Genetic Algorithm and Firefly Algorithm in a Hybrid Approach for Breast Cancer Diagnosis

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Abstract: *Feed-forward neural networks are popular classification tools which are broadly used for early detection and diagnosis of breast cancer. In recent years, a great attention has been paid to bio-inspired optimization techniques due to its robustness, simplicity and efficiency in solving complex optimization problems. In this paper, it is intended to introduce a Genetic Algorithm based Firefly Algorithm for training neural networks. The proposed algorithm is used to optimize the weights between layers and biases of the neuron network in order to minimize the fitness function which is defined as the mean squared error. The simulation results indicate that better performance of the Firefly Algorithm in optimizing weights and biases is obtained when being hybridized with Genetic Algorithm. The proposed algorithm has been tested on Wisconsin Breast Cancer Dataset in order to evaluate its performance and the efficiency and effectiveness of the proposed algorithm by comparing its results with the existing methods. The results of the proposed algorithm were compared with that of the other techniques Firefly Algorithm, Biogeography Based Optimization, Particle Swarm Optimization and Ant Colony Optimization. It was found that the proposed Genetic Algorithm based Firefly Algorithm approach was capable of achieving the lowest mean squared error of 0.0014 compared to other algorithms as mean squared error values for other algorithms were 0.002 for Firefly Algorithm, 0.003 for Biogeography Based Optimization, 0.0135 for Ant Colony Optimization , 0.035 for Particle Swarm Optimization.*

Keywords: *MLP, classification, meta-heuristic optimization, breast cancer, Firefly Algorithm (FA), Genetic Algorithm (GA).*

I. INTRODUCTION

Classification has become an active research area in machine learning and data mining fields. One of the most interesting and challenging tasks in data mining applications is to predict the outcome of a disease. To reduce breast cancer deaths, the most effective way is the early treatment which can be achieved through early detection and diagnosis. The classification of Breast Cancer data can be useful to predict the outcome of some diseases or discover the genetic behaviour of tumors [1]. Feed forward Neural networks (FNNs) which are also known as Multi-Layer Perceptrons (MLPs), are one of the most popular and most widely used NNs techniques in many practical applications due to their effectiveness in classification. However; performance of the NNs depends largely on the success of training process (Kulluk et al., 2012). The process of training a NN generally aims at adjusting the individual weights between each of the individual neurons. At the beginning of the learning process a dataset, which is called as a training set, is passed to the inputs to predict the correct outputs. After finishing the learning process, a test dataset is used in evaluating the generalization and prediction capability of the classifier. The main target of the classification algorithms is to create a model from a set of training data whose target class labels are known and then this model is used to classify unseen instances which can be considered as optimization problem. According to [2], optimization usually tends to achieve the best outcome of a given operation while satisfying certain conditions. Thus, researches in different fields have been studying and developing optimization methods. Generally speaking, optimization algorithms can be divided into deterministic algorithms and stochastic algorithms [3]. The stochastic or meta-heuristic algorithms are broadly used in optimization problems as they are a good alternative to deal with discontinuous objective function, since they are based on randomization and local search. Randomization provides a good way to move away from local search to the search on the global scale. Therefore, almost all meta-heuristic algorithms are suggested to be suitable for global optimization [2]. The main feature of meta-heuristic approaches over the deterministic or derivative-based numerical methods is that they do not require differentiable objective functions or any condition being placed on the objective function [4]. Hybridization of several meta-heuristics is a recently developed trend for improving the performance and robustness of the algorithm .This paper presents a novel hybrid Genetic Algorithm based Firefly Algorithm in order to optimize weights and biases of feed forward neural networks to provide the minimum error for an MLP.

This paper is organized as follows: Section 2 highlights the literature review. Section 3 discusses the materials and methods used in this research. Results and analysis of the numerical experiments is discussed in Section 4. Finally, the paper is concluded in Section 5.

