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A TECHNIQUE FOR TUMOR REGION IDENTIFICATION USING CELLULAR NEURAL NETWORK

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ABSTRACT

In recent times, Magnetic Resonance Imaging (MRI) has turn into a competent appliance for clinical diagnoses and research. For the recognition of different diseases through segmentation methods, this MRI has become an extremely useful medical modality. We have presented an effectual CNN based segmentation technique with lung and brain MRI images in this manuscript. This move towards the target with the aid of the following major steps, which includes, 1) Pre-processing of the brain and lung images, 2) Segmentation using cellular neural network. At first, the MRI image is pre-processed to make it fit for segmentation. At this point, in the pre-processing step, image de-noising is made using the linear smoothing filters, such as Gaussian Filter. After that, the pre-processed image is segmented according to our proposed technique, CNN-based image segmentation. We have developed a hybrid optimization algorithm (ABC+PSO) to design a template in cellular neural network. At last, the different MRI images (brain and lung) are given to the proposed approach to assess the performance of the proposed approach in segmentation process. Fuzzy C-means (FCM) and K-means classification accompanies the Comparative analysis. The accuracy of proposed segmentation approach produces healthier results (93.9% for lung and 96.4% for brain images) according to the comparative analysis, than that of existing Fuzzy C-means (FCM) and K-means classification.

Keywords: *Brain And Lung MRI Image, Cellular Neural Network, Template Design, Gaussian Filter, Employed Bee, Onlooker Bee, Scout Bee*

1. INTRODUCTION

Fear of lung and brain cancer is very much common in advanced countries, as numerous cases of brain and lung cancer are rising day by day. This disease can be cured at an early period, if it is identified. To have a better medical imaging in clinical diagnoses, researchers have been studying how to apply the technique of image processing to the medical imaging field. The digital images are partitioned into disjoint regions in Image segmentation. Image segmentation is the key scheme in target region extraction for medical image, giving tissue measuring and three dimensional reconstructions [10]. The first step in many image analysis applications developed for medical diagnosis is the fragmentation of tissues and structures from medical images. Other applications includes advancement of treatment plans and evaluation of disease progression, which stem from the fact that diseases affect specific tissues or structures, lead to loss, atrophy (volume loss), and abnormalities. Hence an accurate, reliable, and automatic segmentation or fragmentation of these tissues and structures make advancement in the diagnosis and treatment of diseases.

Furthermore, identification and analysis of the scuff manually from MR brain and lung images are normally time consuming, expensive and can generate unacceptably high intraobserver and interobserver variability [40]. The removal of the unnecessary information present in the original MR images and the maintenance of the significant details in the resulting segmented images are the two, often conflicting, requirements, which the

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segmented MR images uses in the medical diagnostic process [41] [42]. MR-image segmentation methods are usually examined on the basis of their ability to differentiate between i) cerebro-spinal fluid (CSF), white matter, and gray matter and between ii) normal tissues and abnormal tissues [43]. Various methods have been explained in recent years for the segmentation of brain tissues from MR image, those are classical pattern recognition methods, image analysis methods, rule-based systems, crisp and fuzzy clustering procedures, feed-forward neural networks, fuzzy reasoning, geometric models to determine scrape boundaries, connected component analysis, deterministic annealing, atlas based methods and contouring approaches [44] [45]. Moreover researches have been done for the segmentation of normal and abnormal tissues in MRI brain images. A few recent correlated works regarding the segmentation of brain tissues are discussed in the following section.

A Cellular Neural Network (CNN) model, which permits certain new approach in signal processing and that can be suitably executed as an integrated circuit, which was a new model invented by Chua and Yang [9]. Since the cells are connected in a two-dimensional (2D) network structure, [11, 12] the CNN that is formed in such a way, that it can able to make simultaneous signal processing. Through a certain set of parameters, the cells in the network structure are connected only with the neighboring cells. "Cloning Template" is the set of parameters that verifies the dynamic performance of the CNN. Image processing is one of the most important functions of CNN which is obtained by the two dimensional network architecture of CNNs that provides an appropriate structure for image processing applications and also for the real time imaging sensors [13, 14]. CNN-based imaging sensors & circuits are accomplished by Complex image processing tasks, as it operates at a much higher speed. At the beginning, image processing techniques such as edge detection, diffusion and dilation ought to be used for realizing complex image processing applications based on the CNN structure. Consequently the overall performance of task gets affected by the quality of the preliminary process.

At first in our planned technique, the input MRI image is pre-processed in order to eradicate the noise and make the image fit for rest of the processes. The Gaussian filter is used in the pre-processing stage. According to our planned technique CNN-based image segmentation, the pre-processed image is fragmented consequently. Owing to the lack of a robust and effective structure in finding out the cloning template, template designing studies are one of the most interesting research areas in the CNN field and this study aims to design the segmenting CNN template through ABC algorithm. By means of the fragmentation of lung and brain images, the CNN template generated by the ABC algorithm is tested.

