Immuno-Computing-based Neural Learning for Data Classification

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***Abstract*—The paper proposes two new algorithms based on the artificial immune system of the human body called Clonal Selection Algorithm (CSA) and the modified version of Clonal Selection Algorithm (MCSA), and used them to train the neural network. Conventional Artificial Neural Network training algorithm such as backpropagation has the disadvantage that it can get trapped into the local optima. Consequently, the neural network is usually incapable of obtaining the best solution to the given problem. In the proposed new CSA algorithm, the initial random weights chosen for the neural networks are considered as a foreign body called an antigen. As the human body creates several antibodies in response to fight the antigen, similarly, in CSA algorithm antibodies are created to fight the antigen. Each antibody is evaluated based on its affinity and clones are generated for each antibody. The number of clones depends on the algorithm, in CSA, the number of clones is fixed and in MCSA, number of clones is directly proportional to the affinity of the antibody. Mutation is performed on clones to improve the affinity. The best antibody emerged becomes the antigen for the next round and the process is repeated for several iterations until the best antibody that satisfies the chosen criterion is found. The best antibody is problem specific. For neural network training for data classification, the best antibody represents the set of weights and biases that gives the least error. The efficiency of the algorithm was analyzed using Iris dataset. The prediction accuracy of the algorithms were compared with other nature-inspired algorithms, such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and standard backpropagation. The performance of MCSA was ahead of other algorithms with an accuracy of 99.33%.**

***Keywords*—AIS; CSA; MCSA; ACO; BBNN**

I. Introduction

Optimization is a process that is widely used in many applications in engineering, for example, optimizing the design of a mechanical part while minimizing the material cost. In computer science, developing algorithms, such as traveling salesman problem, optimize distance while traveling all the cities on an itinerary. In industrial processes such as heat-treat industry, obtaining the desired hardness of the part while minimizing the time through the furnace and lowering the temperature, etc. These are some of the few examples in the engineering domain [1]. The optimization problem regarding artificial neural network is about finding optimal weights and biases of all the neurons in a given neural network architecture designed for specific problem to be addressed. In the traditional back propagation method, the error gradient with respect to the input is propagated backward in the neural network and in the process adjusts the weights connecting the layers of the neural network. However, the drawback of backpropagation is that it is prone to get stuck into local optima and is computationally intensive [2].

Recently a great deal of interest is emerging in looking towards nature to solve optimization problems. Many nature inspired algorithms such as genetic algorithm, swarm based algorithms such as PSO and other algorithms inspired by the group dynamics of animals working together such as Grey Wolf Optimizer (GWO), Bee Colony Optimization and Harris Hawk algorithm have been applied for optimization [3].

Several nature-inspired algorithms have been suggested to train the neural network that does not require back propagation. They successive iterations adjust the weights based on the dynamics of the nature-inspired algorithm being used.

In this paper, two new algorithms based on artificial immune system are proposed to train the neural network. The algorithms are Clonal Selection Algorithm (CSA) and Modified Clonal Selection Algorithm (MCSA). These are global optimization algorithms and take a global view of the problem and look at the problem from above to see the complete picture. The performance of both algorithms was compared with other algorithms such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and backpropagation using the benchmark Iris dataset. The paper is organized as follows. Section II presents an introduction of the Immune System. It gives a brief description of the Immune System. Section III gives details about the Clonal Selection theory and the application areas of the algorithm. Section IV, describes the Iris dataset used for data classification. Section V describes the structure of the neural network used in the work. Section VI describes the implementation of the CSA and MCSA algorithms. It provides the flow diagram of the algorithm and the corresponding explanation of the steps involved. In Section VII, discusses the experiments and results. Section VIII provides conclusions.

II. Introduction of the Immune System

The immune system of our body presents the first line of defense against foreign pathogens that invade our body. It consists of anatomical barriers like mucous membranes and skin, endocytic and phagocytic barriers such as macrophages and physiological barriers such as temperature and pH. It is responsible for identifying the malignant foreign cells entering our body that can cause infections and diseases [4, 5].

