


## Integration of Swarm Intelligence and Artificial Neural Network for Medical Image Recognition

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### ABSTRACT

Neural network technology plays an important role in the development of new medical diagnostic assistance or what is known as "computer aided" that based on image recognition. This paper study the method used integration of back propagation neural network and Particle Swarm Optimizing (PSO) in parts of recognition the X-Ray of lungs for two disease cases (cancer and TB) along with the normal case. The experiments show that the improvement of algorithms for recognition side has achieved a good result reached to 88.398% for input image size 1024 pixel and 500 population size. The efficiency and recognition testes for training method was performed and reported in this paper.

**Keywords:** X-Ray Lung diagnosis, Computer aided; Medical images, Segmentation, Image processing, Recognition, Neural network, Particle swarm optimization.

### تكامل الشبكات العصبية الاصطناعية وذكاء السرب للتمييز الصور الطبية

#### الخلاصة

الهيبن تعد تكنولوجيا الشبكات العصبية الاصطناعية من التقنيات المهمة في تطور حديث مساعدة التشخيص الطبي او ما يعرف بـ "التشخيص بمساعدة الحاسوب" والمعتمد على تمييز الصورة. هذا العمل يدرس امكانية استخدام طريقة تكامل شبكة الانتشار الخفي مع استمثال عناصر السرب في اجزاء من تمييز الأشعة السينية للرئه لحالتين مرضيتين هما السرطان والتدرن الى جانب الحالة الطبيعية.

تبين التجارب بأن تحسين الخوارزميات لغرض عملية التمييز حققت نتائج جيدة وصلت الى كفاءة بمقدار 88,398% لصورة ذات حجم (1024) نقطة وحجم مجتمع (500). تم إجراء اختبارات الكفاءة والتمييز لطرق التدريب وتم ذكرها في هذا العمل.

### INTRODUCTION

**A**rtificial neural networks (ANNs) are computational networks which attempt to simulate of the nerve cell (neurons) of the biological central nervous system. In the past years, ANNs have seen an increasingly interests in

medical image processing. ANNs have been applied to clinical diagnosis or to analysis and interpretation of images and signals with encouraging results. ANNs have a very important role in image analysis, too, being used together with processing of digital image in recognition and classification. ANNs provide a powerful tool to help doctors to analyse, model and make sense of complex clinical data across a broad range of medical applications. Most applications of ANNs to medicine are classification problems [1]. Applications of ANNs in medical image processing generally falls into the following categories: Pre-processing, Image segmentation, and object detection and recognition. Image pre-processing with ANNs generally falls into one of the following two categories: image reconstruction and image restoration. For using ANNs for medical image detection and recognition, the Back Propagation (BP) NN poses most places, other ANNs, i.e. Hopfield ANN, Adaptive Resonance Theory (ART) ANN, radial basis function ANN, Probabilistic ANN, convolution ANN, and fuzzy ANN, have also found their position in medical image detection and recognition [2]. Swarm Intelligence (SI) is one of the scientific fields that are closely related to natural swarms existing in nature, such as ant colonies, bee colonies, and rivers. Among the problem solving techniques inspired from nature are evolutionary computation, ANNs, time adaptive self-organizing maps, ant colony optimization, bee colony optimization, intelligent water drop, and particle swarm optimization.

One of the proposed algorithms in the field of the (SI) is the (PSO) algorithm. The PSO algorithm is an adaptive algorithm based on a social-psychological metaphor; a population of individuals (referred to as particles) adapts by returning stochastically toward previously successful regions. Particle Swarm has two primary operators: Velocity update and Position update. During each generation each particle is accelerated toward the particles previous best position and the global best position. At each iteration, a new velocity value for each particle is calculated based on its current velocity, the distance from its previous best position, and the distance from the global best position. The new velocity value is then used to calculate the next position of the particle in the search space [3].

