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Detection of Biomedical Images by Using Bio-inspired Artificial Intelligent

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K E Y W O R D S

Bio-inspired Artificial Intelligent (AI), Moth Flame Optimization (MFO), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO).

A B S T R A C T

Computer vision and image processing are extremely necessary for medical pictures analysis. During this paper, a method of Bio-inspired Artificial Intelligent (AI) optimization supported by an artificial neural network (ANN) has been widely used to detect pictures of skin carcinoma. A Moth Flame Optimization (MFO) is utilized to educate the artificial neural network (ANN). A different feature is an extract to train the classifier. The comparison has been formed with the projected sample and two Artificial Intelligent optimizations, primarily based on classifier especially with, ANN-ACO (ANN training with Ant Colony Optimization (ACO)) and ANN-PSO (training ANN with Particle Swarm Optimization (PSO)). The results were assessed using a variety of overall performance measurements to measure indicators such as Average Rate of Detection (ARD), Average Mean Square error (AMSTR) obtained from training, Average Mean Square error (AMSTE) obtained for testing the trained network, the Average Effective Processing Time (AEPT) in seconds, and the Average Effective Iteration Number (AEIN). Experimental results clearly show the superiority of the proposed (ANN-MFO) model with different features.

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1. Introduction

Skin associated illnesses along with skin cancers are the foremost well-known illnesses within the complete world. It’s been discovered that one in every 10 people suffer from skin cancers in their whole lifetime. Among a variety of classes of pores and skin connected diseases, skin cancer is one among the most motives for additional than ten thousand deaths yearly within the United States of America [1]. In most events, coming soon diagnosing and treating will recuperation the illness completely. Coming soon revelation of the sickness is crucial as appropriate remedies can be carried out based on the type and the form of ailment [2]. Dermoscopy is one in all the foremost common and noninvasive ways in which to identify the tincture of leather lesions. Examinations accomplished by way of a bare eye have some drawbacks like precision -connected problems; barriers of a human supervisor, etc. computer-assisted methods will expeditiously examine and detect subterraneous structures of the pores and cuticle lesions. This approach offers the best differential among kind's forms of lesion their manifestation and capabilities. However, specialists on skilled expertise support visible experiments and surveillance of Dermoscopic pictures [3].

To lessen diagnostic mistakes and conquer the problem and information about human knowledge, Dermoscopy's pc equipment has grown to be an appealing discipline of research. Various pc helps ways for dividing and classifying pests rely upon the sting of the lesion and a few generic features. This is why a few ways will offer generalized strength because of differences in photo samples. The primary purpose at the back of these differences are several opinions, unequal 'zooming', lighting situations, etc. what is more, pictures might contain some artifacts that may affect the classification of results. Various methods of analyzing and dividing biomedical images of different methods have been developed. Various contouring methods can be used in the biomedical analysis [4-6]. The automatic technique is suggested that applies MFO trained ANN for skin carcinoma classification. The networks are training by very different footage obtained from the American Skin Cancer Society (ASCS) 2017 dataset. The trained NN-MFO supported classifier was then used on wholly completely several unlabeled pictures. The acquired results are comparisons in different ways, like ANN-PSO [7] and ANN-ACO [8].

2. Related Works

Up to now, several techniques have been proposed on the detection of images of skin cancer in different literature and diverse classification accuracies have been reported in the last decade for the skin of the image's cancer diagnostic. The following is a brief description of previous research.

Zhang et al. [9] A proposed the hybrid algorithm to Combining between Back-Propagation algorithm and PSO algorithm to training the weights of feedforward neural networks.

Dhawan et al. [10] A Proposed of associate degree topic with specified qualities that can be used in image process. The medical pictures evaluation responsibilities encompass features, extraction and illustration, Features choice that will be used in image classification.

Silveira et al. [11] introduced a comprehensive comparative analysis of different segmentation methods for detecting skin cancer lesions.

Uzer et al. [12] A Proposed ABC algorithm for the optimization of the feature selection process in the classification of liver and diabetes database, in which there are some excrescent and low - distinctive features.

