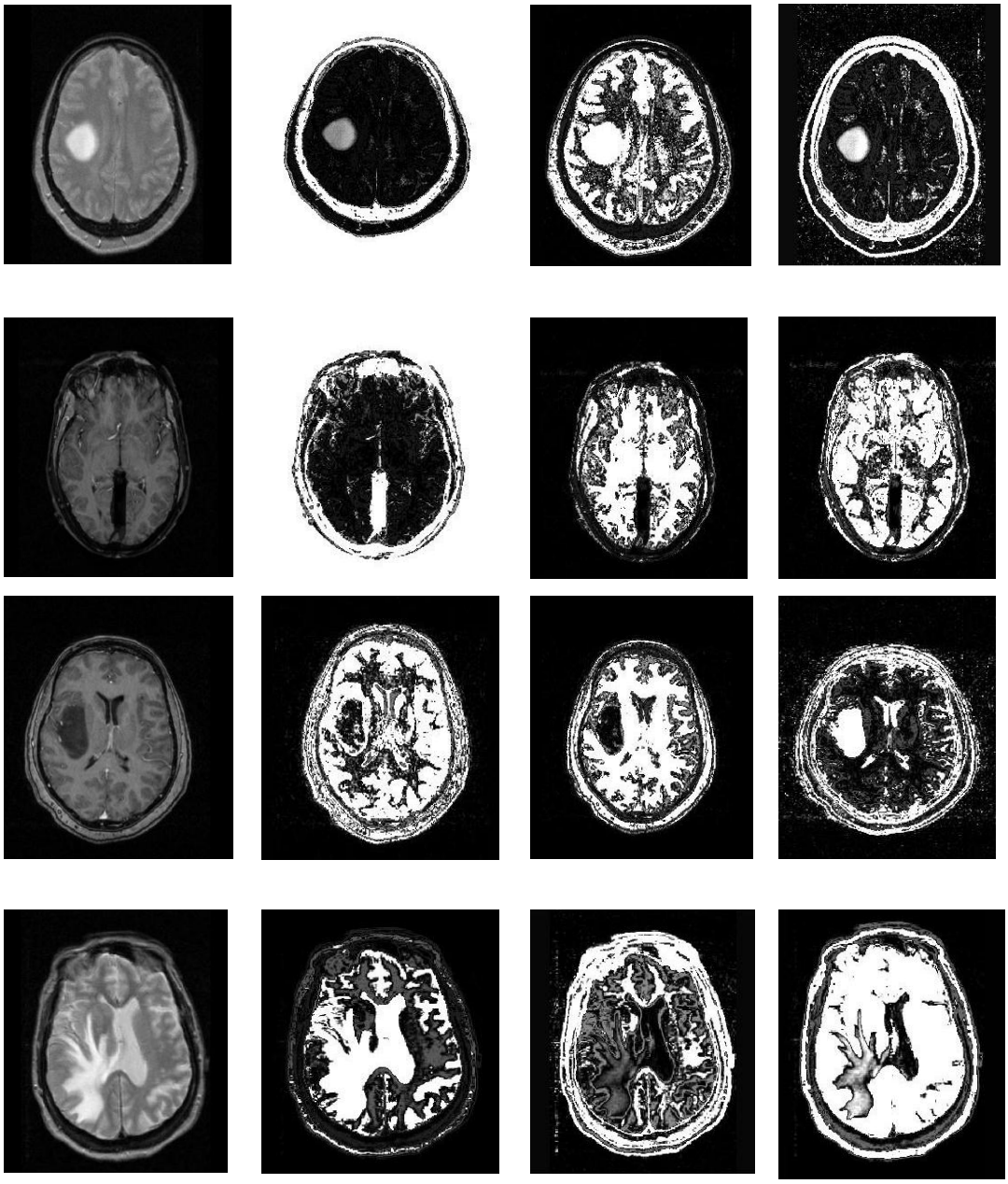
The proposed system for the segmentation and classification of tumors in brain image is implemented in the working platform of MATLAB with the following system configuration. In this proposed methodology we have used Brain MRI database used for proposed method will be taken form the "The Cancer Imaging Archive (TCIA)" provided by the Frederick National Laboratory and the experimental results are compared with existing method.