This paper presents automated image enhancement and method for segmenting anatomy structures in chest x-ray images: lungs and its disease. The medical context of the enhancement algorithms presented is, Area Openings, and for segmentation is, connected component algorithm. This paper is organized as follows. Section 2 prepared data which is true X-Ray images for three lung cases (Cancer, TB and normal). Section 3 presents image processing for X-Ray lung images, which is consist of two stages, first stage the image passes through image enhancement processing to removed noise and not useful texture (ribs, windpipe, dusts, etc.) and the second stage is to segment each part of lungs and reshaped it in one image. Section 4 for building data matrix, which has been done by bringing images that processed in first stage then resized it to desired sizes, then combined it in one data matrix which represents the input layer units and one labeling matrix which represent output labeling. Training neural network is introduced in Section 5, where integration of back propagation with PSO optimization will be presented for the training neural network and producing weights. Simulations and experimental results are provided in Section 6 to demonstrate the efficiency, cost varies epoch, recognition program tested for detection trained and non-trained X-Ray images are provided in section 6. Finally, several conclusions are included in Section 7.

## **NN TRAINING DATA**

The images used to train NN are shots of true X-Ray lung images that put on medical X-Ray viewer which was found in hospitals. The cases classified by specialist doctors and then arranged in three folders in PC (Cancer, TB, and Normal) to be used for building program data matrix. Table (1) has shown types of X-Ray lung images and its numbers.

**Table (1) Types of X-ray images and its numbers.**

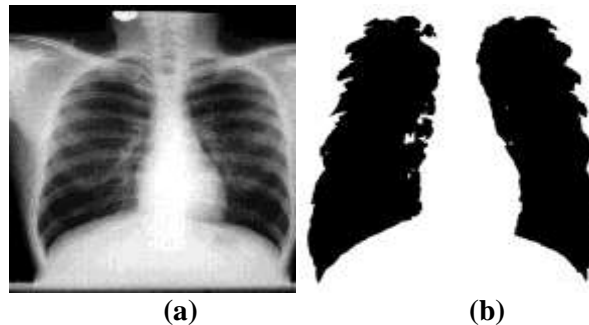
| Type of Images         | Number of Images |
|------------------------|------------------|
| Cancer X-ray           | 147              |
| TB X-ray               | 96               |
| Normal X-ray           | 119              |
| Total Number of Images | 362              |

**X-RAY IMAGE PROCESSING**

This part has been used to processed X-Ray images to removed not useful texture (ribs, windpipe, dusts, etc.); this done used the morphological filtering algorithm for image enhancement type “Area Openings” and Connected-component algorithm for segmentation.

**X-RAY LUNG IMAGE ENHANCEMENT METHOD**

For this method the image processing passed through multiple operations. First converted the x-ray image to gray-scale then converted the gray scaled image to binary image then applying *Area Openings* filter to enhanced x-ray lung Images as shown in Figure (1).



**Figure (1) X-Ray Lung Image: (a) Applying gray-scaled. (b) Converting to binary image with applying Area opening filter.**

This operation used MATLAB’s (bwareaopen) function:

```

Threshold = gray thresh (M);
M = ~im2bw (M, threshold);
M = bwareaopen (M, 90000);
    
```

**SEGMENTATION METHOD**

After enhancement process, (in which the images convert to binary) Connected Components labelling has been applied which separated lungs to two parts left lung Image and right lung images, as shown in Figure (2). This operation used MATLAB’s (regionprops) function for this.[L Ne]=bw label (M); Propied=regionprops (L,'Bounding Box');After segment operation it then recombination in one image and be saved in the lung cases folders.



Figure (2) X-Ray Lung Image after passing all image processing.

**IMAGE PROCESSING PROGRAM**

The program run and then request three folders of lung cases successively, after that the program automatically enhanced and segmented the X-Ray images and then saved it in 3 data folder (cancer, normal and TB) to be used in generation of data matrix. Figures(4, 5 and 6) have shown the image process result with three lung cases.