Shanthi and Bhaskaran [13] A Proposed using the ABC algorithm as a feature choice mechanism to pick the prevalent feature collection within the type of breast cancer in the mammogram picture. The overall execution of the proposed approach becomes as compared with GA and PSO.

Xie et al. [14] developed a new algorithm with a self-generating neural network (SGNN) and features descriptive of the tumor color to get high accuracy with the classifier model for melanomas and benign case.

Mohan et al. [15] A Proposed Magnetic resonance (MR) imaging may be a well-known medical imaging technique that's non-invasive and fabricate top-quality pictures of the anatomical framework of the brain. It provides very vital info for up the clinical designation and reinforces the sanitary brain of the patient.

Oliveira et al. [16] evaluated various categories of the classifier of the feature extraction phase and several feature selection algorithms were compared for the categorization of melanoma.

Al-masni et al, [17] used various dermoscopy datasets for a skin lesion full resolution convolutional network (FrCN) for a better performance when compared with existing methods of melanoma detection that leads to an enhancement in the segmentation analysis.

3. Moth Flame Optimization

Moth Flame Optimization (MFO) is an optimization algorithm inspired from the navigation method of moths. Moths using transverse orientation techniques for navigation at night by keeping a fixed angle with the moonlight direction, so that moths can move for long distances in a straight path. For modeling, the moth transverse orientation, suppose that the moths represent the problem candidate solutions and the position of moths represent the variables of the problem, while the flame indicates the best position of each moth obtained by iteration. Like other population-based metaheuristic algorithms, MFO begins with a random population in the search space; evaluate the best initial solution according to fitness function then updating moth's position according to spiral movement of the moths as follows:

$$x_i^{j+1} = AD_i^j e^{(\epsilon c)(\alpha r)} cos(2\pi(\alpha r)) + f_k^j \quad (1)$$

$$AD_i^j = \left| f_k^j - x_i^j \right| \quad (2)$$

Where x_i^j indicates the ith moth at jth iteration, f_k indicates the kth flame, both moth and flames are candidate solution, but flames are the local best position of moths, AD_i indicates the distance between the ith moth and the kth flame, ϵc is a constant used for the shape of the spiral movement, and αr is a random number $\in [Rc, 1]$ and represents how much moth close to a flame to ensure further moth exploitation, Rc represents convergence constant that linearly reduced from -1 to -2 over an epoch of iterations[18].

Equation (1), describes how moths modify their positions, but not essentially in space between flames [x]. To prevent MFO trapped into local minima position, each moth is binding to modify its position according to only one of the sorted flames, where after each iteration flames are arranged according to their fitness. The number of flames is reduced over the epoch of iterations as shown in Equation (3), since the updating of moth's position according to different locations in the space may decrease the exploitation of the best solutions.

$$nof = round(f_{max} - j\frac{(fl_{max}-1)}{maxit}) \quad (3)$$

Where fl_{max} represents the maximum number of flames, j is the current iteration number, maxit is the maximum iteration number [18].

4. Methods of Image Detection

This section explains extensively on the overall processes that were implemented for this work. It consists of steps of images Detection steps, pre-processing and filtering, feature extraction and normalization, and finally the development of brain image Detection model using ANN as illustrated in Figure 1.

I. Image acquisition

- The digital images are made by one or many images sensor, which, besides varied sorts of sensitive cameras, embrace vary sensors, picturing devices, radars, ultrasonic cameras, etc.
- Depending on the types of sensor, the ensuing image information is standard 2D images, a 3Ds volume, or a picture sequence. The pixels element values usually coincide to strength of light in one or many spectral bands (gray- pictures or color- pictures), however may also be associated with varied physical measurement, like depth, absorption, or coefficient of reflection, magnetic force waves, or nuclear resonances [19].

