ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 3, March 2017

# Identification of Tumour Spread Cells Using ACO

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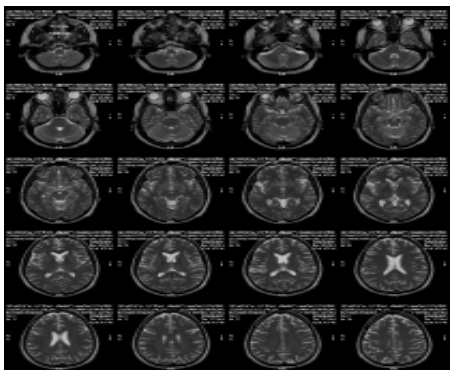
**ABSTRACT:** In recent years, MRI is useful for diagnosing a variety of disorders. One of the main application of Magnetic Resonance Imaging (MRI) is Brain tumour detection. The main objective of this paper is to analyse the brain images in order to know whether the brain is normal or abnormal and also detect the tumour spread cells in the brain. Initially, Pre-processing the MR image to make it fit for noise removal process is carried out by Median Filter and Segmentation using Fuzzy C-Means (FCM). After that, the important feature like size, texture and volume will be extracted using Grey Level Co-Occurrence Matrix (GLCM). At last, Deep Neural Network (DNN) is employed for classification into normal or abnormal. The conclusion is that, ACO is carried out by comparing the results of segmentation and feature extraction methods. Then, the spread cells of the tumour will be detected.

K**EYWORDS:** MRI, Fuzzy C-means, GLCM, Deep neural network.

## I. INTRODUCTION

Glioma is the common brain tumour they can be consider as less aggressive with life expectancy of many years or more aggressive with a life expectancy of at most 2 years. MRI gives the entire images of brain and it is used to diagnose brain tumour. According to WHO, brain tumour can be divided as four groups such as, 1.Pilocytic (slow growing), 2.Astrocytoma (rarely spreads), 3.Anaplastic Astrocytoma, 4.Glioblastoma Multiform (rapid growth and fast spreading). Some tumours are easy to segment and the others like Glioma and Glioblastoma is much more to localize because of poor contrast, tentacle like structure. The main aim of segmentation is to find the location and extension of tumour regions. In this work, we use the method of Deep Neural Network to learn feature hierarchies adapted specifically to the task of tumour segmentation. Specifically, Ant Colony Optimization is for compression, structural damage monitoring etc., in image processing. The proposed work includes the ACO technique for identifying the nearby tumour spread cells.



MRI image of Brain Tumour in different views

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## II. RELATED WORK

In [1] authors used SVM algorithm, this segmentation method is fully automated,which combines Support Vector Machine classification by intensities and textures based on CRF. This approach separates normal and abnormal tissues before that can be classified as cerebrospinal fluid, white matter, grey matter and necrotic, active, edema region in a hierarchical way. This approach includes robustness speed the regularisation at different stages. In [2] authors used Bayesian approach,this approach is supervised and parametric, where the mean and covariance are calculated by the training datasets. This method contains Bayesian model, graph based algorithm and also the segmenting the edema. In [3] Threshold based segmentation is used, in this technique, binary image is used which is very essential task for the segmentation process. This takes the images of regions with various grey values. The procedural determination explains the intensity values that can be separated by desired classes. In [4] authors improved segmentation by implementing Otsu method, this is considered as a global thresholdingmethod. This work doesn't work correctly when the intensity variations of the foreground and background images is high and also sometimes it binarize the whole image then it shows it as a unnecessary part. In [5] Authors had modified to region growing method, this method is a well-developed work for image segmentation but it requires interaction and this fails in producing the desired output of the natural image.

## III. PROPOSED ALGORITHM

### A. *Noise Removal using Median Filter*

The process of noise removal is based on the pixel values. Averaging filter can be used for removing grain noise from an image. In the proposed work, each pixel is set to average value of the pixel and the related variations of the grain are reduced. Without blurring the edges of the image, removing the noise by median filter. Convolution filter is less powerful than median filter. The main aim of the work is to simultaneously reduce noise patterns. Median filter is considered as non-linear filter because it removes noise as well as preserving sharp edges.

### B. *Segmentation using Fuzzy C-means*

Segmentation of tumour is the process of dividing a binary image into many parts like sets of pixels. The purpose of segmentation is to simplify the image to easily analyse. The result of this process is extracting the set of contours from the image. Using the image segmentation process, the isolation of tumour from the rest of the image is easy. In the proposed work, FCM is used and it uses the threshold value. The segmented image can be carried out when the threshold value is 1 otherwise 0. The objective of FCM is to minimize a

$$J(u,v) = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{i,j})^{m}\|x_i - v_j\|^2$$

Where ||xi-vj||, is the Euclidean distance between ith data and j th cluster enter.

### C. *Feature Extraction using GLCM*

After the completion of segmentation, the features should be extracted for the detection of tumour region correctly. Texture feature is mainly for identifying the normal and abnormal patterns. That can be determined as space distribution of grey levels in the nearby region. Grey Level Co-Occurrence matrix (GLCM) carries the details of the positions of the pixels having different grey level values. The texture features of the extraction is contrast, correlation, angular second moment, homogeneity, entropy.