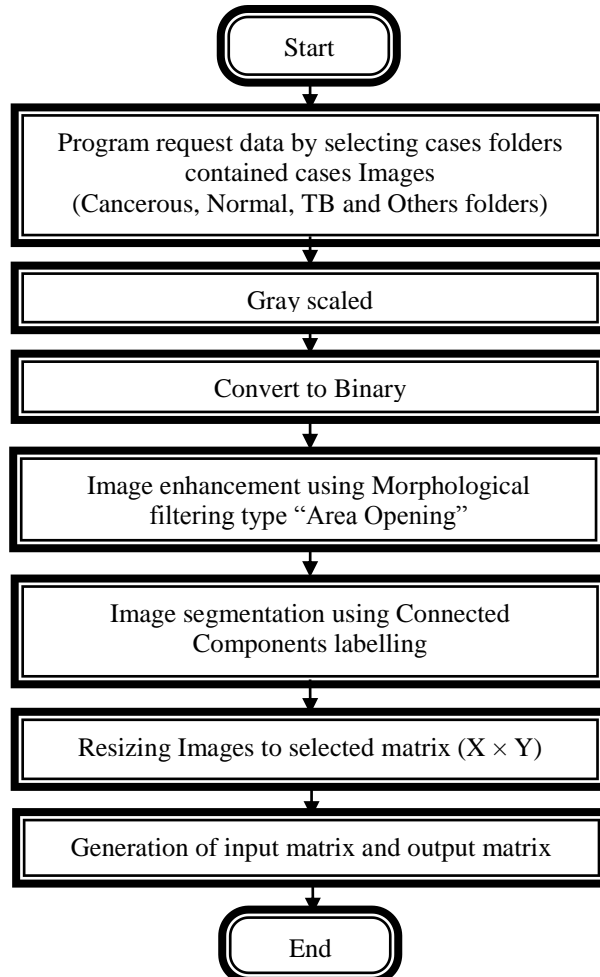


Figure (3) Input/output images matrix Generation scheme.

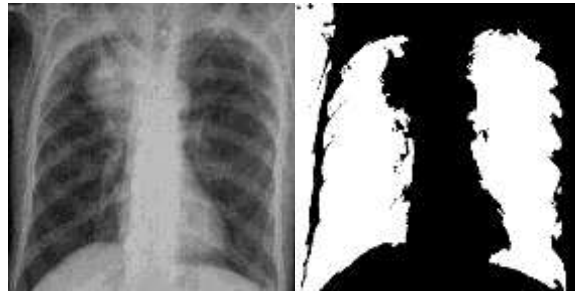


Figure (4) Image processing result for sample of cancer X-Ray lung image.

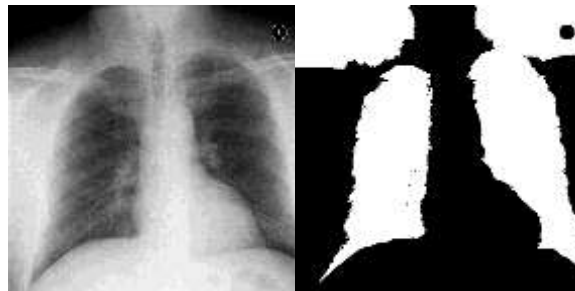


Figure (5) Image processing result for sample of normal X-Ray lung image .

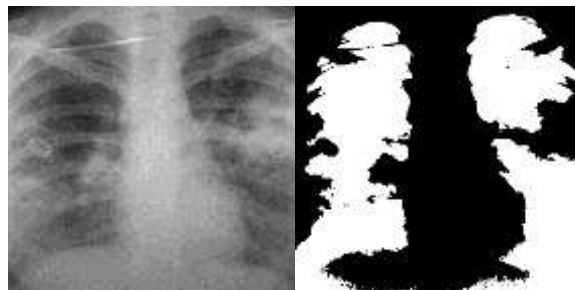


Figure (6) Image processing result for sample of TB X-Ray lung image.

#### IMAGE MATRIX GENERATION

This part used to get data matrix of images after applying enhancement, segmentation. First stage is to run enhance -segment program to process on X-Ray images, the generated images saved in three folders depend on the input case (cancer, Normal and TB), the total time required takes about (1293 second); then run data matrix generation program that resized these images to multiple sizes. The results, computational times and calculation of neurons that needed for training (362 total x-ray images) can be classified in Table (2).

MATLAB code used for resized and generated image matrix has been:

```
Files = dir ('*.jpg');  
str = strcat (files (i).name);  
M=imread(str);  
M=imresize(M,[imagex,imagey]);  
size(M);
```