The immune system has two components, innate immune system and adaptive/acquired immune system. The innate

immune system is inborn immunity, inherited from the mother and is not adaptive to certain kind of pathogen, but acts against the general classes of pathogens. The immune cells can identify the foreign intruders inside the body as pathogens and kill or destroy [6]. The adaptive immune system possesses special features that help them to understand these co-stimulatory signals to combat the externals pathogens. It maintains a stable memory of previously known molecular structures and can adapt to them. The innate system plays a significant role by signaling to the adaptive immune system after a specific pathogen has been eliminated [7].

A. Physiology and its Components

Fig. 1 illustrates the significant components of the immune system and their relative positions across the body. The immune system is made of lymphoid organs. Lymphoid organs comprise of primary and secondary organs. The primary lymphoid organs supervise the production, growth, development, and maturation of lymphocytes, which are special kind of white blood cells that carry special receptors to identify specific pathogens like a lock and key arrangement. The secondary lymphoid organs are the sites where the lymphocytes interact with pathogens [8]. There are two main types of lymphocytes called the B-cells and the T-cells or B-lymphocytes and T-lymphocytes. The B-cells are named after bone marrow because they maturate there and T cells are named after thymus because they maturate in thymus. These cells have receptors on their surface that can recognize specific molecular patterns present on the pathogens. They are also capable of multiplying themselves through a cloning process, and the B-cells are capable of introducing genetic variation during reproduction. Therefore, these cells have their number varied with time and B-cells can have their molecular structure changed as well [9] The two primary lymphoid organs, bone mar- row and thymus, have essential functions in the production and maturation of immune cells. All blood cells are created in the bone marrow and are part of the immune system as B-cells. However, some cells that are produced in the bone marrow but migrate to thymus become T cells. After migrating to the thymus and maturating, they become capable to fight against diseases [10] [11].

B. Antigens, Antibody and Affinity

The first step of an immune response is to recognize the presence of pathogen. Some parts of pathogens that can facilitate an adaptive immune response are called antigens. Antigens have surface molecules called epitopes, that allow them to be recognized by immune cells and molecules. Fig. 2 depicts immune cells, in particular, B-cells, that are able to recognize epitopes of a given antigen. B-cells and T-cells play a significant role in adaptive immune system. Development of Clonal Selection Algorithm was inspired by the B-cells of the adaptive immune system. The B-cell receptor is also known as antibody or immunoglobulin. The B-cells are monospecific because a single type of receptor is present on their surface. On the contrary, antigens can present various patterns of epitopes. The immune cells and molecules are of various types. The affinity between antigen and antibody is determined by the degree of recognition between the two, higher the recognition, better the affinity and vice versa.

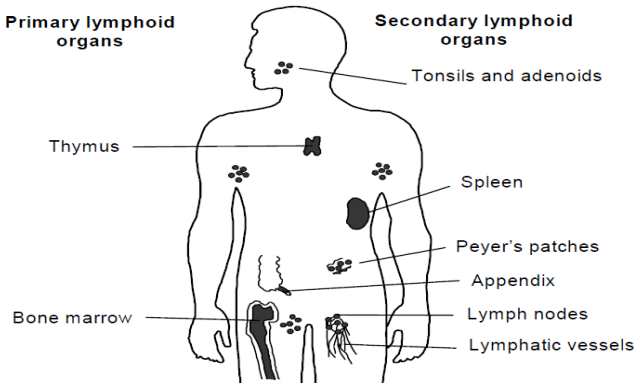

Fig. 1. Physiology of the Immune System [8].

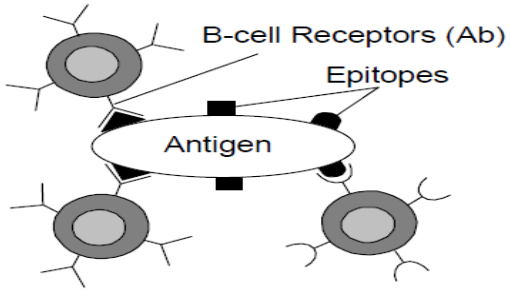

Fig. 2. B-Cells, with their Molecular Receptors Recognizing the Epitopes on Antigens [8].