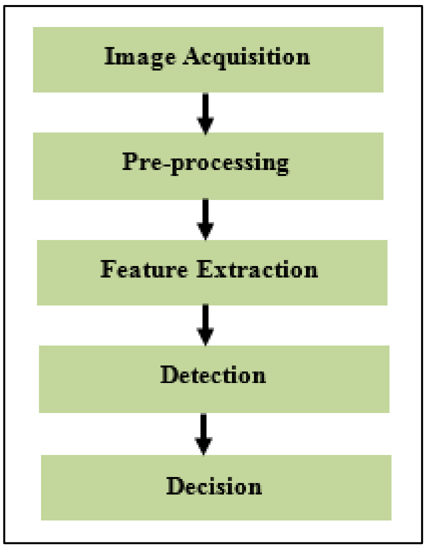

Figure 1: Block Diagram of Image Detection

II. Pre- processing

The primary steps inside the image process chain consist of pre-processing. Loosely outlined, by pre-processing we tend to mean any process of that the input consists of detector data, and of that, the output might be a full image. Pre-processing operations typically be one amongst three categories: image re-construction (to re-construct a picture from variety of detector measurements), image restoration (to take away any deflection introduced by the detector, together with noise) and image enhancement (accentuation of bound desired options, which can facilitate later process steps like segmentation or object recognition) [19].

III. Feature Extraction

The Feature extract is one in each of the foremost necessary steps in all categorization headed issues [20]. Features were required issue into each coaching and testing operations. To extracts feature on the start only one stage distinct (2Dim) wavelet transform (WT) has been implemented in three cases using Daubechies application, DB4 filters on the binary picture. They are illustrated in Figure 2. Use a concept element analysis approach in the cA approximation matrix and the information transaction arrays cH, cV, and cD. Create a matrix of a grayscale overlay of the matrix obtained by taking advantage of Principal Component Analysis (PCA). Then utilize the matrix acquired by PCA, great features are choosing, and calculation as given in lower down [20].
(1) Means: it is just an element from elements matrix.
(2) Standard Deviation: We must calculate the criterion perversion of matrix factors.
(3) Entropy: is a randomness of statistical measuring that can be applying to locate special of the form of the input facts of the picture. That according to as equation.

$$Entropy = -sum\ (p * \log_2\ p) \tag{4}$$

Where: p include a number of histograms.
(4) RMS: The level of root square vector of x, which stated in equation .

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|X_n|^2} \tag{5}$$

(5). Variances: is the quadratic of criterion perversion
(6) Smoothness: given in equation.

$$Smoothness = 1 - \frac{1}{1-a} \tag{6}$$

Where (a): is a total matrix in PCA.
(7) Kurtosis: It measures, however; distribution is prone to excess division. If the dispensation is additionally susceptible to over the conventional dispensation, the unfold worth is going to be larger than three for dispensation; similarly, the dispensation that's less liable to outlier features a flattening value less than three. The dispensation junction as given in the equation.

$$k = \frac{E(x-\mu)^4}{\sigma^4} \tag{7}$$

μ : is medium value (x).
σ : is criterion perversion value (x) .
E : The anticipate values (t).
(8) Skewness : is a degree measurement of data dissymmetry around the mean. If the deviation account is a smaller amount than zeros, the info are going to be more distribute on the left part of the average compare to the correct (right). Likewise, if the deviation account is larger than zero, we will conclude that the info is more distribute on the correct part of the sample medium from the left .
(9) Contrast: It is a measure to calculate the density variation between pixels and is happening on entire images. It is defined in the equation.

$$Contrast = \sum_{i,j} |\ i - j\ |^2\ p(i,j) \tag{8}$$

(10) Correlation Factor: It is a gauge of pixel relates to the progress on the total picture. Link values are not fix to still images. Given in the equation.

$$\boldsymbol{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\ \sigma_j} \tag{9}$$