The contents of this paper are as follows: Section 2 explains the related works. Section 3 explains the CNN structure and cell concept. Section 4 contains problem description information about template design. Section 5 explains our proposed approach and pseudo code of Hybrid algorithm. Section 6 explains the detailed experimental results and discussions and Section 7 describes description on clinical application of this method and section 8 explains the summed up conclusions.

2. REVIEW OF RELATED WORKS: A BRIEF STUDY

Many researches have been offered by researchers concerning MRI brain and lung image segmentation techniques. A concise review of some of the recent researches is presented here.

Rajeev Ratan *et al.*[1] have presented a two dimensional MRI data which helps in finding (in 10-15 minutes operator time) the tumor tissue with a better precision and reproducibility as good as manual segmentation (2-6 hours operator time) making the automatic segmentation practically real for malignant tumors. In this system, after a manual segmentation process the tumor identification has been made for the potential use of MRI data for improving the approximate brain tumor shape and 2D visualization for surgical planning.

Derived from genetic algorithm (GA) and support vector machine (SVM), a hybrid approach for classification of brain tissues in magnetic resonance images (MRI) has been presented by Ahmed Kharrat *et al.* [2]. A wavelet based texture feature set is derived. The optimal texture & features are extracted from normal and tumor regions by using spatial gray level dependence method (SGLDM). These features become the input for the SVM classifier. Genetic Algorithm (GA) is used to solve the problem of choosing the features in classification techniques. These best possible features are used to classify the brain tissues into normal, gentle or mean tumor. The

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performance of the algorithm is evaluated on a series of brain tumor images.

Shafaf Ibrahim *et al*. [3] have put forward an article that was showing the comparison between the performances of Seed-Based Region Growing (SBRG), Adaptive Network-Based Fuzzy Inference System (ANFIS) and Fuzzy c-Means (FCM) in brain abnormalities segmentation. By using proscribed experimental data and the way in which they have been designed, the former knowledge of size of the abnormalities was identified. Different sizes of abnormalities and pasting it onto normal brain tissues was done by cutting. The standard tissues or the background were classified into three different categories. Fifty seven data of every category was fragmented. The segmentation results of the three techniques proposed were compared with the size of the abnormalities obtained by the number of pixels. Adaptive Network-Based Fuzzy Inference System (ANFIS) returns the best segmentation performances in light abnormalities, whereas the Seed-Based Region Growing (SBRG) performed all in dark abnormalities segmentation.

An automatic brain tumor revealing method that uses T1, T2_weighted and PD, MR images to find out any kind of abnormality in brain tissues was revealed by AmirEhsan Lashkari [4]. In this method, Gabor wavelets, energy, entropy, contrast and some other value features such as mean, median, variance, correlation, values of maximum and minimum intensity etc. has been used to attain a clear picture from brain tissues. This method was used to reduce the feature space from a feature selection method. This method is used to do this classification from neural network. To categorize the brain tissues to normal and abnormal classes routinely, which saved the radiologist time, increases the precision and yield of diagnosis was the main aim of this project.

For the fragmentation of lung region on chest, CT images Murat Ceylan *et al.* [5] have derived an efficient method known as Complex-Valued Artificial Neural Network with Complex Wavelet Transform (CWT-CVANN), the combined architecture in that method was composed of two cascade stages: feature extraction with various levels of complex wavelet transform and segmentation with complex-valued artificial neural network. Here, 32 CT images of 6 female and 26 male patients were recorded from Baskent University Radiology Department. (This collection includes 10 images with benign nodules and 22 images with malign nodules. Averaged age of patients is 64. Each CT slice used in this study has dimensions of 752\times 752 pixels with grey level). 99.79% average accuracy rate is obtained in just two seconds of processing time per each CT image using 3rd level CWT-CVANN for segmentation of the lung region. Thus, it was concluded that CWT-CVANN was a comprising method in lung region segmentation problem. A classification approach, known as Vector Seeded Region Growing (VSRG) presented by Chuin-Mu Wang and Ruey-Maw Chen [6]. The seed pixel vectors selection is done by means of standard deviation and relative Euclidean distance by VSRG. The preferred target of interest can be confidential with the brain tissue and brain tumor segmentation and the data dimensionality of MRI can be decreased. For performance evaluation, a series of experiments are conducted and compared to the commonly used c-means method. The results indicate the possible usefulness of this method for MR image classification.

A region-based process for image segmentation, which was able to deal with the concentration of inhomogeneities in the segmentation was found out by Chunming Li et al. [7]. Local clustering criterion function for the image intensities in a region of each point is derived by the model of images with intensity inhomogeneities. This local clustering criterion function was then integrated with respect to the region center to give a global criterion of image segmentation. In a level set formulation, this criterion defined an energy in terms of the level set functions that represented a partition of the image domain and a bias field that accounted for the intensity inhomogeneity of the image. This method was able to simultaneously segment the image and estimate the bias field, by minimizing this energy. The anticipated bias field can be used for intensity inhomogeneity correction (or bias correction). Advantageous performance in the presence of intensity inhomogeneities was obtained by validating the method on synthetic images and real images of various modalities. The proposed method is healthy to initialization, quicker and precise which was proved by many experiments.