III. Clonal Selection Algorithm

A. Clonal Selection Theory

Australian doctor Frank Macfarlane Burnet proposed the clonal selection theory in 1957 [12]. The scientific theory proposed by Macfarlane forms the basis of modern immunology. This scientific theory models the behavior regarding the response of the immune system to invading pathogen [13]. The immune system is comprised of variety of cells and molecules that remain passive and spring into action only when they encounter a pathogen. After the recognition of pathogen, some cells adhere to the invading antigen. Then the B-cells or T cells stimulate the immune system to reproduce those cells that are capable of identifying the antigen. This process of self-reproduction is called cloning and is asexual in nature. The process of cell division [4] achieves asexual Cellular reproduction. Fig. 3 demonstrates the Clonal Selection process. B cells that have higher affinity to the antigen are chosen to clone themselves, however during the process of cloning some mutation may occur. During the process of mutation, some cloned antibodies (B cells) may become better, that is they develop better receptors to fight the antigen by neutralizing them. The mutated antibody B cells with higher affinity to the antigens become memory cells and antibody plasma cells [8]. This process is also known as clonal expansion and generates cloning cells. During the cloning process, some errors may occur that is called mutation and results in alteration in the structure of the cell. The key features of the clonal selection theory are summarized in the following steps [15]:

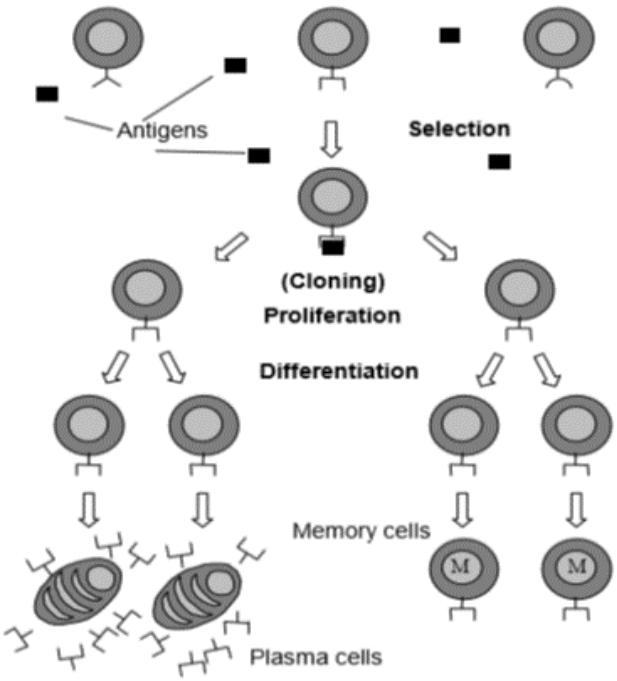

Fig. 3. The Clonal Selection Process [8].

- For a given antigen, generate a random population of different antibodies.
- Keep the antibodies with higher affinity to the antigen and remove the antibodies with lesser affinity to the antigen.
- Clone the antibodies with higher affinity and differentiate them by doing mutation on the clones.

B. Application Areas of CSA

Several engineering applications have been solved using Clonal Selection Algorithm (CSA). Hart and Timmis [16] studied the contribution of CSA to various domains. Table I summarizes the application areas to which CSA algorithm has been applied. These identified areas have been categorized as clustering/classification, for bioinformatics, computer security using image processing, numerical function optimization in adaptive control applications, anomaly detection to find faults in engineering systems, combinatorial optimization for scheduling, sequencing, and routing, and robotics, learning for web mining.

TABLE I. APPLICATION AREAS OF CSA ALGORITHMS

Sl. No	Major areas	Minor areas
1	Clustering	Bio-informatics
2	Computer Security	Image Processing
3	Numeric Function Optimization	Control
4	Anomaly Detection	Robotics
5	Combinatiorial Optimization	Virus Detection
6	Learning	Web mining

1) Machine learning: In recent years, machine learning techniques based on immune systems have been used for classification and pattern recognition of DNA.