1. Contrast

Contrast returns a measure of the intensity contrast between a pixel and its related values over the entire image.

$$\text{Contrast} = \sum_{i=1}^{k}\sum_{j=1}^{k}(i-j)^2 p_{ij}$$

Range = [0 (size (GLCM, 1)-1)^2], contrast is 0 for constant images

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2. Correlation

This is nothing but the several measures of the linear statistical relationship between two random pixels of the entire image.

$$\text{Correlation} = \sum_{i=1}^{k}\sum_{j=1}^{k}\frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r\sigma_c}$$

$$\sigma_r \neq 0, \sigma_c \neq 0$$

Range = [-1 1] correlation is 1 or -1 for positive and negative correlated image.

3. Angular second moment

It is also known as uniformity or energy. The sum f squares of entries in the GLCM measures the image homogeneity. If the pixels are very similar, then the angular second moment will be very high.

$$\text{Energy} = \sum_{i=1}^{k}\sum_{j=1}^{k} p_{ij}^{2}$$

Range = [0 1] energy is 1 for constant image.

4. Inverse Difference Moment

IDM is a local homogeneity and if its grey level is uniform then it is high. Returns a value that measure the closeness of the distribution of element in the G to the diagonal of G.

$$\text{Homogeneity} = \sum_{i=1}^{k}\sum_{j=1}^{k}\frac{p_{ij}}{1+|i-j|}$$

Range = [0 1] homogeneity is 1 for diagonal G.

5. Entropy

The main use of entropy is to define the texture by using input images. And it is defined as,

$$\text{Entropy} = -\sum_{i=1}^{k}\sum_{j=1}^{k} p_{ij}\log_2 p_{ij}$$

Where, k is row or column of square matrix sG probability is the ij-th element of G/n, where n is equal to sum of the element of G, and G is referred simply as co=occurrence matrix

Tumour size identification using region properties

The size of the tumour is identified by using region properties. The extracted features are different from all the images given as input and the segmentation features values are depending upon the formulae given.

**D. *Classification using Deep Neural Network***

1. Deep Learning

It is a method of learning multiple levels of abstraction and representation and it is useful for gathering information related to images, audio and text. The concept of deep learning is from the Artificial Neural Network, Multilayer perceptron and also that contains more hidden layers in the deep learning structure.

2. Supervised training phase:

Apart from all the architectures, Convolution Neural Networks (CNN) has a concept of attractive performance. When compared to the feed-forward neural network, it has the convolutional layers and also having the set of neurons. It may looks like a small s1ub-regions of the user defined image. The process of learning the shared weights is always equivalent to the process of learning filters. Because of the small number of connections, supervised training is more effective and also the filters automatically learn features from the data.

3. Unsupervised training phase

There are three representation of learning methods, feature selection, auto encoders and Boltzmann machines.

Phase I: This is the first one, which selects 14 attributes from the whole data using feature extraction.

Phase II: This is the layer wise architecture represented by visible layers and the hidden layers related to the inherent features of the data. In this approach, Boltzmann machines hidden units are considered as latent random variables and the auto encoders are considered as computational nodes. The function of encoder is to allow the straight forward computation of vector features using the input data.

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4. Model Architecture

The main principle task is to take into account the specific of the data when the process of developing a model structure. The important property of the measured signal is that, the waveform is significantly same for normal and abnormal people. In the visual analysis, this difference cannot be observed. If we take the local behaviour, it tangibly varies for people with abnormality. For achieving the local data structure at the first level of abstraction, we should consider two approaches.

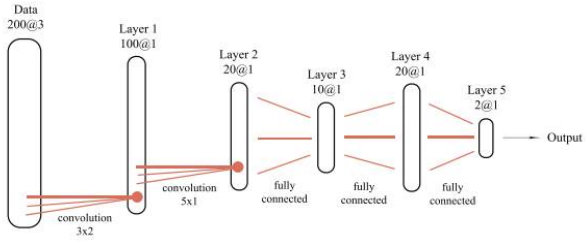
This architecture has five layers,

Step 1: Convolution layer

In this layer, the convolution of each sub region of the data is computed and the resultant values form the output of this first layer. This is categorized by the size and the kernel numbers, convolution steps with height dimensions and width.

Step 2: Max-pooling layer

This layer follow the previous layer and it can performs a down sampling operation for reducing the feature size. This layer takes the input as the rectangular boxes and generates he output of a singular output of each block. And takes the common one in the maximum of block. If the block size is 2X2, then the number of features is reduced by 4 times.




Step 3: Auto encoder

It is a symmetrical neural network which is useful for unsupervised feature learning. This is mainly for reducing the reconstruction error of input data and the output layer and also the activation values of the hidden layers. Encoding if the input vector x ∈ R N in the auto encoder by applying a linear transformation and a nonlinear activation function to x.