A segmentation technique which was based on an extension to the traditional C-means (FCM) clustering algorithm was introduced by Manisha Sutar, and N. J. Janwe [8]. A neighborhood pull, which was needy on the relative location and features of neighboring pixels was considered. To maximize the degree of attraction Particle Swarm Optimization model (PSO) was used. The superiority of the proposed technique to FCM-based method was demonstrated. The segmentation

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method was a component of an MR image-based classification system for tumors, which was being developed.

3. CNN-BACKGROUND REVIEW

Cellular Neural Network (CNN): The Cellular Neural networks (CNN) was invented by Chua and Yang [9] at the University of California in 1988. By using certain regular (rectangular, hexagonal, etc) group of mainly identical dynamical systems called cells which assure two properties: where most interactions are local within a limited radius and all state values are continuous valued signals.

Following are the Chua-Yang definition [9]:

- ❖ A CNN is an N-dimensional regular array of elements (cells) as shown in Fig 1.
- ❖ The cell grid can be a planar array for example with rectangular, triangular or hexagonal geometry, a 2-D or 3-D torus, a 3-D finite array or a 3-D sequence of 2-D arrays (layers)
- ❖ Cells are multiple input & single output processors that are described by one or just few parametric functions.
- ❖ A cell is characterized by an internal state variable, but sometimes it cannot be observable directly from outside the cell.
- ❖ More than one connection network can be present, with different neighborhood sizes.
- ❖ A CNN dynamical system can operate both in continuous (CT-CNN) or discrete time (DT-CNN).
- ❖ CNN data and parameters are typically continuous values.
- ❖ CNN operate typically with more than one interaction i.e. they are recurrent networks.

In terms of speed and capability CNN has several advantages over others. A general architectural structure for CNNs is shown in Fig 1.

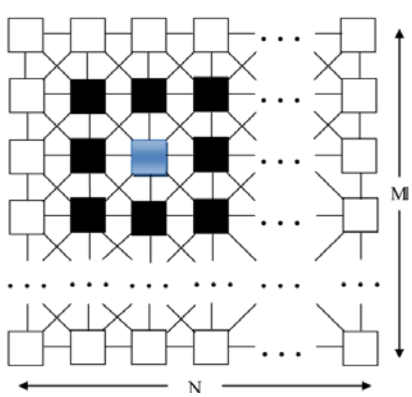

Fig.1. Cellular Neural Network With A 3×3 *Neighborhood*

Each cell in a CNN is directly connected only with the neighboring cells as shown in Fig 1. A cell directly affects only its neighbor cells due to the local inner-cell connections in CNNs. Cells which are not directly connected to this cell are indirectly affected while transiting from the initial phase to a stable phase as a result of the propagation of CNNs continuous time dynamics [9]. The cell concept and the cloning template terms are defined in the following subsections.

Cell: The cell is composed of structurally linear and non-linear circuit elements, such as capacitors, linear resistances, linear and non-linear controlled sources and independent sources which is the basic element of the CNN structure. The first CNN cell structure in the literature proposed by Chua-Yang [9] is shown in Fig 2. Each cell has a state x, a constant input u and an output y. The equivalent block diagram of a continuous time cell is shown in Fig 2 below.

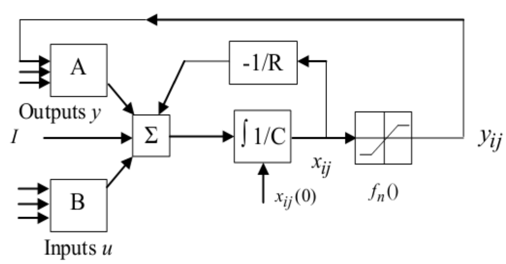

Fig.2. Block Diagram Of One Cell

State equation:

$$C\frac{dv_{xij}(t)}{dt} = -\frac{1}{R_x}v_{xij}(t) + \sum_{C(k,l)\in N(i,j)} A(i,j;k,l)v_{ykl}(t) + \sum_{C(k,l)\in N(i,j)} B(i,j:k,l)v_{ukl}(t) + I \quad (1)$$

Output equation

$$v_{yij}(t) = \frac{1}{2}\left(\left|v_{xij}(t)+1\right| - \left|v_{xij}(t)-1\right|\right) \quad (2)$$

Input equation

$$v_{uij}(t) = E_{ij} \quad (3)$$

Constraint conditions:

$$\left|v_{xij}(0)\right| \le 1 \;,\; \left|v_{uij}\right| \le 1 \quad (4)$$

4. PROBLEM DESCRIPTION OF TEMPLATE DESIGN

Template design: Manipulating a CNN template is one of the most important research topics in this field to get different behaviours successfully. The operation principle of CNN differs from the operation of standard image processing techniques if CNN is interpreted in terms of image processing.

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Owing to the statement that the mask parameter of well-known classical segmentation is not used in the CNN structure and the CNN cloning template is designed according to the CNN structure. Intention of the cloning template that determines the dynamic behaviour of CNN is an essential difficulty as there doesn't exist a comprehensive template design method. To determine such templates, a number of methods have been planned. These methods can be grouped as analytical methods [22-25], local learning algorithms [26, 27] and global learning algorithms [28, 29, and 30]. The complexity point of the problem increases depending on the number of variables and the type of data in all developed methods. In this stage, we are using hybrid algorithm based artificial bee colony and particle swarm optimization for better optimization result.