**Table (2) Image matrix generation: size, generation time and hidden unit required.**

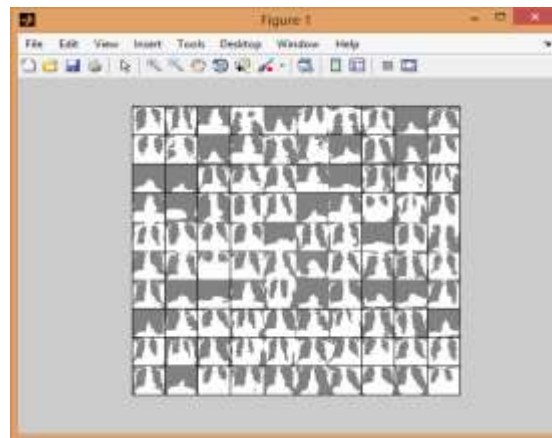
| Resized images | Output Matrix     |               |          | Hidden layer units needed |
|----------------|-------------------|---------------|----------|---------------------------|
|                | Input layer units | Output labels | Time/sec |                           |
| 1   8 × 8      | 64                | 3             | 94       | ~ 50                      |
| 2   16 × 16    | 256               | 3             | 96       | ~ 170                     |
| 3   32 × 32    | 1024              | 3             | 96       | ~ 700                     |
| 4   64 × 64    | 4096              | 3             | 97       | ~ 2700                    |

**TRAINING NEURAL NETWORK BY INTEGRATION BACK PROPAGATION AND PSO**

The PSO–BP is an optimization algorithm combining the PSO with the BP. The PSO is employed to enhance the NN training. The model consists of an input layer, hidden layer and an output layer. Inputs are taken as Images for three cases of lung disease. Weights on connections are chosen as random images initially. Then a transfer function (Sigmoid function) is applied on the weighted sum of inputs, which transfers the output to next layer which now is hidden layer. Then at all neurons of hidden layer, input value is compared to threshold value and result is compared to original one which were found, if the results do not match then back propagation algorithm is applied by which weights of previous connections are adjusted. Particle swarm optimization applied to Integrate back propagation neural network for optimizing.

**VISUALIZING THE DATA**

This part used to load the input data and display it on a 2 dimensional plot Figure (7) by calling the MATLAB's (display Data) function. There are 362 training X-ray Images used in Input matrix, where each training Images is an X pixel by Y pixel gray scale image of the digit. Each pixel is represented by a floating point number indicating the gray scale intensity at that location



**Figure (7) 2D displaying Data.**

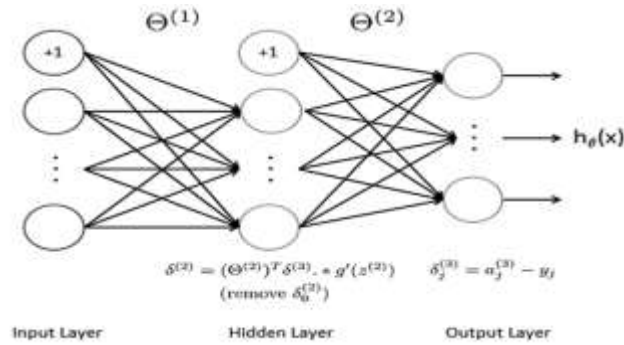
The 8×8, 16×16, 32×32 and 64×64 grid of pixels is “unrolled” respectively into a 64, 256, 1024 and 4096 dimensional vectors. Each of these training images becomes a single row in data matrix. This gives an X by Y matrix where every row is a training image for an X-Ray lung digit image.

$$X = \begin{bmatrix} (x^{(1)})^T \\ (x^{(2)})^T \\ \vdots \\ (x^{(m)})^T \end{bmatrix} \quad \dots (1)$$

The second part of the training set is a 362-dimensional vector  $y$  that contains labels for the training set. For using three cases of lung the labels therefore are 3 labels (1, 2, and 3).

**BACK PROPAGATION ALGORITHM**

This part implements the back propagation algorithm. The procedure for this BP algorithm can be summarized as follows: [10].



**Figure (8) Back propagation Updates [10].**

1. Setting the input layer’s values  $a^2$  to the  $t$ -th training example  $x^{(t)}$ . Perform a feed forward pass (Figure8), computing the activations  $(z^{(2)}, a^{(2)}, z^{(3)}, a^{(3)})$  for layers 2 and 3. It needing to add  $a+1$  term to ensure that the vectors of activations for layers  $a^{(1)}$  and  $a^{(2)}$  also include the bias unit.

