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A Comparative study on Classification of Learning Disability Using Soft Computing with AIS Techniques

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ABSTRACT-- Identification or diagnosis of students with learning disabilities (LD) is a complex task because of the ambiguity in selecting the best procedure which required a lot of manpower and resources and due to the lack of nationally agreed standard. Learning Disability is a heterogeneous group of disorders which affect listening, speaking, reading, writing, reasoning, Math and social skills of an individual. Hence an early identification of warning signs, proper assessment, effective intervention, can help LD children to succeed in school life. Here classification of LD is attempted using soft computing techniques along with artificial immune system algorithms (AIS) and their performance is evaluated. AIS algorithms like AIRS1, AIRS2, Parallel AIRS and CLONALG algorithms show better performance in classification than the other soft computing algorithms.

KEYWORDS: Learning Disability, Naive Bayes, Back Propagation, SOM, AIRS1, AIRS2, Parallel AIRS, CLONALG Algorithm.

1. INTRODUCTION

The main aim of the proposed work is to compare the performance of different soft computing techniques and AIS algorithms for classification of LD. Soft computing techniques learn from experimental data and deals with the uncertain values and imprecise data. It plays a vital role in image processing, data compression, classification, clustering and decision support systems. Artificial immune systems (AIS) are a class of computationally intelligent systems inspired by the principles and processes of the vertebrate immune system. The algorithms typically exploit the immune system's characteristics of learning and memory to solve problems such as intrusion detection, data clustering, and classification and search problems. Their development and application domains follow soft computing paradigms such as artificial neural networks and evolutionary algorithms.

2. LEARNING DISABILITY

A learning disability (LD) is a neurological disorder that affects the brain's ability to receive process, store and respond to information. The term learning disability is used to describe the seeming unexplained difficulty a person of at least average intelligence has in acquiring basic academic skills. These skills are essential for success at school and work, and for coping with life in general. LD is not a single disorder. It is a term that refers to a group of disorders. As a result, a person can be of average or above-average intelligence, not have any major sensory problems (like blindness or hearing impairment), and yet struggle to keep up with people of the same age in learning and regular functioning. Most of the people have problems with learning and behavior disability from time to time[1].

During the school years, parents and educators should be on the alert for consistent and persistent patterns of difficulty that children and adolescents may experience over time as they may signal an underlying learning disability (LD).There are many people and specially the children as young are ignored due to the lack of the knowledge of the Learning disability problem. Learning disability problem can co-occur with other disorders so it is important to keep careful and complete records of observations and impressions so they can be shared among Parents, educators and related service providers when making important decisions about needed services and supports. The Learning Disable Student always has some specific symptom related to the Learning. Learning is the continuous process where the people try to Learn in their entire Life. Therefore when people cannot try to Learn then have certain symptom related to that which shows that the person or the students have Learning disability.

3. METHODS

3.1. NAIVE BAYES CLASSIFIER

A Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions and referred as "independent feature model"[2]. A naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. Depending on the precise nature of the probability model, naive Bayes classifiers can be trained very efficiently in a supervised learning setting. In many applications, parameter estimation for naive Bayes models uses the method of maximum likelihood and this method works for classification.

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3.2. BACK PROPAGATION ALGORITHM

The backpropagation learning algorithm can be divided into two stages: propagation and weight update.
Stage 1: Propagation
Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

Stage 2: Weight update
For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Subtract a ratio (percentage) of the gradient from the weight.

Repeat phase 1 and 2 until the performance of the network is satisfactory [3].

3.3. SELF ORGANIZING MAPS(SOM)

The stages of the SOM algorithm are
1. Initialization – Choose random values for the initial weight vectors wj.
2. Sampling – Draw a sample training input vector x from the input space.
3. Matching – Find the winning neuron I(x) that has weight vector closest to theinput vector, i.e. the minimum value of $\mathbf{d_j(x) = \sum_{i=1}^{D}(x_i - w_{ji})^2}$
4. Updating – Apply the weight update equation $\mathbf{\Delta w_{ji} = \eta(t)T_{j,I(x)}(t)(x_i - w_{ji})}$
where $\mathbf{T_{j,I(x)}(t)}$ is a Gaussian neighbourhood and η(t) is the learning rate.
5. Continuation – keep returning to step 2 until the feature map stops changing[4].

3.4. ARTIFICIAL IMMUNE RECOGNITION SYSTEM ALGORITHM (AIRS)

The function of the AIRS algorithm is to prepare a pool of recognition or memory cells (data exemplars) which are representative of the training data the model is exposed to and is suitable for classifying unseen data. The lifecycle of the AIRS system can be represented as in Fig1.