5. PROPOSED TECHNIQUE FOR TUMOR REGION IDENTIFICATION USING CELLULAR NEURAL NETWORK

The density of the images and lack of models of the composition that absolutely capture the probable deformations in each structure, make the Segmentation of medical imagery is a complicated and demanding process. It is well-known that brain and lung tissue has a complex structure, and thus, its segmentation is an essential step for our proposed method. Preprocessing and CNN based segmentation are the two phases in our proposed method. In pre-processing phase, applying Gaussian filtering is done using remove unwanted noise. In segmentation phase, lung and brain tissues segmentation has done using cellular neural network (CNN). CNN template design process is designed using artificial bee colony algorithm. The Block diagram of the proposed technique is shown schematically in Fig 3.

Fig 3. Overall Block Diagram Of Our Proposed Approach

5.1 Pre-Processing Using Gaussian Filter

MRI lung and brain images cannot be openly given as the input in the proposed technique. So it is obligatory to perform pre-processing on the input image, so that the image gets transformed to be relevant for further processing. The pre-processing is carried out for loading the input MRI images to the MATLAB environment and also it removes any type of noise present in the input images. The input image is passed through a Gaussian filter to reduce the noise as well as improve the image quality.

Gaussian Filter: A Gaussian filter [34] is a filter whose impulse response is a Gaussian function. Gaussian filters are formed to shunt overshoot of step function input while reducing the rise and fall time. Gaussian filter has the minimum possible group delay. In mathematical terms, a Gaussian filter changes the input signal by convolution with a Gaussian function and this change is also called as Weierstrass transform. The Gaussian function is non-zero for $x \in [-\infty, \infty]$ and would notionally necessitate an infinite window length. The filter function is said to be the kernel of an integral transform. The Gaussian kernel is continuous, not discrete.

The cut-off frequency of the filter is taken from the ratio between the sample rate F_s and the standard deviation σ.

$$F_c = \frac{F_s}{\sigma}$$

The 1D Gaussian filter is given as,

$$g(x) = \frac{1}{\sqrt{2\Pi\sigma}} e^{\frac{-x^2}{2\sigma^2}}$$

The impulse response of the 1D Gaussian Filter is given as,

$$g(x) = \frac{1}{\sqrt{2\Pi\sigma}} e^{\frac{-\sigma^2 u^2}{2}}$$

Here, the input image is passed through a Gaussian filter to reduce the noise as well as improve the image quality in the pre-processing for advance processing.

5.2 Tumour region identification using Cellular neural network

The target of the proposed approach is to effectively determine the segmentation template design of the CNN with an optimization mechanism set up by using suitable quality metric and training images.

5.2.1 Structuring the CNN Template Using Hybrid Algorithm

In this section, the working mechanism of the hybrid algorithm is presented and explained as a new approach to design templates in this section.

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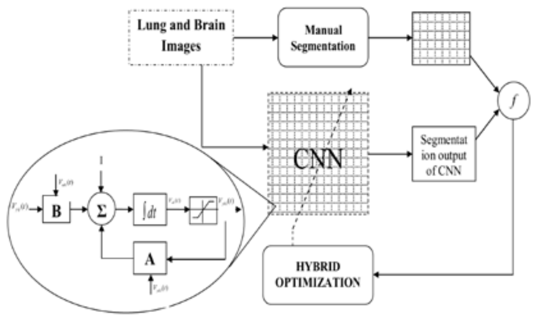

Fig.4. Template Design Mechanism Of The Hybrid Algorithm Based CNN Segmentation

The hybrid algorithm based template design mechanism of the CNN is shown in Fig 4. The output image of the CNN converges to the chosen image by adjusting the template of the CNN by means of the ABC and PSO algorithm is seen in the Hybrid template design mechanism. The template set produced by the ABC and PSO algorithm and sends the same to the CNN. CNN runs by using this set and training image (manual segmented image), and it generates an output image. By comparing the output image of the CNN and the manual segmented image, the fitness value of the objective function is calculated. The hybrid algorithm evaluates with this fitness value in order to obtain better results.

Hybrid Optimization procedure

- ***Assign the control parameter values***
  Control parameters of proposed algorithm are set as;
  Colony size, CS=5
- ***Initialize the population of solutions***

The colony size of employed bees (n_e) is equal to the colony size of onlooker bees (n_o) in the population.

$$\text{Fitness function} = \frac{A \cap B}{A \cup B}$$

Where, $A \rightarrow Manually\ \ segmented\ image$

$B \rightarrow CNN\ \ segmented\ image$

Running of ABC optimization can be explained as follows: First, we initialize the positions of five *D* × *SN* matrix of employed bees, randomly using uniform distribution in the range (0, 1) and each row of the matrix represents a template set, a possible solution to the problem, in the ABC optimization. *D* is the dimension of the problem and *SN* is the size of the colony. Consider five *D* × *SN* initial templates matrix of employed bees are given below,