(11) Energy : Is a total of squares components in a gray standard presence matrix, given in the equation:

$$\boldsymbol{Energy} = \sum_{i,j} p(i,j)^2 \tag{10}$$

(12) Homogeneity : It is a gauge of distribute components in gray-levels common presence matrix. It is defined in the equation:

$$\boldsymbol{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{11}$$

IV. Detection

There are many ways in which grouping the present view detection algorithm. Grouping may well be supported analysis contribution in detection strategies, or supported parameters on knowledge used, supported element info used, or supported information accessible from adjuvant knowledge, or supported picture attributes used. Primarily based or an analyst's function, view detection is supervised and unsupervised detection. Primarily based on parameters on data used view will be detected as constant quantity and non-parametric detection. Supported picture element data, view detection will be per-pixel, sub-pixel, per-field, and sequence detection. The picture can be labeled as knowledge-loose and knowledge-primarily based detection [21].

V. Decision

● pass/Fail on computerized inspection packages.
● Fit / no-match in recognition packages.
●Flag for in addition human evaluate in medical, scientific, military, security, and other programs.

VI. Analysis of Dataset

The NN is a type inspired via the neural interaction that may be used correctly to study complicated styles. Understanding patterns result in the future prediction of a given value. The shape of the standard NN sort consists of many artificial neural organized in multiple layers. The neurons of the layer contacted with the neural in their previous and resultant layers. Throughout the training part, knowledge states are fed into NN the response is in comparison with the anticipated results. The difference among the predicted result and the reaction from ANN is utilizing as an error. This quantity of error is employed to regulate the weights related to NN to enhance its performance. An identical operation is performed for every instance of the data. Within the last of the training section, you're expected to own the best set of weights won't to minimize the chance of misclassification. During the testing section, NN is tested with a collection of unknown information and its reaction is verify to the degree for performance. Figure 3 is depicted NN regular. Traditional practice algorithms don't guarantee optimum coaching, as they will hinder the native optima whereas trying to find the simplest solutions. To make sure that NN has the optimum variety of weights throughout the coaching section, the error ought to be reduced, which will be thought of improvement trouble. One of the foremost widespread coaching algorithms is that the Back Propagation algorithmic rule (BPA), this algorithmic rule has been extensively used for the network coaching purpose. BPA appears to be tormented by multiple issues like simply comprise native minima and its low convergence speed. Several attempts are created to boost the performance of BPA, whereas alternative simply used process evolutionary algorithms (EAs) to switch BPA within the training section. EAs are universal population-primarily based meta-heuristic optimizations algorithms. Most of the EAs were inspired by natural phenomena or living creatures. EAs use mechanisms inspired by biological evolutions, like reproductions, mutations, recombination, and selections. Every individual within the population may be a candidate resolution. The fitness function determines the quality of the candidate solutions.

