Addressing Classification Issues in Artificial Immune Network System

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ABSTRACT--- Immune systems have greater impact in all living creatures for their sustaining (survival) against diseases. Immune responses are triggered whenever foreign bodies invade to the body and encode attack strategies. To suppress its dominancy WBC accelerates its count to maximum extent. In this article we made the thorough study of various immune network theory and their classification issues are encountered. Finally to attain better classification accuracy suggestions are given.

KEYWORDS-- Artificial immune system, artificial immune network system, Natural immune system

I. INTRODUCTION

Several living organisms pose immune systems which exist naturally in body and / or induced by vaccines. This induced or artificially enhanced immune system is called artificial immune system. Natural immune system initate antigen to defend against upcoming foreign bodies. The body has many opposing mechanisms, which amongst others are the dermal region of the body, the membrane that covers the deep organs and vessels, and the stretchy protective scheme. The adaptive immune system reacts to a specific foreign body material or pathogenic material (referred to as antigen). During these reactions the adaptive immune system adapts to better detect the encountered antigen.

Different theories exist in the study of immunology regarding the functioning and organizational behavior such as classical view, clonal, danger and network theories.

B-Cell response to the fragmented cell, by secreting lymphocytes. This reaction is known as the primary response. The immune system uses the B-Cells with memory status in a secondary response to frequently observed antigens of the similar structure. The secondary response is faster than the primary response, since no HTC signal or binding to the memory B-Cell is necessary for producing antibodies.

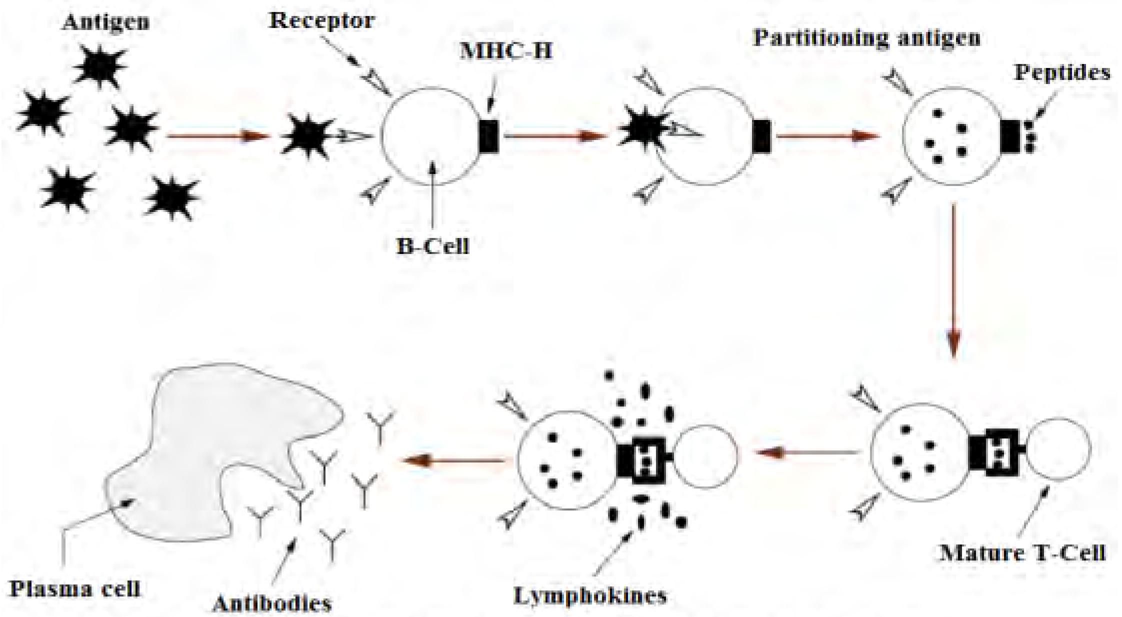

Fig : B-Cell Develops into Plasma Cell, Producing Antibodies

Burnet states that the classical view of the system is to differentiate between self and foreign particle within the body. The recognition of antigens leads to the creation of specialized activated cells, which in activates or destroys these antigens. Within the natural system, antigens are constituents in the body that might trigger immunological response. An immune reaction is that the body's respond to antigens so the antigens are eliminated to stop impairment to the body. Antigens may be either microorganism, fungi, parasites and/or viruses.

Clonal selection [7] theory describe the selected antigens are stimulated for conformed immune response to foreign cells. Those selected antigen with better fitness are duplicated. Based on the affinity measures, best clones are mutated.

The main idea of the danger theory [13, 14] is that the immune system discerns between what is hazardous and non- hazardous in the body. It differs from the classical view in that the immune system responds only to harmful foreign cells. This foreign cell is seen to be dangerous to the body if it causes body cells to stress or die. Matzinger gives two motivational reasons for defining the new theory, which is that the immune system needs to adapt to a changing self and that the immune system does not always react on foreign or non-self. Although cell death is common within the body, the immune system only reacts to those cell deaths that are not normal programmed cell death (apoptosis), i.e. non apoptotic or necrotic deaths. When a cell is infected by a virus, the cell itself will send out a stress signal (known as signal 0) of necrotic death to activate the antigen presenting cells (APCs) Thus, co-stimulation of an APC to a helper T-Cell is only possible if the APC was activated with a danger or stress signal. Therefore, the neighboring cells of an APC determines the APC's Thus, from a danger immune system perspective a T-Cell only needs to be able to differentiate APCs from any other cells.