Initial Templates =

$$\begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{1,4} & a_{1,5} & a_{1,6} \\ a_{1,7} & a_{1,8} & a_{1,9} \end{bmatrix} \begin{bmatrix} a_{2,1} & a_{2,2} & a_{2,3} \\ a_{2,4} & a_{2,5} & a_{2,6} \\ a_{2,7} & a_{2,8} & a_{2,9} \end{bmatrix} \begin{bmatrix} a_{3,1} & a_{3,2} & a_{3,3} \\ a_{3,4} & a_{3,5} & a_{3,6} \\ a_{3,7} & a_{3,8} & a_{3,9} \end{bmatrix}$$

$$\begin{bmatrix} a_{4,1} & a_{4,2} & a_{4,3} \\ a_{4,4} & a_{4,5} & a_{4,6} \\ a_{4,7} & a_{4,8} & a_{4,9} \end{bmatrix} \begin{bmatrix} a_{5,1} & a_{5,2} & a_{5,3} \\ a_{5,4} & a_{5,5} & a_{5,6} \\ a_{5,7} & a_{5,8} & a_{5,9} \end{bmatrix}$$

Many cycles constitutes the ABC algorithm process. The employed bees phase, the onlooker bees phase and the scout bees phase are the three phases in each cycle. The employed bees are sent to the sources and the nectar amounts of the sources visited are calculated for the first phase. Onlooker bees are sent to their sources and their nectar amounts are determined for the second phase. The scout bee is located on a randomly selected new source for the third phase.

Firstly, the position of a food source (*xi*) represents a feasible solution of problem and the amount of nectar of the food source indicates the fitness value of the associated solution in the ABC algorithm. A set of food sources positions $\{x_1,\ldots,x_{ne}\}$ is produced randomly:

$$x_i = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min})$$

Where $i = 1, \ldots, SN$ and $j = 1,\ldots,D$ is the number of food sources and D is number of optimization parameters. Also, it must be noted that $SN = n_e = n_o$.All counters associated with solutions are reset to 0 in this phase. After initialization, the fitness value of each solution is calculated and is obtained. The fitness value of the objective function is calculated by comparing the output image of the CNN and the manual segmented image. The ABC algorithm evaluates with this fitness value in order to obtain better results.

Cycle =1

- ***Employed Bees phase***

The colony of employed bees can be expressed by n_c dimension vector $\bar{x}(n) = (x_1(n),\ldots,x_{n_e}(n))$, where n is cycle value of ABC algorithm. To evolve quality of solutions, employed bees change their position from the current position to neighboring source positions by using the following equation:

$$v_{ij} = x_{ij} + \phi(x_{ij} - x_{kj}) \tag{5}$$

Where, $j \in \{1,\ldots,D\}, k \in \{1,\ldots,SN\}, k \neq j$, j and k are randomly chosen index. ϕ_{ij} is a real number produced randomly in the range [0,1].

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After producing v_i, to select better solution for next generation, greedy selection operator is applied. Probability distribution of this operator can be given as follows:

$$P\{x_i, v_i\} = \begin{cases} 1, f(v_i) \geq f(x_i) \\ 0, f(v_i) < f(x_i) \end{cases}$$

where $f(v_i)$ and $f(x_i)$ are nectar amounts of food sources at v_i and x_i, respectively. If v_i is better solution than x_i, the employed bee memorizes position of v_i, otherwise position of x_i is retained. In the end of this process, if a better solution cannot be obtained, the trials counter associated with the solution is incremented by 1, and otherwise it is reset to 0.Finally, we obtain three $D \times SN$ template from the employed bee phase can be given as follows.

Employed bee templates

$$= \begin{bmatrix} e_{1,1} & e_{1,2} & e_{1,3} \\ e_{1,4} & e_{1,5} & e_{1,6} \\ e_{1,7} & e_{1,8} & e_{1,9} \end{bmatrix} \begin{bmatrix} e_{2,1} & e_{2,2} & e_{2,3} \\ e_{2,4} & e_{2,5} & e_{2,6} \\ e_{2,7} & e_{2,8} & e_{2,9} \end{bmatrix} \begin{bmatrix} e_{3,1} & e_{3,2} & e_{3,3} \\ e_{3,4} & e_{3,5} & e_{3,6} \\ e_{3,7} & e_{3,8} & e_{3,9} \end{bmatrix}$$

- ***The Onlooker Bees Phase***

Following the completion of the employed bees phase, the phase of onlooker bees is started by choosing an employed bee from the colony. The onlooker bees phase is related to the previous phase. The possibility of the selection process depends on the fitness values of the solutions and many selection schemas such as roulette wheel and stochastic universal sampling can be used. In this phase, we have used neighbourhood function of particle swarm optimization for better optimization results. PSO operator can be described as follows:

$$\begin{cases} V_i^{r+1} = \omega V_i^{(r)} + c_1 rand_1(o)(Pbest_i - Y_i^{(r)}) + c_2 rand_2(o)(Gbest - Y_i^{(r)}) \\ Y_i^{(r+1)} = Y_i^{(t)} + V_i^{r+1} \end{cases} \tag{6}$$