II. RELATED WORK:

Based on the literature, many of Machine Learning approaches have been employed for cancer detection using Wisconsin breast cancer dataset. Tüba Kıyan and Tülay Yıldırım [5] have conducted an experiment in order to evaluate the performance of the statistical neural network structures, Radial Basis Network (RBF), General Regression Neural Network (GRNN) and Probabilistic Neural Network (PNN). Overall classification accuracies were 96.18% for RBF, 97.0% for PNN, 98.8% for GRNN and 95.74% for MLP. Jaree Thongkam et al. [6] constructed a prediction model for breast cancer diagnosis by a combination of the AdaBoost and random forests algorithms .They achieved a classification accuracy of 94.4%. Emina Aličković and Abdulhamit Subasi [7] have proposed using different techniques for getting better accuracy reaching to a classification accuracy of 92.97% for Naïve Bayes, 93.15% for decision tree, 96.66% for MLP, 97.72% for SVM. Gouda I. Salama et al. [8] have compared the accuracy of different classification techniques reaching to a classification accuracy result of 95.9943% for Naïve Bayes, 95.279% for MLP, 95.1359% for decision tree, 96.9957% for SVM, 94.5637% for KNN. S. Swathi et al. [9] have evaluated the performance of different Neural Network structures: Radial Basis Function (RBF), General Regression Neural Network(GRNN), Probabilistic Neural Network (PNN), Multi-layer Perceptron model and Back propagation Neural Network(BPNN) . Overall classification accuracies were 96.18% for RBF, 97.0% for PNN, 98.8% for GRNN, 95.74% for MLP and 99.28% for BPNN. G. Ravi Kumar et al. [1], have evaluated the performance of six classification techniques reaching to a classification accuracy of 95.59% for decision tree, 96.79% for Naïve Bayes, and 94.78% for MLP, 96.79% for logistic regression, 97.59% for SVM and 95.19% for KNN. Zehra Karapinar Senturk and Resul Kara [10], have evaluated the performance of seven different classification algorithms .They achieved a classification accuracy of 96.485% for Naïve Bayes, 94.44% for decision tree, 96.39% for MLP, 92.755% for Discriminant Analysis, 96.395% for SVM, 95.15% for KNN and 95.555% for Logistic Regression.

Alternatively, many modern meta-heuristic algorithms have been also employed to train FNNs, like Particle Swarm Optimization (PSO) Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Biogeography Based Optimizer (BBO). In this study, a new approach using the recently developed heuristic algorithm Firefly Algorithm is employed in a hybrid manner with Genetic Algorithm so as to establish an accurate classification model for training feed-forward neural network to optimize the values of weights and biases which aims at minimizing the mean squared error (mse) which is considered as the objective function of this study.

III. MATERIALS AND METHODS:

This section presents a brief introduction to the dataset used in this paper, MLP, the proposed Genetic Algorithm based Firefly Algorithm (GA-FA) and its parameter setting.

A. DATA SET:

Breast cancer Wisconsin medical set is selected from UCI machine learning database. Wisconsin breast cancer was supported by Dr. William H Wolberg et al. This data can be found in UCI machine learning database. In this paper, publicly available Wisconsin Diagnostic Breast Cancer (WDBC) dataset [1] was used. Those dataset samples arrive periodically as Dr. Wolberg report in his clinical cases. In this study, the performance of proposed approach was tested on this medical dataset. The detailed description of the attributes found in this dataset listed in Table.1.

I. TABLE.1
WISCONSIN BREAST CANCER DATASET ATTRIBUTES

	Attribute	Domain
1	Clump Thickness	1 – 10
2	Uniformity of Cell Size	1 – 10
3	Uniformity of Cell Shape	1 – 10
4	Marginal Adhesion	1 – 10
5	Single Epithelial Cell Size	1 – 10

[1] Breast Cancer Wisconsin (Diagnostic) Data Set ,https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)

6	Bare Nuclei	1 – 10
7	Bland Chromatin	1 – 10
8	Normal Nucleoli	1 – 10
9	Mitoses	1 – 10
10	Class	2 for benign, 4 for malignant

B. MULTI-LAYER PERCEPTRON:

One of the most commonly used neural network architectures in biomedical applications is Multi-Layer Perceptron (MLP). It belongs to the class of supervised neural networks since it is trained in a supervised manner to be able to predict outcome for new data [11]. It consists of a network of nodes arranged in layers. A typical MLP network consists of three or more layers of processing nodes: an input layer, one or more hidden layers and an output layer [12]. The most important parts of MLPs are the connection weights and biases. Training an MLP aims at finding optimum values for weights and biases so as to achieve desirable outputs based on certain given inputs.