2) Robotics: Clonal Selection Algorithm has been applied to the path planning for mobile robots to simulate some form of self-organizing group behavior [17].

3) Computer security: The problem of a system being attacked by virus or hackers has become common these days. Therefore, protecting computers from intruders is one of the biggest challenges nowadays. The immune system based algorithm, like the Clonal Selection Algorithm and negative selection algorithm for the intrusion detection system, have been proposed for this field [18]. Thus, the immune system inspired algorithms are the source of inspiration to combat computer viruses and network intruders.

4) Optimization: Immune based algorithms are applied to find the solution for optimization processes. The Clonal Selection Algorithm for optimization starts by defining an objective function. The pattern memorization capabilities for memory cells are used to create a model for pattern recognition. Other features of Clonal Selection Algorithm like self-organization memory, recognition of antigen, adaptation ability, immune response shaping and the ability to get out of local minima helps to achieve optimization [19].

5) Scheduling: The job shop scheduling problems have also been addressed by Clonal Selection algorithm.The algorithm helps to generate realistic scheduling solutions efficiently [20].

IV. IRIS DATASET

Iris dataset is one of the well-known benchmark problems introduced by Ronald Aylmer Fisher to test the new pattern recognition algorithms. The Iris dataset consists of 50 samples each for the three flower species viz. Iris Setosa, Iris Versicolor and Iris Virginica [21]. The dataset consists of four features namely, sepal length, sepal width, petal length, and petal width. The problem is to identify the category of any iris flower based on its four input characteristics of sepal length, sepal width, petal length, petal width [22]. Table II shows an extract from the Iris data set, where a plant with a sepal length of 5.7 can be either a Virginica or a Versicolor. This indicates that each type of the species has no distinguishable length and width ranges, based upon which the classification is done implying that any plant can only be classified by considering all its interrelated features, making the classification more complex. Fig. 4 displays a scatter plot of features of the Iris.

TABLE II. EXTRACT FROM THE IRIS DATASET

Sepal Length	Sepal Width	Petal Length	Petal Length	Species
4.8	3.4	1.6	0.2	Setosa
5.7	2.8	4.1	1.3	Versicolor
5.7	2.5	5.0	2.0	Virginica

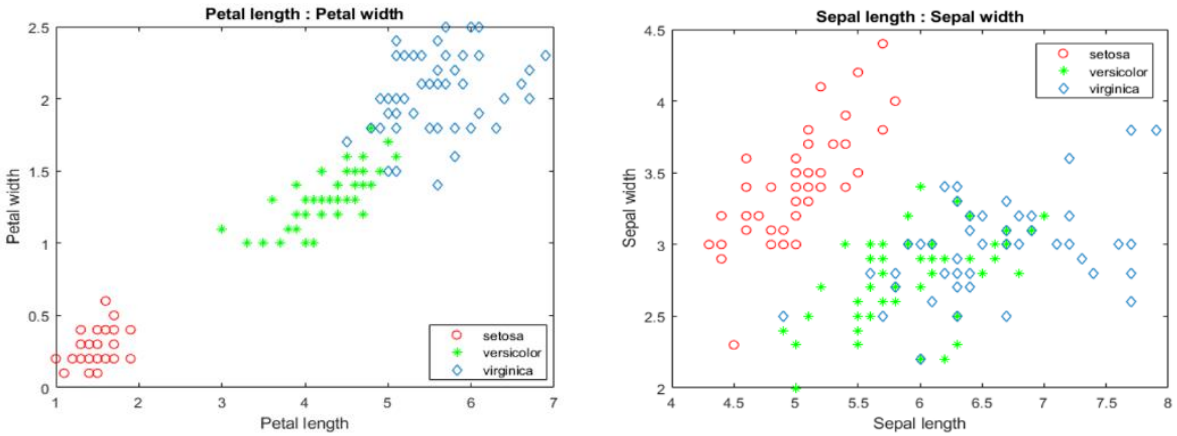

Fig. 4. A Simple Scatter Plot of 4 Features of the Iris Dataset.