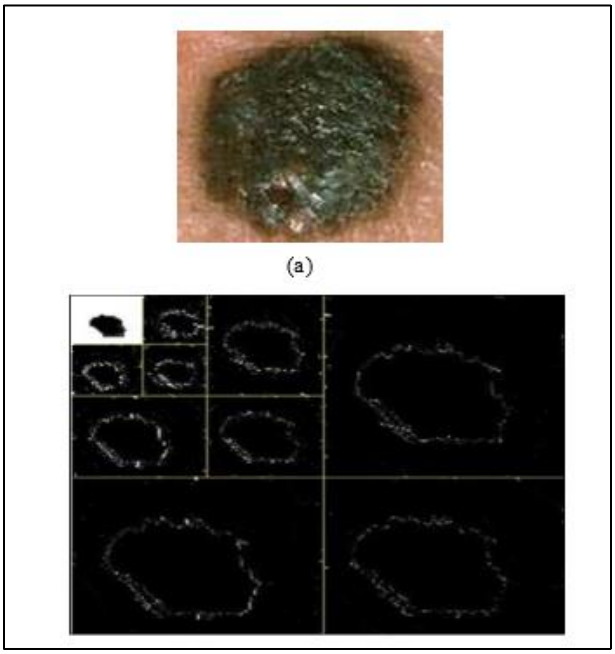

Figure 2: (a) Authentic Images (b) After using Daub chies DB4filter

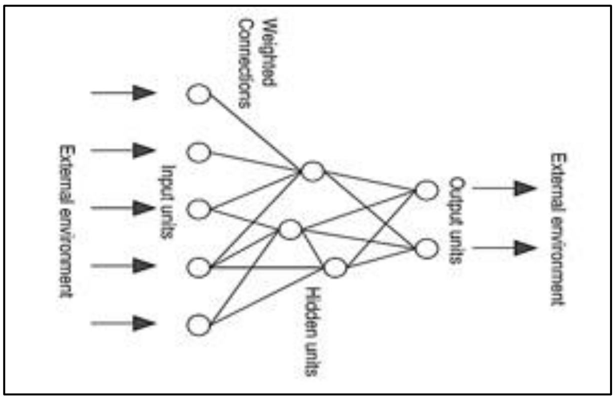

Figure 3: General NN architecture

Each EA has its global and local search mechanism to guide the population towards an optimum or near optimum solution by iterations. The general rules used to optimize neural network weights using EAs can be summarized as:

- Consider the weights vector of the neural network as a single population particle in the swarm.
- Each swarm is a matrix consists of population size (popsize) rows and several weights (ndim) columns.
- Initialize the swarm matrix randomly according to the bounds of the search space .
- Evaluate the Mean Square Error (MSE) for each particle and evaluate the best particle and its location in the swarm matrix.
- Consider the particle with the minimum MSE is the global best *(gbest)* solution and each other is a local solution (*lbest*).
- Run the optimization algorithm to modify each particle *lbest* and the global *gbest*.
- Check if the iteration reached its maximum value.

We can suggest a general training process of ANNs using population-based algorithms. As we have observed that population, based algorithms make a random population because the first step of optimization, the populace might be in general $\in R^{Ni*M}$, wherein N represents the wide variety of answer vectors, whilst M represents the size of the trouble to be optimized. The position of the training set of rules is to be sure and test the candidate N answers inside the population, and then alter the answer vector in an iteration method in line with the used set of rules to get the fittest solutions. However, within the case of supervised learning of NNs the target operate is that the Mean Square

Error (MSE), the weights of the network are totally optimized after we get terribly minimum or zero MSE, show in Figure 4. One goal of this confrontation was to offer an exposure According to the ISIC (International Skin Imaging Collaboration [1]) archive to a enhance development of machine-controlled carcinoma identification procedures from Dermoscopic pictures. Photos with different resolutions (from1022X767 to 6748X4499), photographic angles, and lightning situations. Some pictures of this collection contain some synthetic. Three types of pictures were examined in this paper: Namely Angioma, Basal Cell-Carcinoma, Lentigo Simplex. Test pictures show in Figure 5.
In this current work, error reduction is used in the target function to achieve optimum weights group.
Therefore, pre-technology detection algorithms can be used to ensure convergences with the global optimum level. Thus, Bio-inspired Artificial Intelligent (AI) optimization methods, such as existing PSO, ACO, and MFO methods can be used to training NN.