Where:

$$\begin{aligned} a_k^{(1)} &= \text{Unit } k \text{ in layer 1 (the input layer)} \\ z_k^{(2)} &= a_k^{(1)} \times \Theta^{(1)} \\ a_k^{(2)} &= \text{Sigmoid}(z_k^{(2)}) \\ z_k^{(3)} &= a_k^{(2)} \times \Theta^{(2)} \\ a_k^{(3)} &= \text{Sigmoid}(z_k^{(3)}) \\ h_\theta(x^{(i)}) &= a_k^{(3)} \end{aligned}$$

For each output unit  $k$  in layer 3 (the output layer), set

$$\delta_k^{(3)} = a_k^{(3)} - y_k \quad \dots (7)$$

Where:  $y_k \in \{0, 1\}$  indicates whether the current training Image matrix  $x^{(t)}$  belongs to class  $k$  ( $y_k = 1$ ), or if it belongs to a different class ( $y_k = 0$ ).

2. For the hidden layer  $l = 2$ ,

$$\delta^{(2)} = (\Theta^{(2)})^T \delta^{(3)} * \phi'(z^{(2)}) \quad \dots (8)$$

3. Accumulating gradient from using the following formula:

$$\Delta^{(l)} = \delta^{(l+1)}(a^{(l)})^T \quad \dots (9)$$

### Training Neural Network by Integrate Back Propagation and PSO Swarm Optimization

After training NN with back propagation algorithm, it then optimized by applying PSO swarm optimization on it. When the PSO algorithm is used in evolving weights of feed forward neural network, every particle represent a set of weights, there are three encoding strategy for every particle, the equation used for PSO optimization is shown in follows: [11?].

$$v_{id}(t+1) = w * v_{id}(t) + c_1 * rand() * [p_{id}(t) - v_{id}(t)] + c_2 * rand() * [p_{gd}(t) - v_{id}(t)] \dots (10)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad 1 \leq i \leq n \quad 1 \leq d \leq D$$

Where:  $c_1, c_2$  are the acceleration constants with positive values;  $rand()$  is a random number between 0 and 1;  $w$  is the inertia weight. In addition to the parameters  $c_1$ , and  $c_2$  parameters, the implementation of the original algorithm also requires placing a limit on the velocity ( $v_{max}$ ). After adjusting the parameters  $w$  and  $v_{max}$ , the PSO can achieve the best search ability.

In PSO a number of simple entities the particles are placed in the search space of some problem or function, and each evaluates the objective function at its current location. Each particle then determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have been moved. Eventually the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to an optimum of the fitness function.

Each individual in the particle swarm is composed of three D-dimensional vectors, where D is the dimensionality of the search space. These are the current position  $\vec{x}_i$ , the previous best position  $\vec{p}_i$ , and the velocity  $\vec{v}_i$ . Current position is evaluated as a problem solution. If that position is better than any that has been found so far, then the coordinates are stored in the second vector,  $\vec{p}_i$ . The value of the best function result so far is stored in a variable that can be called pbesti (for “previous best”), for comparison on later iterations. The objective, of course, is to keep finding better positions and updating  $\vec{p}_i$  and pbesti. New points are chosen by adding  $\vec{v}_i$  coordinates to  $\vec{x}_i$ , and the algorithm operates by adjusting  $\vec{v}_i$ , which can effectively be seen as a step size.

The procedure for this PSO-BP algorithm can be summarized as follows:

**Step 1:** Initialize a population array of particles with random positions and velocities on D-dimensions in the search space.

**Step 2:** loop.

**Step 3:** For each particle, evaluate the desired optimization fitness function in D-



variables.

**Step 4:** Compare particle's fitness evaluation with its  $pbest_i$ . If current value is better than  $pbest_i$ , then set  $pbest_i$  equal to the current value, and  $\vec{p}_i$  equal to the current location  $\vec{x}_i$  in D-dimensional space.

**Step 5:** Identify the particle in the neighborhood with the best success so far, and assign its index to the variable  $g$ .

**Step 6:** Change the velocity and position of the particle according to the equation (10)

**Step 7:** If a criterion is met (usually a sufficiently good fitness or a maximum number of iterations), exit loop.

**Step 8:** end loop.

The parameter  $w$ , in the above PSO-BP algorithm also reduces gradually as the iterative generation increases, just like the PSO algorithm. The flow chart of PSO program is shown in Figure (9).

### BP-PSO PROGRAM

The program run and then loaded Image matrix data (input layer and output labels), after that the program initialized weight and then applying back propagation to get weight then applying PSO to optimized it. The iteration value used for trained ANN has been set to value of (1000) to get the best performance, the value of variable between -6 and 6,  $R$  are random number, the values of  $c1$  equal  $c2 = 2$  and the maximum velocity  $v_{max}$  to be (0.1).