Network theory suggests that B-cells in interconnected network analyze and differentiate the self and non-self-cells. Activated B-cells transfers the knowledge of threat caused by foreign cells to adjacent B-cells which results in formation of network model.

In section 2 discuss about overview of artificial immune system. Section 3 discuss about general algorithm of immune network and other similar algorithms. Section 4 discuss about related classification issues in artificial immune system and section 5 conclude the artificial immune network classification needs to be enhanced and for further improving accuracy suggestions are drawn.

II. ARTIFICIAL IMMUNE SYSTEM OVERVIEW

An artificial immune system (AIS) models the natural immune system's ability to detect cells foreign to the body. The result is a new computational paradigm with powerful pattern recognition abilities, mainly applied to anomaly detection.

Different views on how the natural immune system (NIS) functions have been developed, causing some debate among immunologists. These models include the classical view of lymphocytes that are used to distinguish between self and non-self, the clonal selection theory where stimulated B-Cells produce mutated clones, danger theory, which postulates that the NIS has the ability to distinguish between dangerous and non-dangerous foreign cells, and lastly, the network theory where it is assumed that B-Cells form a network of detectors. ALC (Artificial lymphocyte cells) The ALCs in a network based AIS act with one another to find out the structure of a non-self pattern, leading to the formation of ALC networks. The ALCs in a network co-stimulates and/or co-suppress one another to adapt to the non-self-pattern.

III. IMMUNE NETWORK ALGORITHM

To The network theory was first modeled by Timmis and Neal [4] resulting in the artificial immune network (AINE). In network theory one antibody find out the antigen pattern then it forms network with neighbor antibody and suppress that antigen. General flowchart of artificial immune network is shown in fig 2. First normalize the training data and to initialize the ARB (Artificial Recognition Ball) and Antigen population randomly. Set the maximum number of available resource and calculate the affinity between Antigen and also with ARB. Finally select maximum resource ARBs clone and mutate that and integrate the mutated clones in population.

Demerit of general immune network algorithm is sharing the resource pool and fixed resource for all population. And population is increase at huge number of ARB in every population and resulting form the premature convergence.

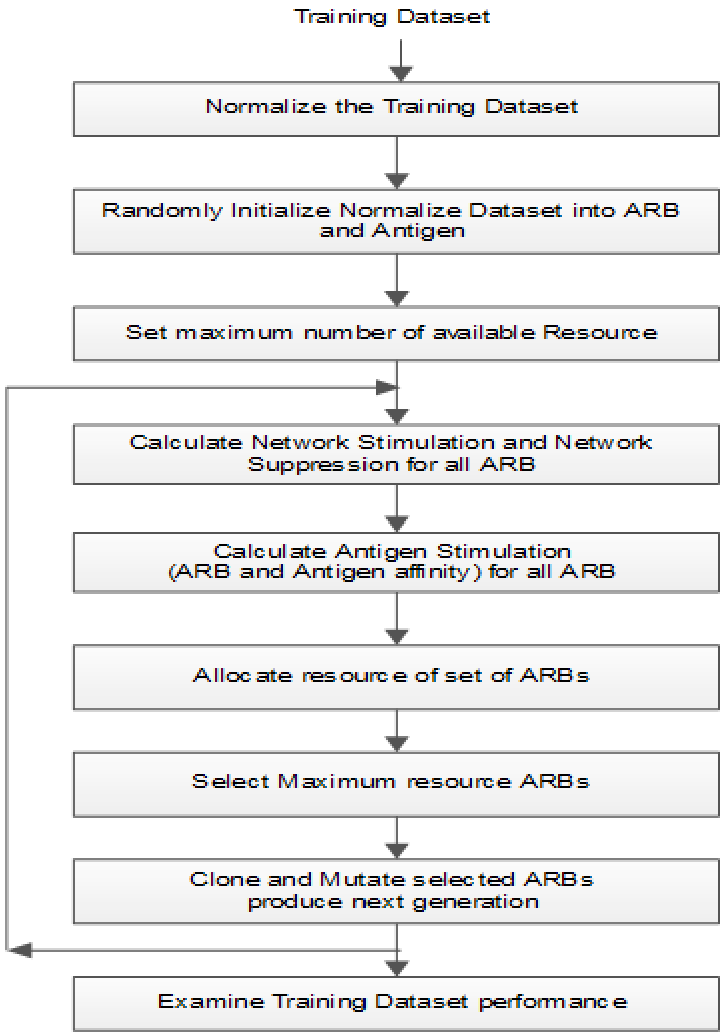

Fig 2: Schematic representation of immune network flowchart.