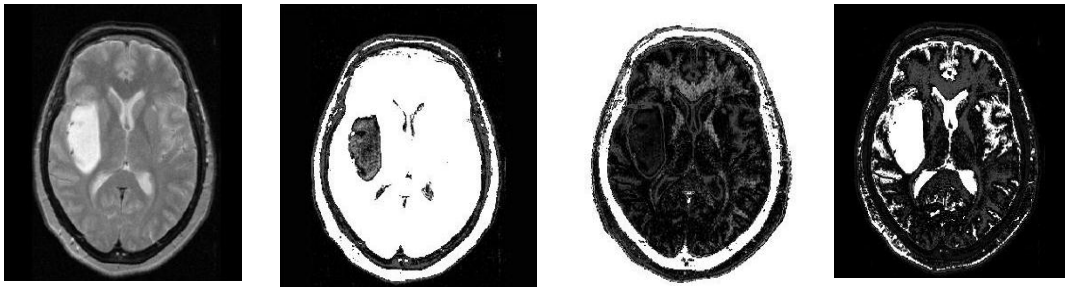
The proposed method uses a process for segmentation of brain tumor by mixture model to segment into white matter (WM), grey matter (GM), cerebrospinal fluid (CSF) and remaining unclassified samples as outliers.

4.1 Segmentation Results

A healthy brain matter can be classified into three tissues, white matter (WM), cerebrospinal fluid (CSF) and gray matter (GM) and remaining outliers. In our proposed method initially we have considered different images with and without tumor which is shown in Fig. 2. The segmented image for the input images are shown in Fig. 2. In order

to evaluate the performance evaluation of the segmented images we have used the following parameters Dice Index, Jaccard Index, True Positive Fraction (TPF), False Negative Fraction (FNF), False Positive Fraction (FPF) and True Negative Fraction (TNF).





(a) (b) (c) (d)

Figure. 2 Segmented images: (a) input images, (b) white matter, (c) grey matter and (d) cerebrospinal fluid

The performance chart for the Table 1 is given in Fig. 3, we can see that the proposed method has attained improvement in all metrics like Dice index, Jaccard index, TPF, FNF, FPF, and TNF this results shows analytically showed the effectiveness of the proposed method.

The formula used for calculating these parameters are

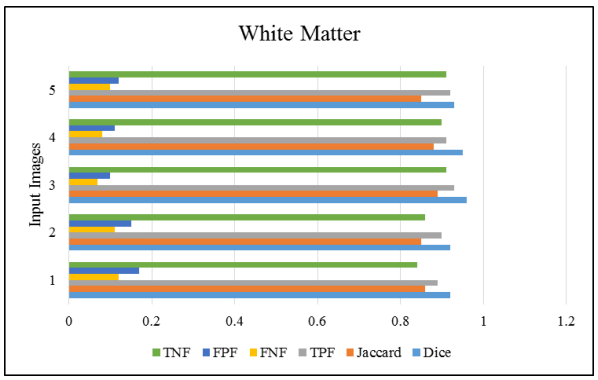
$$\text{TPF} = \frac{R_t \bigcap R_g}{R_g} \tag{26}$$

$$\text{FNF} = \frac{R_g - R_t}{R_g} \tag{27}$$

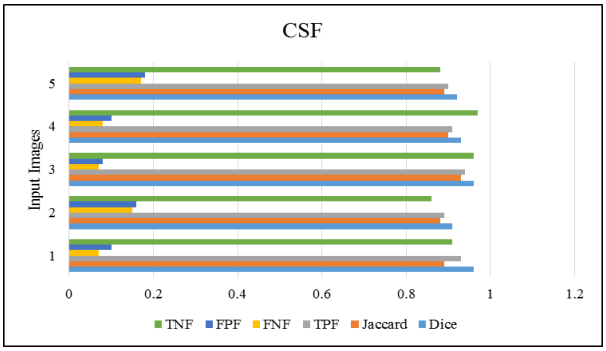
$$\text{FPF} = \frac{R_t - R_g}{R_g} \tag{28}$$