The MATLAB's update particle velocity is:

```
vel == C*(w.*vel + c1 *r1.*(localpar-par) +c2*r2.*(ones(popsiz,1)*globalpar-par));
```

```
w=(maxit-iter)/maxit; r1 = rand(popsiz,npar); r2 = rand(popsiz,npar);
```

The MATLAB's update particle positions are:

```
par = par + vel; overlimit=par<=varhi ;underlimit=par>=varlo;
```

```
%par=par.*overlimit+not(overlimit).*varhi;
```

```
%par=par.*underlimit.*varlo;
```

```
pmax=max(max(par;((pmin=min(min(par));
```

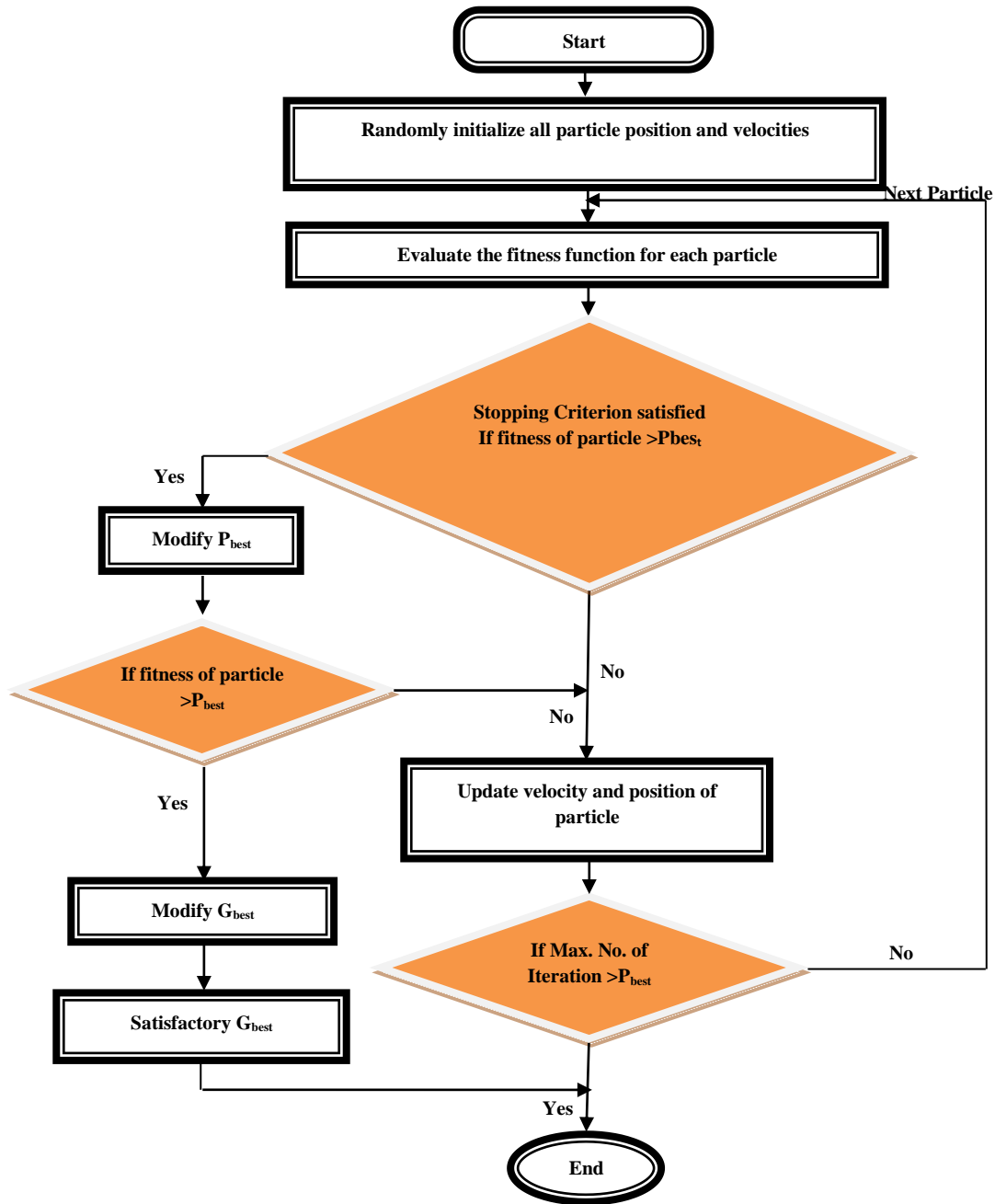


Figure (9) PSO-BP program scheme.