The above PSO operator function is replaced for fitness function in onlooker bees phase and a random actual number within the range [0, 1] is generated for each source to decide whether a modification is to be made on an onlooker bee position. If the generated number is less than the PSO operator value in Equation (6), then the onlooker bee changes position by using Equation (1) to find new solutions. New selection is applied to the modified source and then if the new position is better than the old position, the memory of the onlooker bee is updated, otherwise the old position is kept. As per the result of this process, the counter associated with onlooker bees is incremented by 1 or reset to 0 similar to the operation in the employed bee phase. If a counter value of employed bees and onlooker bees reaches its "limit" value, the source of this counter is discarded and that will be the end of the cycle. The scout bee discovered a new food source and it replaces the abandoned source. This operation can be defined as follows:

$$x_i(n+1) = \begin{cases} x_{\min} + ramd(0,1)(x_{\max} - x_{\min}), & counter \geq \lim it \\ x_i(n), & counter < \lim it \end{cases}$$

Finally, we obtain three $D \times SN$ template from the onlooker bee phase can be given as follows.

Onlooker bee templates

$$= \begin{bmatrix} o_{1,1} & o_{1,2} & o_{1,3} \\ o_{1,4} & o_{1,5} & o_{1,6} \\ o_{1,7} & o_{1,8} & o_{1,9} \end{bmatrix} \begin{bmatrix} o_{2,1} & o_{2,2} & o_{2,3} \\ o_{3,4} & o_{1,5} & o_{1,6} \\ o_{1,7} & o_{1,8} & o_{1,9} \end{bmatrix} \begin{bmatrix} o_{1,1} & o_{1,2} & o_{1,3} \\ o_{1,4} & o_{1,5} & o_{1,6} \\ o_{1,7} & o_{1,8} & o_{1,9} \end{bmatrix}$$

- ***Scout Bees Phase***

In the scout bees phase, in which template is separated from population is arranged by controlling the testing counters by comparing these counters with the parameter named "*limit*". A new template set produced arbitrarily is replaced instead of the removed templates, if the testing counter value of a template set reaches the *limit* value, where this set is removed from the population. At last, we obtain one new $D \times SN$ template from the scout bee phase can be given as follows.

$$\text{Scout bee template} = \begin{bmatrix} s_{1,1} & s_{1,2} & s_{1,3} \\ s_{1,4} & s_{1,5} & s_{1,6} \\ s_{1,7} & s_{1,8} & s_{1,9} \end{bmatrix}$$

Subsequently, we determine quality matrix from seven templates (employed bee phase=3, onlooker bee phase =3 and scout bee phase=1), and we choose best one template from these seven templates. Consequently, this best template and another two templates

(randomly selected) are given to the employed bee phase. The above process is repeated again for every cycle.

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Pseudocode of Hybrid Algorithm

- Initialize the population of templates $[M \times N]_i .....[M \times N]_n$
- Evaluate the population
- cycle=1
- repeat
- Produce new solutions (template positions $v_{i,j}$ in the neighbourhood of $x_{i,j}$ for the employed bees using the formula $v_{i,j} = x_{i,j} + \phi_{ij}(x_{i,j} - x_{k,j})$ (k is a solution in the neighbourhood of i , ϕ is a random number in the range [k,1]) and evaluate them
- Apply the greedy selection process between $x_{i,j}$ and $v_{i,j}$. Calculate the probability values $p\{x_i\}$ for the solutions x_i by means of their fitness values using the equations (1)

$$p\{x_i\} = \frac{f(x_i)}{\sum_{i=1}^{SN} f(x_i)} \tag{1}$$

In order to calculate the PSO operator values of solutions we employed the following equation (eq. 2):

$$\begin{cases} V_i^{r+1} = \omega V_i^{(r)} + c_1 rand_1(o)(Pbest_i - Y_i^{(r)}) + c_2 rand_2(o)(Gbest - Y_i^{(r)}) \\ Y_i^{(r+1)} = Y_i^{(t)} + V_i^{r+1} \end{cases} \tag{2}$$

Produce the new solutions (new positions) v_i for the onlookers from the solutions x_i, selected depending on $p\{x_i\}$, and evaluate them

- Apply the greedy selection process for the onlookers between x_i and v_i.
Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution x_i for the scout using the equation (3)

$$x_i = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min}) \tag{3}$$

- Memorize the best template (solution) achieved so far
- cycle =cycle+1
- until cycle = Maximum Cycle Number (MCN)

Fig 5. Pseudocode of Hybrid algorithm

5.3.2 CNN segmentation using the optimal template

After template design process is completed, CNN image segmentation will be subsequently conducted. In order to segment the lung and brain region," n" neighborhoods were used for the CNN templates A and B, which represent the feedback and feed-forward connections, respectively. Another CNN template I was used as an offset matrix. According to eqn (1), the output of CNNs lies on the feedback template A, control template B and I. They are set as below in our experiment:

$$A = \begin{bmatrix} T_{1,1} & T_{1,2} & T_{1,3} \\ T_{1,4} & T_{1,5} & T_{1,6} \\ T_{1,7} & T_{1,8} & T_{1,9} \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad I = 0.6$$