$$\text{TNF} = 1 - \frac{R_t - R_g}{R_g} \tag{29}$$

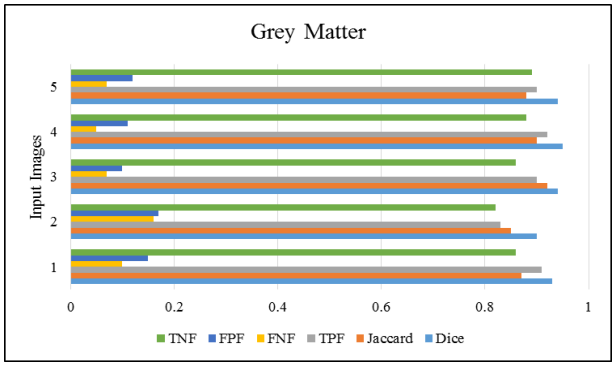
Where R_t is the resulting image and R_g is the ground truth image. The performance for the different types of images are shown below in table.



(a)



(b)



(c)

Figure. 3 Performance Graph for the segmented image: (a) white matter (WM), (b) cerebrospinal fluid (CSF) and (c) gray matter (GM)

Table 1. Performance Metrics of Segmented Images

Metrics	**White Matter**					**Grey Matter**					**CSF**				
Images	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Dice	0.92	0.92	0.96	0.95	0.93	0.93	0.90	0.94	0.95	0.94	0.96	0.91	0.96	0.93	0.92
Jaccard	0.86	0.85	0.89	0.88	0.85	0.87	0.85	0.92	0.90	0.88	0.89	0.88	0.93	0.90	0.89
TPF	0.89	0.90	0.93	0.91	0.92	0.91	0.83	0.90	0.92	0.90	0.93	0.89	0.94	0.91	0.90
FNF	0.12	0.11	0.07	0.08	0.10	0.10	0.16	0.07	0.05	0.07	0.07	0.15	0.07	0.08	0.17
FPF	0.17	0.15	0.10	0.11	0.12	0.15	0.17	0.10	0.11	0.12	0.10	0.16	0.08	0.10	0.18
TNF	0.84	0.86	0.91	0.90	0.91	0.86	0.82	0.86	0.88	0.89	0.91	0.86	0.96	0.97	0.88

3.2 Classification Results

After the segmentation of white matter (WM), grey matter (GM), cerebrospinal fluid (CSF) there are some samples which are unclassified that samples are considered as outliers that region consists of tumor cell. In order to identify, a DTCWT based feature extraction along with additional eight types of features are extracted from the outliers. These features are given to the DEA based ANN for classification of brain tumor. The contigency table is given in Table 2.

Table 2. Contingency Table

Actual Class	**Predicted Class**	
	Normal	**Abnormal**
Normal	TN	FP
Abnormal	FN	TP

Table 3 represents the statistical measures of the proposed system for the given brain MRI images dataset. Sensitivity value represents the percentage of recognition of actual value and Specificity value represents the percentage of recognition of actual negatives. Accuracy is the degree of closeness of measurements of a quantity to its actual (true) value.