Step 4: Restricted Boltzmann

Restricted Boltzmann machine (RBM) has a two layer bipartite model with a set of visible units, set of hidden units and symmetrical connections between the hidden and visible variables.

5. Deep learning classification

Finally, after many convolutional and max-pooling layers, the single one-dimensional vector ca be converted from the obtained features. Then the classification layers are fully connected and normally use one output per the class label.

E. Spread cell identification using ACO

The parameters taken in this process are total ants K and Tinit which is the initial value of pheromone matrix. Then the construction of ant solution gets possible through the local search on the solution space which is the image matrix. Ants decide to move from node i to another j through the probabilistic action rule which is given as,

$$P_{ij}(n) = \frac{((T_{i,j})^{n-1}}{\sum_{j\epsilon\Omega_i}((T_{i,j})^{'}}$$

Then the local pheromone update is performed by the equation

$$Tij = (1-\varphi)\, Tij + \varphi\, To$$

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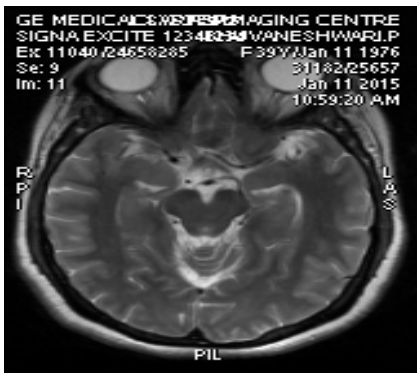
The offline pheromone update is performed by the equation

$$T_{ij} = \begin{cases} (1-\rho)T_{ij}^{(n-1)} + \rho.\Delta_{ij}^{(k)} & \text{,if (i,j) belongs to best tour} \\ T_{ij}^{(n-1)} & \text{,else} \end{cases}$$

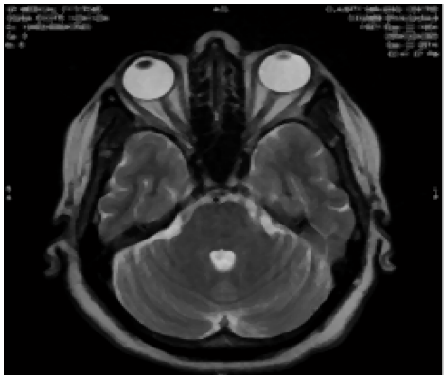
Exploitation is nothing but to attain the maximum probability path. After applying ACO to the segmented image, it is found that it increases the accuracy of the fuzzy C-mean segmentation to a great extent. At the same time it will increase the computational time. But it will reduce the time of 50%. The Max-Min Ant system (MMAS) is a direct stage over the AS. The main changes used in MMAS is as, first is, after each iteration only one ant is allowed to add pheromone. Then the second one is, the permitted range of the pheromone strength is limited to the interval because of avoiding the search stagnation. The last one is, at the upper limit the pheromone trails are initialized and it causes a higher exploration at the start of the algorithm.

## IV. SIMULATION RESULTS

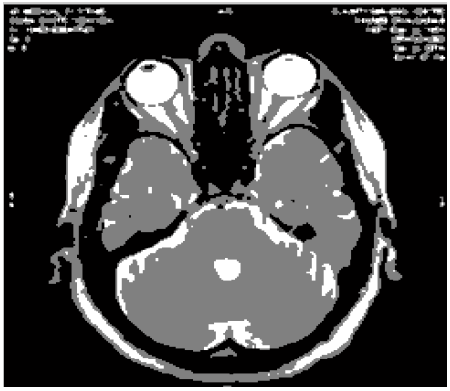
The exact location of brain tumour is found out by applying our proposed work using matlab simulator. And also Graphical User Interface is developed for easy way of approaching the results. In our design, we have taken the number of clusters as 3 because of the letters in the input we have given. Finally, the spread cells from the given input is also detected as well as the exact location of tumour is found out



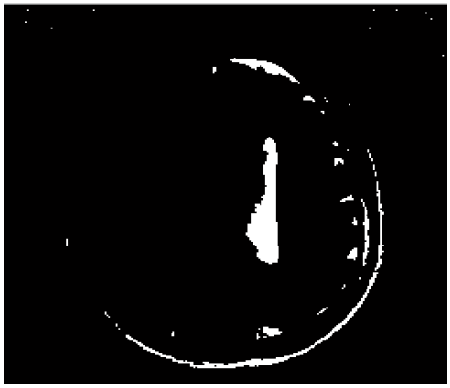

Input Image



Noise removed image from the input



Tumour segmented image



Spread cells from the segmented image

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

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## V. CONCLUSION AND FUTURE WORK

The less accuracy of FCM is due to its sensibility to the initialisation process. For increasing the accuracy of FCM in the segmentation process, Ant Colony Algorithm (ACA) is used. ACA initializes the cluster center to the best proper value then increasing the accuracy in the segmentation process. At the same time, it also increases the computational time also. For reducing the computation time, max-min ant system is also used. This reduces time nearly 50% of ACA

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