Then Eq. (1) is rewritten as follows:

$$dv_{xij}(t) = \sum_{C(k,l)\in N(i,j)} A(i,j;k,l) v_{ykl}(t) + 0.6$$

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Finally, the overall segmentation process is explained as follows,

$$dx = -x + con(x, template) + con(x, zero\,matrix\,template) + I$$

Where,

$dx \rightarrow$ segmented image

$x \rightarrow$ is the original image,

$$con(x, template) = \sum_{k_1=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} a(k_1, k_2) b(x - k_1, template - k_2)$$

$$con(x, zeromateix\,template) = \sum_{k_1=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} a(k_1, k_2) b(x - k_1, zeromatrix\,template - k_2)$$

and $I \rightarrow$ is bias (offset matrix)

6. THE SIMULATION RESULTS AND DISCUSSION

The Segmentation technique using lung and brain MRI images and the investigational results are described in this sector. The planned approach is implemented in MATLAB (matlab version 7.10). At this juncture, the proposed lung and brain MRI image segmentation technique is tested by using medical images taken from the publicly existing sources.

6.1. MRI image dataset description

From the publicly available sources, the MRI image dataset that we have utilized in our proposed lung and brain image segmentation technique is taken. This MRI image dataset contains 20 brain MRI images in which 10 lung images and the other 10 brain images. The Brain and lung image dataset are used to evaluate the performance of the proposed technique. In this, the 10 images are utilized for the training purpose and the remaining 10 images are utilized for testing purpose.

The Fig 6 shows some of the sample lung and brain MRI images

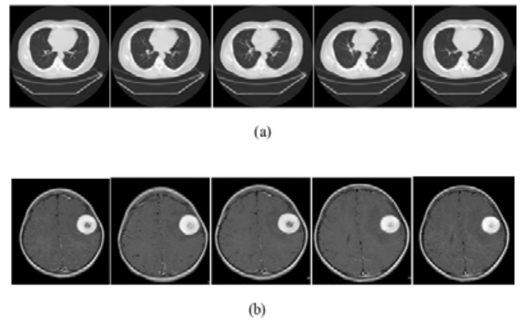


Fig.6. MRI Sample Image Dataset, (A) Lung MRI Images (B) Brain MRI Images

6.2. Experimental results

A procedure of partitioning an image into distinct regions is denoted by Image segmentation. Physical segmentation of brain and lung from MR images is a tough and time consuming task. A competent CNN based system is proposed to segment brain and lung from MR images.

Brain image section

The obtained experimental results such as, initial population templates, fitness and corresponding segmented lung and brain images are shown in below figures. Fig 7 shows 5 initial templates and its corresponding best fitness and segmented image and fig 8. shows 50 and 100 iteration template and its corresponding best fitness and segmented image.

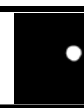
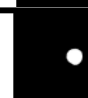
. Initial population-templates	Fitness	Segmented brain image
$\begin{bmatrix} 0.347895 & 0.528758 & 0.524788 \\ 0.857628 & 0.812541 & 0.688457 \\ 0.402568 & 0.824578 & 0.575826 \end{bmatrix}$	0.90568	
$\begin{bmatrix} 0.370627 & 0.956002 & 0.905943 \\ 0.560156 & 0.642465 & 0.607045 \\ 0.256622 & 0.342146 & 0.503923 \end{bmatrix}$	0.80426	
$\begin{bmatrix} 0.284789 & 0.884309 & 0.204764 \\ 0.245822 & 0.190408 & 0.197664 \\ 0.457894 & 0.347854 & 0.941338 \end{bmatrix}$	0.88564	
$\begin{bmatrix} 0.440217 & 0.204816 & 0.944881 \\ 0.990748 & 0.445887 & 0.141419 \\ 0.284065 & 0.412172 & 0.604896 \end{bmatrix}$	0.87898	
$\begin{bmatrix} 0.283212 & 0.613843 & 0.740216 \\ 0.241747 & 0.137318 & 0.301676 \\ 0.327778 & 0.4340167 & 0.516848 \end{bmatrix}$	0.86875	

Fig.7.Initial Templates And Its Corresponding Best Fitness And Segmented Image

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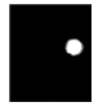
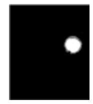
Iteration	Template	Best Fitness	Segmented brain image
After 50 Iteration	$\begin{bmatrix} 0.318609 & 0.371206 & 0.493132 \\ 0.609509 & 0.689036 & 0.585461 \\ 0.502967 & 0.390263 & 0.402219 \end{bmatrix}$	0.95478	
After 100 Iteration	$\begin{bmatrix} 0.487710 & 0.435105 & 0.477025 \\ 0.432391 & 0.722428 & 0.515227 \\ 0.551652 & 0.457365 & 0.453143 \end{bmatrix}$	0.95697	

Fig.8.After 50 And 100 Iteration Template And Its Corresponding Best Fitness And Segmented Image

Lung image section

Fig 9 shows 5 initial templates and its corresponding best fitness and segmented image and fig 10 shows 50 and 100 iteration template and its corresponding best fitness and segmented image.