Table 3. Statistical measures of the proposed system

S. No	**Measures**	**Result**				
		Proposed DEA-ANN	**PSO-ANN**	**ANN**	**SVM**	**Fuzzy**
1	Sensitivity	94%	95%	93.47%	95.12%	100%
2	Specificity	100%	100%	100%	90.24%	90.69%
3	PPV	100%	100%	100%	90.69%	90.68%
4	NPV	88%	89%	92.30%	94.87%	100%
5	FPR	0%	0%	0%	9.75%	9.30%
6	FDR	8.5%	7.3%	6.5%	4.87%	0%
7	Accuracy	98.99%	97.5%	96.34%	92.68%	95.12%

From Table 3, we can see that our proposed method has obtained a classification accuracy of 98.99% compared with other classifier like for the case of PSO based ANN it gives 97.5%, ANN it gives 96.34%, SVM it gives 92.68% as well as in the case of fuzzy it gives 95.12%. In the case of sensitivity we obtained 94% for proposed, 95% for PSO-ANN, 93.47% for ANN, 95.12% for SVM, 100% for fuzzy. In the case of specificity the results of proposed, PSO based ANN and ANN is 100%, SVM is 90.24% and 90.69% for fuzzy like this for remaining parameters also we have obtained better

results. To further prove that the proposed method is the best for brain tumor identification we made a comparision with some research papers which is shown in Table 4.

Table 4. Comparsion analysis with previous works

S. No	**Technique**	**Accuracy**
1	Naïve Bayesian classification [28]	88.2%
2	Classification using Decision Tree [28]	96%
3	Ensemble system and LH and HL wavelet sub-bands features [29]	94.5%
4	Histogram with support vector machine (MTH with SVM) [30]	91.13 %
5	Modified MTH with hybrid kernel-based SVM (MMTH with HKSVM) [31]	94.32%
6	Proposed Method	98.99%

From the comparitive shown in Table 4 the proposed method has achieved better accuracy with 98.99% than the existing methods. From these experimental results we say that the proposed method is well suitable for brain tumor identification scheme.

5. CONCLUSION

Brain tumor identification from mixture model based segmentation is presented here. The proposed methodhas the brain MRI which is segmented into white matte (WM), grey matter (GM), cerebrospinal fluid (CSF) and outliers by using confidence level of ordering. The DTCWT features along with eight type of features are extracted from the outliers and given for classification stage.The texture features and intensity based features considered here are contrast, correlation, homogeneity, energy, entropy, standard deviation, skewness and kurtosis. In classification stage, Dolphin Echolocation Algorithm (DEA) - artificial neural network (ANN) is used as classifier in which the extracted features are trained and based on the tumor region in brain MRI image is detected. Experimental results shows that the proposed method has better results compared with existing methods.It further suggests that the proposed method is promising method for brain tumor identification in medical image application.

REFERENCES

[1] G Dong, and M Xie, "Color clustering and learning for image segmentation based on neural networks", *IEEE Transactions on Neural Networks*, Vol. 16, No. 4, pp. 925–936, 2005.

[2] K Tan, and N Isa, "Color image segmentation using histogram thresholding–Fuzzy C-means hybrid approach", *Pattern Recognition*, Vol. 44, No. 1, pp. 1-15, 2011.

[3] R Muthukrishnan, and M Radha, "Edge detection techniques for image segmentation", *International Journal of Computer Science & Information Technology*, Vol. 3, No. 6, 2011.

[4] L Wang, and C Pan, "Robust level set image segmentation via a local correntropy-based K-means clustering", *Pattern Recognition*, Vol. 47, No. 5, pp. 1917-1925, 2014.

[5] D Collins , and J Pruessner, "Towards accurate, automatic segmentation of the hippocampus and amygdala from MRI by augmenting ANIMAL with a template library and label fusion", *Neuroimage*, Vol. 52, No. 4, pp. 1355-1366, 2010.

[6] L Wang, Y Chen, X Pan, X Hong, and D Xia, "Level set segmentation of brain magnetic resonance images based on local Gaussian distribution fitting energy", *Journal of neuroscience methods*, Vol. 188, No. 2, pp. 316-325, 2010.

[7] N Lopes, P Couto, H Bustince, and P Melo-Pinto, "Automatic histogram threshold using fuzzy measures", *IEEE Transactions on Image Processing*, Vol. 19, No. 1, pp. 199-204, 2010.