The tests was tested the efficiency of weights generated for different values of population size taken (100, 250 and 500). The weight efficiency, memory and computational time that have been achieved for each input have been classified in Table (3).

Table (3) Consumption of system resources and efficiency of weight generated for 1000 iteration, R1= (0.8), R2= (0.2), c1=c2=2 and v<sub>max</sub> = 0.1.

| Input layers | Data Matrix     |     |                    | Consumption of system resources |                           |                          | Efficiency of the weight generated |
|--------------|-----------------|-----|--------------------|---------------------------------|---------------------------|--------------------------|------------------------------------|
|              | Population size |     | Hidden layer units | CPU                             | Net Requirement of memory | Computational time / Sec |                                    |
| PSO          | 64              | 100 | 50                 | 44%                             | 90MB                      | 64                       | 85.359 %                           |
| PSO          | 64              | 250 | 50                 | 46%                             | 100 MB                    | 171                      | 86.188 %                           |
| PSO          | 64              | 500 | 50                 | 60%                             | 150 MB                    | 343                      | 86.188 %                           |
| PSO          | 256             | 100 | 170                | 51%                             | 130 MB                    | 445                      | 84.53 %                            |
| PSO          | 256             | 250 | 170                | 42%                             | 350 MB                    | 1126                     | 85.912 %                           |
| PSO          | 256             | 500 | 170                | 41%                             | 2400 MB                   | 2240                     | 83.149 %                           |
| PSO          | 1024            | 100 | 700                | 51%                             | 3600 MB                   | 6987                     | 86.74 %                            |
| PSO          | 1024            | 250 | 700                | 50%                             | 8400 MB                   | 17905                    | 87.293 %                           |
| PSO          | 1024            | 500 | 700                | 56%                             | 17250MB                   | 63475                    | 88.398 %                           |
| PSO          | 4096            | 100 | 2700               | 45%                             | 23950MB                   | 38856                    | 84.254 %                           |
| PSO          | 4096            | 250 | 2700               | Error "Over System Memory"      |                           |                          |                                    |
| PSO          | 4096            | 500 | 2700               | Error "Over System Memory"      |                           |                          |                                    |

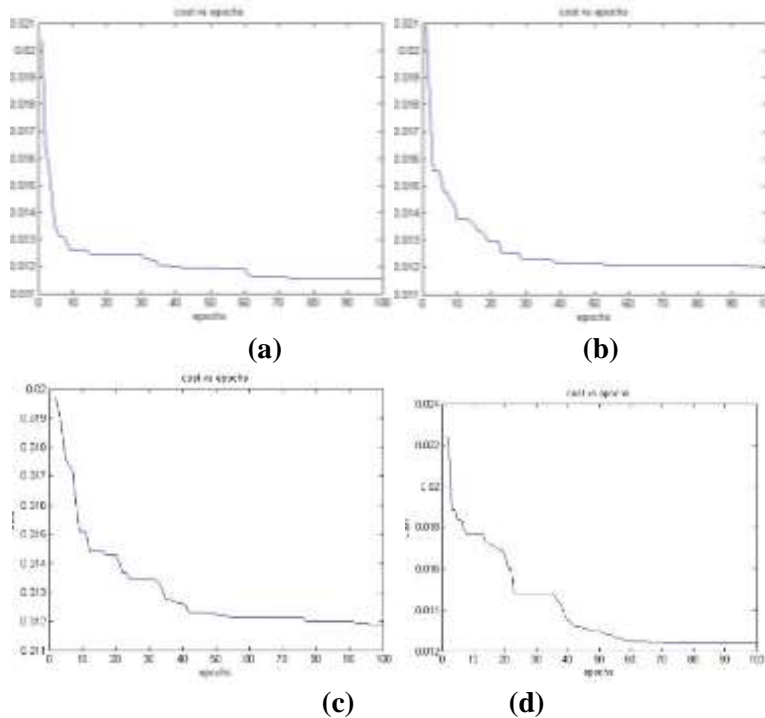


Figure (10) Cost gained with epochs of PSO with 100 population size for: a) 8x8 images matrix, b) 16x16 images matrix, c) 32x32 images matrix, d) 64x64 images matrix.