V. Artificial Neural Network

Artificial Neural Network (ANN) has been successfully used for data classification [23] [24]. The most common algorithm is the back propagation algorithm. This algorithm has two phases: the forward phase and the backward phase. In the forward phase, the outputs for given set of inputs are predicted and in the backward phase gradient of the error is propagated backward and adjusting the weights and the biases in the process. The initial weights and biases are randomly chosen [26] [27]. However, new evolutionary algorithms are emerging that train the weights and biases using evolutionary approach. Genetic algorithms, swarm algorithms and immune system based algorithms come under this category. These algorithms do not have the backward phase and on the contrary, weights are adjusted in every iteration depending on the fitness criterion [25].

In this paper, two neural-network learning algorithms based on the human immune system, namely, Clonal selection Algorithm (CSA) and Modified Clonal Selection Algorithm (MCSA) are proposed to adjust the weights and biases of the neural network.

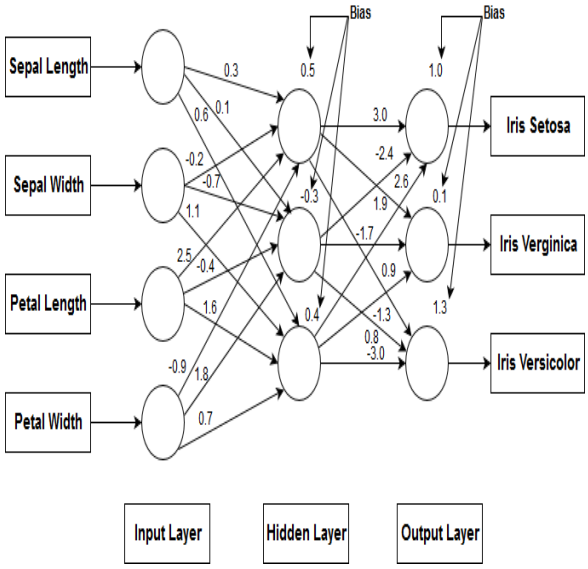

Fig. 5. FFNN Structure for the Iris Data Problem.

Fig. 5 shows the Feed- Forward Neural Network (FFNN) structure for the Iris data classification. The structure of the neural network is determined at the beginning taking into consideration the dimension of the data. Iris data has four inputs namely sepal length, sepal width, petal length and petal width, therefore there are four neurons in the first layer, it has three categories of output, and therefore there are three neurons in the output layer, corresponding to the three Iris species, namely Iris Setosa, Iris Versicolor and Iris Virginica. It has one hidden layer with three neurons. A Neural Network stores the knowledge in the form of weights. The goal is to find optimized sets of weights and biases so that the Iris flowers are correctly classified. The activation function used for the neural network is the sigmoid function. The sigmoid function is mathematically represented by equation (1).

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \quad (1)$$

VI. Implementation of CSA and MCSA

In this section training of the neural network, using CSA and MCSA is described. Table III shows the terminology of Immune system as applied to neural networks. Fig. 6 presents the flowchart for training the neural network to find the weights and biases of the neural network for Iris data classification using CSA. The following steps A thru G describe the complete procedure.

TABLE III. Terminology of Immune System Applied to Neural Network

Immune System	Neural Network Model
Antigen	Initial Solution in terms of weights and biases
Antibody	Candidate Solution in terms of weight and biases.
Gene	Weight or Bias
Affinity	Fitnes value of each antibody to antigen in terms of classification acuracy
Cloning	Creation of multiple copies of antibody
Mutation	Change in one or more genes of antibody
Population	Number of initial antibodies
Generation	Number of iterations