C. THE PROPOSED GENETIC ALGORITHM BASED FIREFLY ALGORITHM (GA-FA) AND PARAMETER SETTING:

Although Firefly Algorithm has a lot of merits like simplicity, robustness and being precise, it suffers from some demerits like slow convergence, getting trapped into several local optima. Firefly algorithm accomplishes local search as well and sometimes is not able to completely get rid of them [14]. In addition Firefly algorithm does not have memory capability so it cannot remember any history of better situation for each firefly and this causes them to move regardless of its previous better situation, and they may end up missing their situations[13] , [14].

To overcome the above mentioned limitations of Firefly Algorithm (FA), hybrid algorithm with GA is proposed. GA is a very effective way of finding reasonable solutions of high quality for complex optimization problems. Unlike Firefly Algorithm, GA is a derivative-free technique which has rapid convergence characteristics and is capable of escaping from local minima. The main idea behind using GA is due to its genetic operators crossover and mutation in generating new solutions as crossover and mutation rates can affect the convergence of GA.

In the proposed model, the initial population of GA is assigned by solution of FA. The total number of iterations is chosen to be the same for GA and FA. The proposed model is divided into two stages. At first stage, FA is run and generates the best solutions which are given as initial population of GA in the second stage. At end of second stage, the best solutions generated by GA are considered to be the best solutions at all and the value generated by GA for mean squared error (mse) is also considered as the minimum value of the fitness function at all. Pseudo code of the proposed model is shown in Fig,1

```
Initialize Firefly Algorithm parameters
Define the objective function f(x), x=(x_1,x_2,x_3,......,x_d)^T
Initialize a population of fireflies x_i (i = 1,2,......,n)
While (t<MaxGenerations)
    For i=1: n (all n fireflies)
        For j=1: i
            Light intensity I_i at x_i is determined by f(x_i)
            If (I_i > I_j)
                Move firefly i towards j in all d dimensions
            Else
                Move firefly i randomly
            End If
Attractiveness changes with distance r via e^(-γr^2)
Determine new solutions and revise light intensity
        End For j
    End For i
Rank the fireflies according to the light intensity and find the current best
End While
Use current best generated by FA to initialize the population of GA
Evaluate initial population
Repeat
    Perform competitive selection
    Apply genetic operators to generate new solutions
    Evaluate solutions in the population
Until some convergence criteria is satisfied
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Fig.1 Pseudo code of the proposed Genetic Algorithm based Firefly Algorithm (GA-FA)

In this section the proposed Genetic Algorithm based Firefly Algorithm is benchmarked using Wisconsin Breast Cancer Dataset obtained from the University of California at Irvine (UCI) Machine Learning Repository [15]. The mean squared error function (mse) is used as error function of the training phase of all algorithms and as a fitness function for Genetic Algorithm. It is defined by equation (1).

$$mse = \sum_{k=1}^{q} \frac{\sum_{i=1}^{m}\left(o_i^k - d_i^k\right)^2}{q}$$

Where q is the number of training samples, m is the number of outputs, d_i^k is the desired output of the i^{th} input unit when the k^{th} training sample is used, and o_i^k is the actual output of the i^{th} input unit when the k^{th} training sample appears in the input.
The structure of the MLPs is determined by the following equation:

$$H = (2 \times N) + 1 \qquad (2)$$