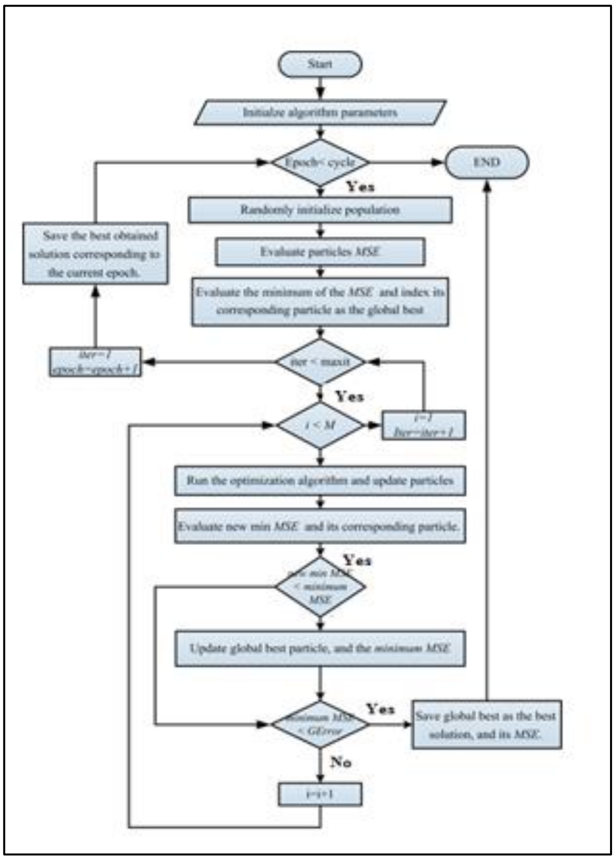

Figure 4: General Meta heuristic training flow chart

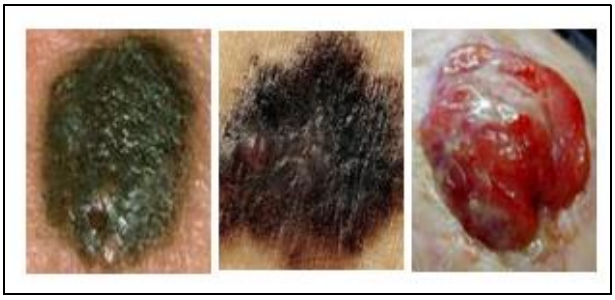

Figure 5: Different types of skin cancers under test Angioma (B) Basal Cell-Carcinoma (C) Lentigo Simplex [1]

5. Simulation Results

The simulations are achieved with the aid of using the proposed NNs detection of skin carcinoma problem using population-based algorithms to optimize the synaptic weights connections of the proposed network. However, the proposed general training method shown in section (5) has been applied, for the detection of real data and comparing the performance of these algorithms according to this task. To detection of skin cancer dataset using ANN a network with 11 input neurons, 13 hidden neurons, single hidden layer, and 3 outputs neurons, tan-sigmoid and log sigmoid activation functions for hidden and outputs layer has been used. The weights were bounded between [-5, 5]. The parameters of the algorithm were the same as the parameters illustrated in Table 1. Table 2 shows the algorithms training records, in which MFO dislikes other tested algorithms has maintained a 100% detection rate through the whole 10 iteration epochs, it also gets the minimum AMSTE and the most effective lowest average processing time and average iteration number. On the other hand, ACO has been gotten the minimum AMSTR. The full data of results are recorded in Table 3.

Figure 6 shows random epochs convergence curves, where it is obviously that MFO has a faster convergence curve. However, for the purpose of testing and implementation, the compared algorithms MATLAB 2017 has been used on a core i7 2.4 GHZ CPU computers with 8 GB RAM.

The network is trained by employing the (PSO, ACO, MFO) algorithms to achieve the values of the weights for each node interconnection and bias terms until the output layer neurons values are as close as possible to the actual outputs . The Mean Squared Error of the network (MSE) can be defined as below:

$$MSE = \frac{1}{2}\sum_{k=1}^{g}\sum_{j=1}^{m}(Y_j(k) - T_j(k))^2 \tag{12}$$

Here m is the number of nodes in the output , g is the number of training samples , $Y_j(k)$ defines" the desired output, and $T_j(k)$ is the real output.

The Correct rate detection (RD) is the first metric, which can be defined as below.

$$RD = \frac{No.of\ Pixels\ Correctly\ Classified}{Total\ Pixels\ in\ the\ Test\ Dataset} \tag{13}$$

In these two experiments we have proposed two stopping criteria conditions; if the MSE reached its minimum required value, or if an algorithm has gotten 100% detection rate. Input data patterns are divided into 2 data types; training and testing, 80% of input data sets are used for training, while 20% are used for testing of the trained network.

6. Discussion

In this work, the application of the structure based on artificial neural networks supported by metaheuristic has been investigated and has been employed and trained to detect Dermoscopic images. The outcomes of three various techniques are; comparison in Tables 2, 3 and Figure 6. Of the results obtained, it can be concluded that MFO, training on ANN, produces better outcomes than other techniques with 100% accuracy. The equal technique to a greats training data- set can lead up to the best predictive type.