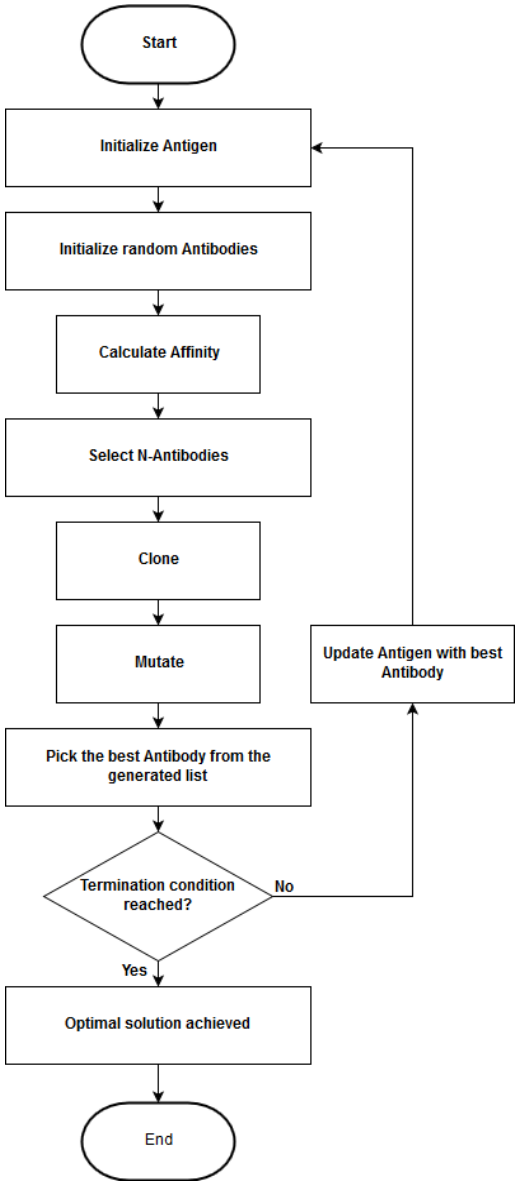

Fig. 6. Flowchart Diagram, Describing Phases of the CSA [9].

A. Antigen Creation

Antigen refers to a foreign body that attacks the human body such as toxin in the form of virus, bacteria or fungus. In response to the antigen, body creates antibodies and the process of cloning multiplies superior antibodies. Mutation operation is performed on the clones to improve their affinity to overpower and kill the antigen.

Initial antigen for neural network should be in the form of potential solution of weights and biases. Therefore, an array of random weights and biases appropriate to the structure of the neural network is created as antigen.

Fig. 7 shows a sample antigen corresponding to neural network illustrated in Fig. 5. The antigen is an array of 27 individual elements; 21 elements represent the weights of the neural network and the remaining six elements represent the biases of the neurons in the neural network.

B. Creation of Antibodies

In response to the initial antigen, several antibodies with the same format are created to fight the antigen. For this problem of training the neural network using CSA, 20 antibodies were generated in response to one antigen.

C. Affinity Calculation

The affinity of each created antibody is calculated according to the objective function of the problem that is being optimized. The objective function for the neural network training is classification accuracy, which is defined by the number of correct predictions divided by the total training samples as described in equation 2.

In equation 2, n represents the number of examples correctly classified and *N* represents the total number of training samples. The higher the classification accuracy, higher the fitness of the antibody. In other words, the CSA attempts to find a set of weights and biases that increases the classification accuracy.

$$Classification\ accuracy = \frac{n}{N} \quad (2)$$

The Fitness of the antibody is calculated as described in equation 3.

$$Fitness\ of\ Antibody\ = classification\ accuracy \quad (3)$$

Now, the affinity of antibody to the antigen is calculated as the difference between their fitness as shown in equation (4).

$$Affinity\ of\ Antibody = Antibody_{\ fitness} - Antigen_{\ fitness} \quad (4)$$

The antibodies with higher fitness than antigen are considered going forward.

D. Selection of Antibodies

Five antibodies that have the highest fitness among the 20 antibodies are selected.

E. Clone the Antibodies

Multiple copies of the selected antibodies are created. CSA creates fixed number of antibodies and MCSA creates clones proportional to the affinity of the antibody.

1) Cloning for the CSA: For the CSA algorithm, the number of clones Nc is fixed to 10 and is the same for all the selected antibodies. Hence, for every iteration 10 clones are generated for each of the 5 selected antibodies.