Where H is the number of hidden nodes and N is the number of attributes as suggested in [16] by Kolmogorov theorem which states that one hidden layer and 2N+1 hidden neurons sufficient for N inputs (Siti Mariyam Hj Shamsuddin, 2004). The min–max normalization was used for the used dataset as it contains data with different ranges. The normalization method formulation is as follows:
Fig.1 Pseudo code of the proposed Genetic Algorithm based Firefly Algorithm (GA-FA)

Suppose that we are going to map x in the interval of [a, b] to [c, d]. The normalization process is done by the following equation:

$$\acute{x} = \frac{(x-a)(d-c)}{(b-a)}$$

Fine tuning of the algorithm parameters is an essential issue in improving the algorithm performance. It is very difficult task for the most of meta-heuristic algorithms to find a general procedure to get the best set of parameters [17]. According to the problem considered here, the parameters of the proposed algorithm are tuned based on several extensive pre-tests. In Firefly Algorithm, the first important parameter to be considered is the randomization parameter (α).It is a value in the range of [0,1] so it was set to 0.5.The second parameter is the absorption coefficient (γ) which controls the light intensity between two fireflies so it is responsible for determining the speed of convergence of Firefly Algorithm. It was set to 1 so as to guarantee a quick convergence of the algorithm to the optimal solution. The third parameter is the initial attractiveness (β_0). It was chosen to be 1. Finally the population size and maximum number of iterations were set to 50and 250 respectively in order to be adequate to the dataset used here [18]. On the other hand, parameters of the Genetic Algorithm were as following:

Double vector was used as population type. Roulette Wheel selection was used. Heuristic crossover with default value of Ratio 1.2 was used as recommended in [19]. Uniform mutation with (1) pm mutation coefficient of 0.01 and crossover rate pc of 0.8 was used. Initial population N of size 50 was randomly created and used in experiment and the maximum number of iterations was set to 250. The mean squared error function was used as the fitness function. For all algorithms, the population size was set to 50. For a fair comparison, all algorithms were terminated when a maximum number of iterations (250) were reached. For data verification, the results of the proposed algorithm were compared with some of the most popular swarm-based optimization techniques like Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Biogeography Based Optimization (BBO). The values for the main parameters of GA-FA are provided in Table.2. The main difference in the proposed algorithm over Genetic Algorithm is that the initial population Genetic Algorithm phase is not randomly created. The best solution obtained by Firefly Algorithm phase is set as initial population for Genetic Algorithm phase. All other parameters were set to the same above mentioned values. Parameter tuning of the other algorithms are chosen as suggested in [20].

II. TABLE.2
THE ALGORITHM PARAMETERS

(3)

The number of iterations for firefly algorithm	250
Population size	50
Randomization parameter (α)	0.5
Initial attractiveness (β_0)	1
The light absorption coefficient (γ)	1
The number of iterations for Genetic algorithm	250
Population size	50
Population Type	Real coded
Selection	Roulette wheel
Crossover	Heuristic crossover (default value of Ratio 1.2)
Mutation	Uniform (probability = 0.01)

IV. PERFORMANCE EVALUATION:

In this phase, the performance of each classification technique including Firefly Algorithm (FA), Genetic Algorithm (GA) and the proposed Genetic Algorithm based Firefly Algorithm (GA-FA) is evaluated using three common statistical measures; classification accuracy, sensitivity and specificity. These measures are defined in terms of true positive (TP), true negative (TN), false positive (FP) and false negative (FN). A true positive decision occurs when the positive prediction of the classifier coincided with a positive prediction of the physician. A true negative decision occurs when both the classifier and the physician suggest the absence of a positive prediction. False positive occurs when the system labels benign case as a malignant one. Finally, false negative occurs when the system labels a positive case as negative (benign). Accuracy measures the classifier's ability to produce the level of accurate diagnosis [21]. Equation (4) shows the accuracy formula.

$$Accuracy = ACC = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) * 100\% \quad (4)$$

Sensitivity is used to measure the classifier's ability to identify the correct positive samples. It may be also referred as a True Positive Rate [21]. Senstivity formula is given by equation (5).

$$Senstivity = TPR = \left(\frac{TP}{TP + FN}\right) * 100\% \quad (5)$$

Specificity measures the ability of classifier to predict the correct negative samples. It may be also referred as a True Negative Rate [21]. Specificity formula is given by equation (6)

$$Specificity = TNR = \left(\frac{TN}{TN + FP}\right) * 100\% \quad (6)$$

A confusion matrix is a matrix which contains information about actual and predicted classifications done by a classification model. Its data is commonly used in order to evaluate performance of such systems. Table.3 shows the confusion matrix for a two class classifier [22]:

III. TABLE.3
CONFUSION MATRIX OF a TWO CLASS CLASSIFIER

		Predicted	
		Negative	**Positive**
Actual	**Negative**	TN	FP
	Positive	FN	TP

Table.4 indicates the confusion matrix for the proposed models whose values were used in equations (4), (5) and (6) in order to calculate Accuracy, Sensitivity and Specificity respectively for both WBCD dataset:

IV. TABLE.4
CONFUSION MATRIX of the PROPOSED MODELS

Algorithm		**Confusion matrix**	
Firefly Algorithm (FA)		**Predicted benign**	**Predicted malignant**
	True benign	365	14
	True malignant	7	211
Genetic Algorithm based Firefly Algorithm (GA-FA)		**Predicted benign**	**Predicted malignant**
	True benign	363	16
	True malignant	1	219

Based on Fig.2, it can be clearly seen that the accuracy of GA-FA is 97.162% while that of FA is 96.482%, the sensitivity of GA-FA is 99.545% which is higher than that of FA which equals 96.789%.The specificity of the proposed algorithm is 95.778% while that of FA is 96.306%. Basically, the highest accuracy and sensitivity and the lowest MSE according to Fig.3 belongs to the GA-FA which implies the effectiveness and robustness of the proposed algorithm.

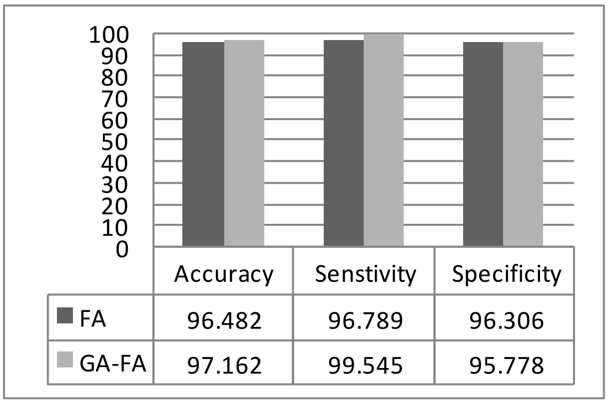

Fig.2: Performance measures of the proposed algorithm

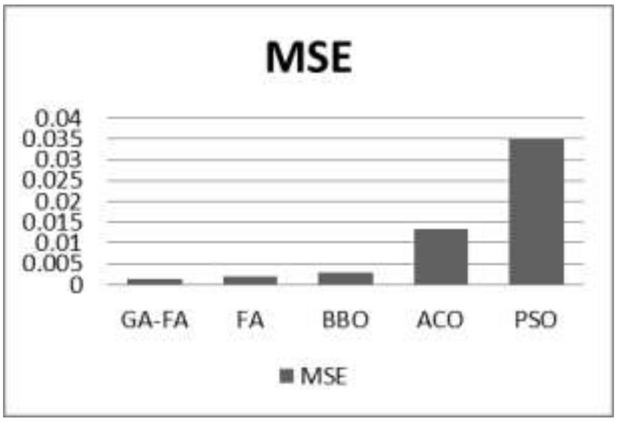

Fig.3: Comparison of MSE of the proposed algorithm and other meta-heuristic algorithms

V. CONCLUSION:

This work investigated the efficiency of applying the Genetic Algorithm based Firefly Algorithm (GA-FA) which hybridizes the solution construction mechanism of Genetic Algorithm and Firefly Algorithm as a meta-heuristic optimization technique for training neural networks by optimizing the weights between layers and biases of the neuron network so as to minimize the fitness function which is defined as the mean squared error. The optimized model is assessed according to different evaluation criteria and compared with models optimized using other meta-heuristic algorithms which are Ant Colony Optimization, Particle Swarm Optimization and Biogeography Based Optimization. Evaluation results show that developed model using the Genetic Algorithm based Firefly Algorithm outperforms other meta-heuristic algorithms in achieving higher accuracy and lower mean squared error.

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