Table 1: Implemented algorithms default parameters

No.	Alg.	Algorithms parameters
1-	**PSO**	The higher certain of the search range =maximum of search space range, the lower certain of the search range =minimum of search space range, acceleration coefficients c1=c2= 2. Inertia weight is time varying linear decreasing. Maximum and minimum inertia weight are 0.9 and 0.45, population size=30, maximum iterations= 100.
2-	**ACO**	Food number=15, the opportunity values are calculated through the use of fitness and normalize through dividing utmost fitness value , Population size= 30, maximum iterations= 100.
3-	**MFO**	Population size= 30, maximum iterations= 100.

Table 2: Detection Problem Algorithms Performance

Alg.	AMSTR	AMSTE	ARD%	AEP (sec)	AEIN
PSO	0.165	0.159	67.93%	5.75	98
ACO	**0.086**	0.0949	95.24%	2.306	78
MFO	0.097	**0.0884**	**100%**	**1.05**	**52.3**

Table 3: Full Records of Algorithms Training ANN for Detection

Training MSE			
NO.	**PSO**	**ACO**	**MFO**
1	0.149	0.0915	0.0964
2	0.185	0.0732	0.0927
3	0.162	0.0946	0.1
Testing MSE			
NO.	**PSO**	**ACO**	**MFO**
1	0.136	0.092	0.081
2	0.192	0.0947	0.0933
3	0.151	0.098	0.091
Detection Rate %			
NO.	**PSO**	**ACO**	**MFO**
1	70.381	95.617	100
2	65.164	96.203	100
3	68.250	93.872	100
Effective Processing Time (sec)			
NO.	**PSO**	**ACO**	**MFO**
1	3.52	1.47	0.83
2	5.91	3.61	1.05
3	7.83	1.84	1.29
Effective Iteration Number (Iter)			
NO.	**PSO**	**ACO**	**MFO**
1	100	73	49
2	98	82	57
3	96	79	51

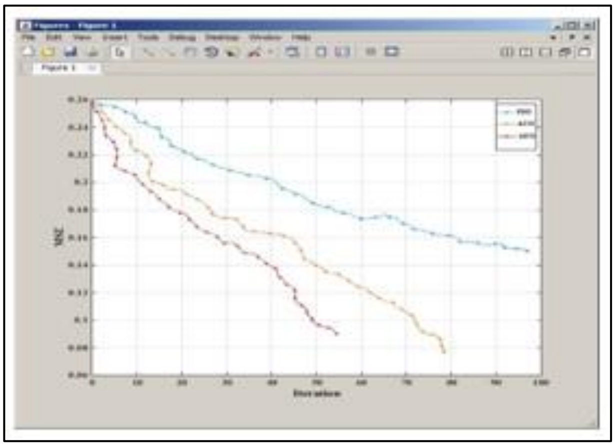

Figure 6: Random Epoch Algorithm Convergence Curves

7. Conclusions

This paper is using features extraction for three images of skin carcinoma and ANN training with recently proposing evolutionary population-based algorithms (MFO, ACO, & PSO) to detect these images and compared between all results of algorithms. The results have shown that the MFO performance has gotten the highest detection rates with a minimum number of iterations. From the experiments, we can conclude:

1. Using feature extraction beginning single-stage distinct (2Dim) Wavelet Transform (WT) has been enforced three cases using Daubechies application, DB4 filter on the skin carcinoma images.
2. The usage of too many neurons inside the hidden layer should result in an over fitting problem. Therefore a few compromises must be reached among too many and few neurons within the hidden layer .
3. Decreasing neuron bias little bit will produce minimum improvement in performance parameters except ACO algorithm needs to more bias reduction.
4. Increasing number of population search will improve the classification rate but with more processing time.
5. The ANN performance parameters will be retarded when increasing the space limits of algorithm search.

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