2) Cloning for the modified CSA: For the modified CSA algorithm, the number of clones Nc for each antibody are proportional to the affinity of antibody. Higher the affinity value, higher is the number of clones Nc. The number of clones Nc for MCSA is obtained by equation (5). The maximum number of clones created is 10, hence, Ni is 10, x_{max} is the highest affinity and x_{min} is the lowest affinity value of antibodies during any given iteration. xi is the affinity value of ith antibody. Equation (5) is used to find the number of clones created for antibody with an affinity x_i. Ceil (.) is the operator that rounds its argument towards the next higher integer.

0.3	-0.2	2.5	-0.9	0.1	-0.7	-0.4	1.8	0.6	1.1	1.6	0.7	0.5	-0.3	0.4	3.0	-2.4	2.6	1.9	-1.7	0.9	-1.3	0.8	-3.0	1.0	0.1	1.3

Fig. 7. A Sample Antigen of the Iris Neural Network.

0.3	-0.2	2.5	-0.9	0.1	-0.7	-0.4	1.8	0.6	1.1	1.6	0.7	0.5	-0.3	0.4	3.0	-2.4	2.6	1.9	-1.7	0.9	-1.3	0.8	-3.0	1.0	0.1	1.3

(a)

0.3	-0.2	2.5	2.6	0.1	-0.7	-0.4	1.8	0.6	1.1	1.6	0.7	0.5	-0.3	0.4	3.0	-2.4	-0.9	1.9	-1.7	0.9	-1.3	0.8	-3.0	1.0	0.1	1.3

(b)

Fig. 8. Reciprocal Exchange Mutation for the CSA Algorithm. (a) Original Antibody. (b) Antibody after Mutation.

0.3	-0.2	2.5	-0.9	0.1	-0.7	-0.4	1.8	0.6	1.1	1.6	0.7	0.5	-0.3	0.4	3.0	-2.4	2.6	1.9	-1.7	0.9	-1.3	0.8	-3.0	1.0	0.1	1.3

(a)

0.3	-0.2	2.5	2.6	0.1	-0.7	0.5	1.8	0.6	1.1	1.6	0.7	-0.4	-0.3	0.4	3.0	-2.4	-0.9	1.9	-1.7	0.1	-1.3	0.8	-3.0	1.0	0.9	1.3

(b)

Fig. 9. Reciprocal Exchange Mutation for the Modified CSA Algorithm. (a) Original Antibody. (b) Antibody after Mutation.

$$N_c = ceil\left(N_i \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \right) \quad (5)$$

F. Mutation

The mutation is the process of randomly altering the given chromosome to introduce diversity in the population. Mutation operation enables to achieve global optimization and thus helping to escape from local optimization. In immune system based algorithms, mutation is performed on antibodies with an intent to enhance their ability to better attack the foreign antigen. There are many types of mutation operations such as shift right or left, alter a gene, transpositions, inversion within a random window etc. In this work, the reciprocal exchange mutation is implemented on the cloned antibodies. The best antibody created after cloning and mutation becomes the antigen for the next iteration.

1) Mutation in CSA: A single point reciprocal exchange mutation is performed in CSA wherein two random points are selected and the genes are exchanged as shown in Fig. 8.

2) Mutation in modified CSA: The modified CSA algorithm uses hypermutation. In hypermutation, the number of mutation points varies inversely proportional to the affinity of antibody. The number of mutation points is low when the affinity of the antibody is high and vice-versa. This is known as affinity maturation. The intent is to preserve the high affinity antibodieswithout much disturbing them, and to improve the affinity of antibodies which are not that good. The number of mutation points for reciprocal exchange of genes is given by equation (6).

$$M_p = 2 \times ((N_i + 1) - N_c) \quad (6)$$

Where Mp is the number of mutation points, Nc is the number of clones, and Ni is the maximum number of clones allowed which is 10 for this research. Fig. 9 shows a sample reciprocal exchange mutation process for the modified CSA.

G. Stopping Criteria

The process iterates until the termination condition is reached; that is the antibody according to criterion chosen is found or the desired number of iterations has been reached, which is chosen as 50 iterations for this research.