1. Self-stabilizing AIS

The self-stabilizing AIS (SSAIS) was developed by Neal [8] to simplify and improve AINE. SSAIS have no limited of number of resources in shared pool is principal advantage. Resource level capacity increases to fulfill the Highest ARB stimulation. The SSAIS produce end results as a model which is flexible and scales well with continuously changing data sets, and genuinely stable AIS. SSAIS model have more time complexity to represent the diversity of networks with gathered knowledge that exist in resultant network holding weak data.

2. Dynamic weighted B-cells

A DWB-Cell represents an influence zone, which can be defined as a computation functional cost that shrinks with the time since the antigen has been presented to the network and with the spatial distance between the DWB-Cell and the offered antigen.

Dynamic weighted B-cells model attempts to control proliferation of B-cells whenever new antigen enters its reconstructs subnet without affecting old subnets.

The DWB-model has proved to be sturdy to noise, adaptive and scalable in learning substance structures.

3. Enhanced Artificial Immune Network

Nasraoui et al. [9] states the AINE requires dual pass through mechanism that the substance training set (session patterns). To neglect proactive convergence of the population of ARBs, the amount of resources allotted to ARB was calculated as

$$\alpha_1 \times (\log l_{arb\ i})$$

Where $l_{arb\ i}$ the stimulation level of the ARB and α_1 is some positive constant.

An advantage of this system is once the mixing of the mutated clones; the ARBs with identical B-Cell illustration are integrated into one ARB. Amalgamation of identical ARBs confines the high rate of growth.

The Euclidian distance utilized in AINE was interchanged by the trigonometrically cos similarity exists between 2 session patterns.

4. Adapted Artificial Immune Network

A modification in AINE to the training set is customized as the antigen set in the model with a set of randomly initiated antibodies. The model in [5] arbitrarily assigns itself the patterns within the implements training set to the substance set and antibody set. The later modification to model is in the initialization of the network affinity threshold (NAT). The Network affinity threshold was computed as mean distance among all the patterns in the antigen set.

The excellence of the altered model in [6] advances the model [5] in that the extreme network size is inadequate to the number of training patterns in the training set and firm constellations are formed with a nominal number of control strategy parameters.

5. aiNet

De Castro and Von Zuben [10, 11] developed this aiNet model. An emblematic network model comprised of vertices (the B-Cells or antibodies) which are associated by edges to form node pairs. A Cost value (edges or links strength) is apportioned to each edge, to specify the resemblance between two nodes. Thus, the network that is designed throughout training is obtained by an edge-weighted graph.

It uses Euclidean distance as a metric of affinity (or divergence), d (Tp, ABj), between a training pattern, Tp, and an antibody, ABj, in the network. A higher value of d (Tp, ABj) insists higher degree of conflicting behavior between an antibody and an antigen training pattern.

Advantage of aiNet is capability of minimizing data replication and to attaining a reduced representation of the data.

Demerit is some of the drawbacks of the aiNet model are the enormous number of constraints that need to be quantified and that the cost of computation increase is directly proportional to the number of variables of a training pattern.

IV. CLASSIFICATION ISSUES

Grzegorz Dudek [1] not only proposed Multi class classifier but also applied AISFLS algorithm for forecasting applications and their results are obtained which converges to aspects of user static parameters both for controlling local and globally selected features. AISFLS algorithm also applied for unsupervised learning with deep consideration of AB encoding. Multiclass classifier presented apoptosis process which eliminates noisy data and AISFLS clones run parallel to detect redundancies.

AC-AIS methodology finds easier or simplest way to discover best rule to handle Enormous Data sets holding huge rule set. AC-AIS make use of the evolutionary principle to integrate rule mining and classification process. Further contributions to be made on search space explorations using Enhanced techniques [3].

Remote sensing applications with multi-/hyper spectral images are processed by ABnet with consistent performance shows better results than conventional classifier. ABnet does not limited to remote sensing applications but also applied for large voluminous data. May be used as effective option for it. Extended work suggested in this article to use AIS model to extract feature from Hughes Phenomena [2].

Mail server personate to spam messages which is controlled by black listing in general. Anti-spam filter designed is based on behavior characteristics and continual detection of similar group of spams. C collective feedback response gathered is also used for recognition of spams experienced by Web user community [12].

V. CONCLUSIONS

Prevailing Artificial immune system models are evaluated so far lacks ideal and its counter effect regarding classification had some noted anomalies which degrades the performance measures and other related issues. Tandem operations have to be made rapidly to yield desired classification accuracy. In addition to that classification scheme must tackle the scalable network system which tends to change with dynamic data and prediction of accuracy is additional overhead but provides compromising results. Calibrations are done to get consistent results.

Further Enhancement is made for immune network system at preliminary level of network parameters with optimization techniques may be a possible solution to resolve classification issue which in turn promote accurate results and challenging task yet to be resolved is efficiency of classification is cent percent is still impossible.

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