[8] A Aquino, M Gegúndez-Arias, and D Marín, "Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques", *IEEE Transactions on Medical Imaging*, Vol. 29, No. 11, pp. 1860-1869, 2010.

[9] A Qin, and D Clausi, "Multivariate image segmentation using semantic region growing with adaptive edge penalty", *IEEE Transactions on Image Processing*, Vol. 19, No. 8, pp. 2157-2170, 2010.

[10] Y Tarabalka, J Chanussot, and J Benediktsson, "Segmentation and classification of hyperspectral images using watershed transformation", *Pattern Recognition*, Vol. 43, No. 7, pp. 2367-2379, 2010.

[11] M Abbasgholipour, M Omid, A Keyhani, and S Mohtasebi, "Color image segmentation with genetic algorithm in a raisin sorting system based on machine vision in variable conditions", *Expert Systems with Applications*, Vol. 38, No. 4, pp. 3671-3678, 2011.

[12] J Senthilnath, N Kalro, and J Benediktsson, "Accurate point matching based on multi-objective genetic algorithm for multi-sensor satellite imagery", *Applied Mathematics and Computation*, Vol. 236, pp. 546-564, 2014.

[13] M Jaffar, A Arfan, A Hussain, and A Majid Mirza, "Fuzzy entropy based optimization of clusters for the segmentation of lungs in CT scanned images", *Knowledge and Information Systems*, Vol. 24, No. 1, pp. 91-111, 2010.

[14] J Jiang, P Trundle, and J Ren, "Medical image analysis with artificial neural networks", *Computerized Medical Imaging and Graphics*, Vol. 34, No. 8, pp. 617-631, 2010.

[15] H Masoumi, A Behrad, M Pourmina, and A Roosta, "Automatic liver segmentation in MRI images using an iterative watershed algorithm and artificial neural network", *Biomedical Signal Processing and Control*, Vol. 7, No. 5, pp. 429-437, 2012.

[16] A Jayachandran, and R Dhanasekaran, ,"Brain tumor severity analysis using modified multi-texton histogram and hybrid kernel SVM", *International Journal of Imaging System and Technology*, Vol. 24, No. 1, pp. 72–82, 2014.

[17] L Chen, C Chen and M Lu, "A Multiple-Kernel Fuzzy C-Means Algorithm for Image Segmentation," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 41, no. 5, pp. 1263-1274, Oct. 2011.

[18] S Ahmed, K Iftekharuddin and A Vossough, "Efficacy of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 2, pp. 206-213, March 2011.

[19] S Shen, W Sandham, M Granat and A Sterr, "MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization," *IEEE Transactions on Information Technology in Biomedicine*, vol. 9, no. 3, pp. 459-467, Sept. 2005.

[20] M Havaei, A Davyb, D Warde-Farleyc, A Biardc, A Courvillec, Y Bengioc, C Palc, P Jodoina, and H Larochelle, "Brain tumor segmentation with deep neural networks", *Medical Image Analysis*, Vol. 35, pp. 18-31, 2016.

[21] A Demirhan, M Törü and İ Güler, "Segmentation of Tumor and Edema Along With Healthy Tissues of Brain Using Wavelets and Neural Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 4, pp. 1451-1458, July 2015.

[22] G Vishnuvarthanan, M Rajasekaran, P Subbaraj, and A. Vishnuvarthanan, "An unsupervised learning method with a clustering approach for tumor identification and tissue segmentation in magnetic resonance brain images", *Applied Soft Computing*, Vol. 38, pp. 190-212, 2016.

[23] S Pereira, A Pinto, V Alves and C Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1240-1251, May 2016.

[24] G Yang, Y Zhang, J Yang, G Ji, Z Dong, S Wang, C Feng and Q wang, "Automated classification of brain images using wavelet-energy and biogeography-based optimization", *Multimedia Tools and Applications*, Vol. 75, pp. 15601-15617, 2015.