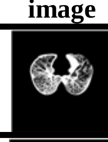
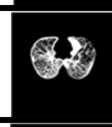
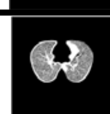
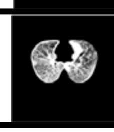
Initial population-templates	Fitness	Segmented lung image
$\begin{bmatrix} 0.201926 & 0.197413 \\ 0.041216 & 0.761348 \end{bmatrix}$	0.90145	
$\begin{bmatrix} 0.242168 & 0.292168 \\ 0.195885 & 0.654325 \end{bmatrix}$	0.79856	
$\begin{bmatrix} 0.223295 & 0.243605 \\ 0.09495 & 0.844736 \end{bmatrix}$	0.79584	
$\begin{bmatrix} 0.222901 & 0.284127 \\ 0.465225 & 0.574030 \end{bmatrix}$	0.78795	
$\begin{bmatrix} 0.248216 & 0.201466 \\ 0.487448 & 0.589145 \end{bmatrix}$	0.798465	

Fig.9.Initial Templates And Its Corresponding Best Fitness And Segmented Image

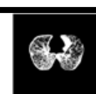
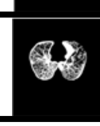
Iteration	Template	Best Fitness	Segmented lung image
After 50 Iteration	$\begin{bmatrix} 0.184926 & 0.157413 \\ 0.071501 & 0.741348 \end{bmatrix}$	0.90546	
After 100 Iteration	$\begin{bmatrix} 0.068105 & 0.094142 \\ 0.253027 & 0.723916 \end{bmatrix}$	0.90247	

Fig.10.After 50 And 100 Iteration Template And Its Corresponding Best Fitness And Segmented Image

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6.6. Comparative analysis and discussion

Our proposed segmentation technique of CNN against the Fuzzy C-means and K-means clustering techniques are compared. The sorting techniques which we have utilized for comparative analysis are Fuzzy C-means clustering and K-means clustering. The relative analysis of the diverse classification methods against our approach is offered in this section. Comparative analysis has taken three images (3 lung images and 3 brain images). For brain section, by analyzing the Fig 11, our proposed approach achieves better accuracy (96.4%) in first image, (96.1%) in second image and (95.1%) in third image. For lung section, by analyzing the Fig 12, our proposed approach achieves better accuracy (88.3%) in first image, (93.9%) in second image and (88.2%) in third image. Entirely, our approach performs considerably better than fuzzy c-means clustering and K-means clustering. The accuracy values of three methods are plotted as a graph shown in Fig 11.

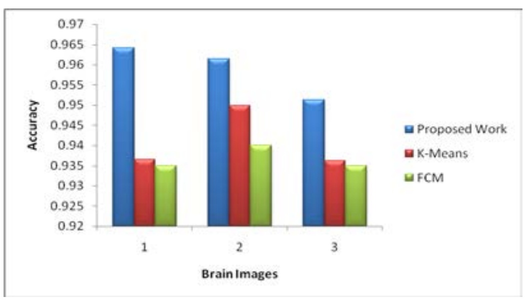

Fig.11.Comparative Analysis Graph Of Brain Images

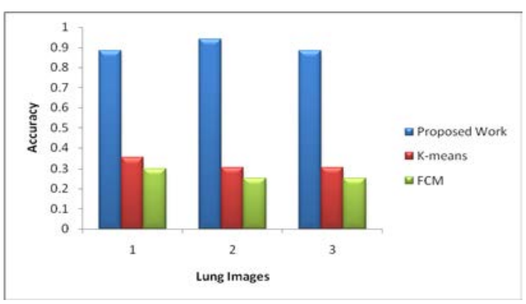

Fig.12. Comparative Analysis Graph Of Lung Images

7. DESCRIPTION ON CLINICAL APPLICATION OF THIS METHOD

Clinical application of the segmentation technique as follows,

- ➢ The segmented brain is used to visualize and quantitatively analyze anatomical and functional cortical structures. Brain-related diseases such as epilepsy and stroke are treated using Magnetic resonance imaging (MRI)-guided neural surgery.
- ➢ Segmented brain provide an anatomical framework for functional visualization, which finds a potential use in neuroscience research and neurosurgical planning owing to advances in function MRI (fMRI).
- ➢ Moreover, the use of segmented brain images is widely used in cortical surface mapping, volume measurement, tissue classification and differentiation, functional and morphological adaptation assessment, and characterization of neurological disorders such as multiple sclerosis, stroke, and Alzheimer's disease.

8. CONCLUSION

In the medical field, Lung and Brain MRI Image segmentation is an important and challenging factor. We have presented an effective lung and brain images segmentation approach with MRI images in this document. The competence is achieved with brain and lung MRI images, and the segmentation based on cellular neural network. Comparative analysis is carried out Fuzzy C-means (FCM) and K-means classification. The accuracy of proposed segmentation approach produces better results than that of existing Fuzzy C-means (FCM) and K-means classification from the comparative analysis.

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