**X-RAY IMAGES RECOGNITION TEST (PRACTICAL TESTS)**

Recognition has been tested using recognition program to identify lung case for each input image. First program has been tested on images that train used to train NN and then it been tested with images that are not trained. The program tested by used different weights that produced from two training method (back propagation and the integrated way) for same iteration value of (1000), the back propagation recognition

results and BP-PSO recognition results have been classified in Table (4) and Table (5).

**Table (4) Recognition Results for trained X-Ray images.**

| Type of Recognition |        | Image matrix size | X-Ray lung image Cases |        |         |        |              |        |
|---------------------|--------|-------------------|------------------------|--------|---------|--------|--------------|--------|
|                     |        |                   | Cancer (147)           |        | TB (96) |        | Normal (119) |        |
|                     |        |                   | Detect                 | Failed | Detect  | Failed | Detect       | Failed |
| 1                   | BP-PSO | 8x8               | 122                    | 25     | 84      | 12     | 108          | 11     |
| 2                   | BP-PSO | 16x16             | 122                    | 25     | 88      | 8      | 100          | 19     |
| 3                   | BP-PSO | 32x32             | 134                    | 13     | 86      | 10     | 110          | 9      |
| 4                   | BP-PSO | 64x64             | 133                    | 14     | 82      | 14     | 90           | 29     |

**Table (5) Recognition Results for non-trained X-Ray images.**

| Type of Recognition |    |        | Population size | X-Ray lung image Cases |        |         |        |             |        |
|---------------------|----|--------|-----------------|------------------------|--------|---------|--------|-------------|--------|
|                     |    |        |                 | Cancer (24)            |        | TB (15) |        | Normal (22) |        |
|                     |    |        |                 | Detect                 | Failed | Detect  | Failed | Detect      | Failed |
| 8x8                 | 1  | BP-PSO | 100             | 16                     | 8      | 2       | 13     | 22          | 0      |
|                     | 2  | BP-PSO | 250             | 13                     | 11     | 11      | 4      | 22          | 0      |
|                     | 3  | BP-PSO | 500             | 14                     | 10     | 14      | 1      | 21          | 1      |
| 16 x 16             | 4  | BP-PSO | 100             | 14                     | 10     | 5       | 10     | 21          | 1      |
|                     | 5  | BP-PSO | 250             | 18                     | 6      | 6       | 9      | 16          | 6      |
|                     | 6  | BP-PSO | 500             | 14                     | 10     | 5       | 10     | 19          | 5      |
| 32 x 32             | 7  | BP-PSO | 100             | 15                     | 9      | 4       | 11     | 18          | 4      |
|                     | 8  | BP-PSO | 250             | 15                     | 9      | 9       | 6      | 21          | 1      |
|                     | 9  | BP-PSO | 500             | 18                     | 6      | 14      | 1      | 19          | 5      |
| 64 x 64             | 10 | BP-PSO | 100             | 19                     | 5      | 9       | 6      | 20          | 2      |

**CONCLUSIONS**

From the conducted experiments, we can get conclusions that for the following points:

- The emphasis of this paper is to develop a neural network training method used for building a program for X-Ray lung diagnosis that may help doctors in their diagnosis.
- The PSO-BP training results shown that the efficiency of weight updated increased depending on increasing of population size and number of iteration.
- The computational requirement especially memory have been increased rapidly as the input layer size increased and when the population size increased.
- The applying of image processing on X-Ray images before trained it with neural network given advantage that reduce the error and increasing the efficiency that due to the removing un useful features that may be dispersal the NN and it made be possible to reduce the input layer (resized image to small size about 8x8) without fearing from data loses.
- PSO-BP recognition results of trained and non-trained images shown relatively reducing in recognition errors as the input size and population increased, for cancer images detection (that total number 147 images), the tested have been appeared an increased in correction detection from (122 images) for 64 input size to be raised to (133 images) for 4096 input size which improved about (7.47%), and four non-trained cancer images detection (that total number 24 images), the tested have been appeared an increased in correction detection from (16 images) for 64 input size to be raised to (19 images) for 4096 input size for same population size which improved about (12.5%). For the same input size of 64 with different population sizes, the tested have been appeared an increased in correction detection of TB images from (2 images) for 100 population size to be rise to (11 images) for 250 population size and to (14 images) for 500 population sized which improved about (80 %).

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