VII. Results and Discussion

This research compares the classification accuracy of the proposed Clonal Selection algorithms (CSA and MCSA) with standard backpropagation algorithm and swarm based algorithms namely Ant Colony Algorithm (ACO) and Particle Swarm Optimization (PSO). All algorithms find the appropriate sets of weights and biases for neural network of Fig. 5 for the correct data classification with respect to iris data. Fig. 10 shows the comparative performance of the five algorithms in terms of the accuracy of prediction of the three classes of the iris data, viz., Setosa, Versicolor and Virginica. All the five algorithms predict class 1 i.e. Setosa with an accuracy of 100% but not class 2 and 3. Fig. 11 shows the comparison of the classification accuracy of all the five algorithms. The accuracy obtained by the CSA is 96.67 and for the MCSA 99.333. Table IV gives the overall accuracy and accuracy for each class of the Iris flower for all the five algorithms. It establishes that modified Clonal Selection Algorithm is best at accurate data classification.

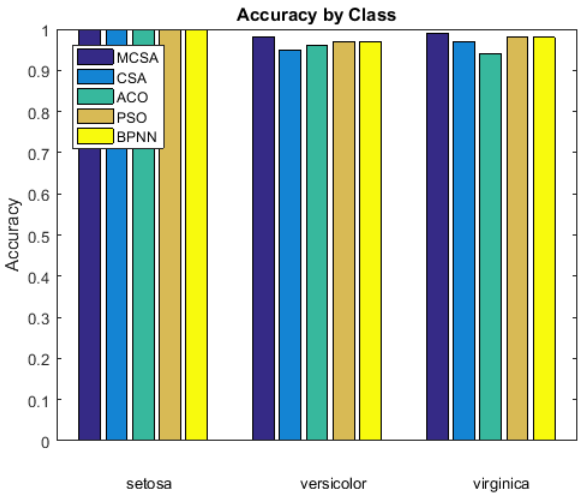

Fig. 10. Accuracy by Class.

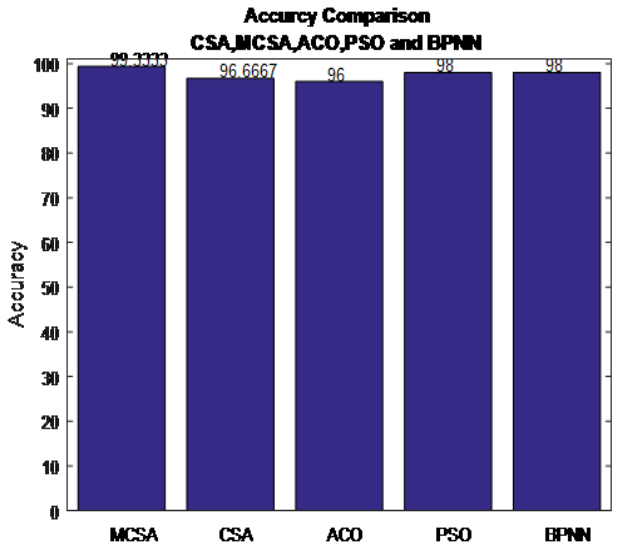

Fig. 11. Classification Accuracy for MCSA, CSA, ACO, PSO and BPNN.

TABLE IV. OVERALL ACCURACY AND ACCURACY OF EACH CLASS

	Accuracy	Accuracy by Class		
		Class 1	*Class 2*	*Class 3*
BPNN	98.00	1	0.97	0.98
ACO	96.00	1	0.96	0.94
PSO	98.00	1	0.97	0.98
CSA	96.67	1	0.95	0.97
MCSA	99.33	1	0.98	0.99

VIII. CONCLUSION

In this paper, two neural-network training algorithms based on CSA and MCSA were proposed to optimize the weights and biases of the network for accurate Iris data classification. The algorithms will work for any dataset. However, the architecture of the neural network will have to be redesigned taking into consideration the dimensions of the data. The structure of antigen and antibodies will need to conform to match the architecture of neural network. The accuracy obtained by the CSA is 96.67% and for the MCSA 99.33. Thus, MCSA is a better performing algorithm.

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