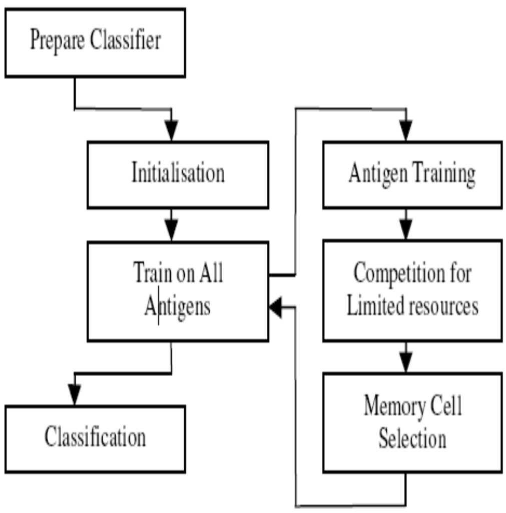

Figure 3.4.1. Life Cycle of AIRS

This algorithm is composed of four main stages.
1) Initialization: Normalize all items in the data set suchthat the Euclidean distance between the feature vectorsof any two items is in the range of [0, 1]. Create arandom base called the memory pool (M) from trainingdata. Antigenic Presentation: for each antigenic patterndo:

2) Memory cell identification and ARB generation:Clone and mutate the highest affinity memory cell andadd them to the set of ARBs (P).
3) Competition for resources and development of acandidate memory cell: Process each ARBs throughthe resource allocation mechanism. This will result insome ARB death, and ultimately controls the population.Calculate the average stimulation for each ARB. Cloneand mutate a randomly selected subset of the ARBsleft in P based in proportion to their stimulation level.While the average stimulation value of each ARB of thesame class as the antigen is less than a given stimulationthreshold repeat step 3.
4) Memory cell introduction : Select the highest affinityARB from the last antigenic interaction. If the affinity ofthis ARB with the antigenic pattern is better than that ofthe previously identified best memory cell mc then addthe candidate (mc-candidate) to memory set M. Additionally,if the affinity of mc-match and mc-candidate isbelow the affinity threshold, and then remove mc-matchfrom M.
Cycle: Repeat steps 2, 3, 4 until all antigenic patterns havebeen presented.
The classification is performed in a k-nearest neighbor approach.Each memory cell is iteratively presented with eachdata item for stimulation. The system's classification of a dataitem is determined by using a majority vote of the outputs ofthe k most stimulated memory cells[5].

3.5. PARALLEL AIRS

The approach to parallelising AIRS was simple, involving the following steps in addition to the standard training scheme[6]:
1. Divide the training data set into *np*number of partitions, where *np*is the number
of desired processes running AIRS
2. Allocate a training partitions to processes and prepare memory pools
3. Gather the *np* number of memory pools
4. Use a merging scheme for creating a master memory pool for classification

3.6. CLONALG ALGORITHM

This algorithm is suitable to perform tasks such a smachine learning, pattern recognition, and optimization and works as follows:
1. Generate a set of N candidate solutions (antibody repertoire) in a shape-space to be defined by the problem under study.
2. Select n1 highest affinity cells in relation to the antigen set to be recognized or to the function being optimized.
3. Clone (generate identical copies of) these n selected cells. The number of copies is proportional to their affinities: the higher the affinity, the larger the clone size (number of offspring).
4. Mutate with high rates (hypermutation) these n selected cells with a rate inversely proportional to their affinities:the higher the affinity, the smaller the mutation rate.
5. Reselect n2 highest affinity mutated clones to compose the new repertoire.
6. Replace some low affinity cells by new ones.
7. Repeat steps 2 to 6 until a given stopping criterion is met[7].

4. DISCUSSION AND RESULTS

A questionnaire is prepared as in Appendix A which is based on manual of DSM [12]. Datasets are collected from nearby schools and further it is classified for LD.Simulation results are obtained for each classification algorithm which is represented in Table 6.1.AIS algorithms like AIRS1, AIRS2, parallel AIRS and CLONALG show better classification accuracy than that of other soft computing techniques. Table 6.2 summarizes the results of all errors during the simulation. Figure 6.1 and figure 6.2 represents the classification results and comparative study of parameters of all techniques used.

Table 6.1 : Simulation results of all algorithms

Algorithm (Total Instances - 230)	Correctly Classified Instances % (Values)	Incorrectly Classified Instances % (Values)	Kappa Statictics
Naive Bayes	79.1946 (118)	20.8054 (31)	0.4532
Back Propagation	76.5101 (114)	23.4899 (35)	0
SOM	60.4027 (90)	30.8725 (46)	0.153
AIRS	79.1946 (118)	20.8054 (31)	0.0578

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Parallel AIRS	79.8658 (119)	20.1342 (30)	0.3585
CLONALG	83.2215 (124)	16.7785 (25)	0.4968

Table 6.2 : Training and simulation errors

Algorithm (Total Instances - 230)	Mean Absolute Error	Root Mean Squared Error	Relative absolute error (%)	Root Realtive Squared error (%)
Naive Bayes	0.2081	0.4561	62.642	112.3323
Back Propogation	0.2349	0.4847	70.7249	119.3597
SOM	0.3768	0.5054	123.1752	129.1112
AIRS 1	0.2081	0.4561	62.642	112.3323
Parallel AIRS	0.207	0.3937	62.3352	96.9591
CLONALG	0.1678	0.4096	50.5178	100.8774

Figure 6.1 : Classification Result

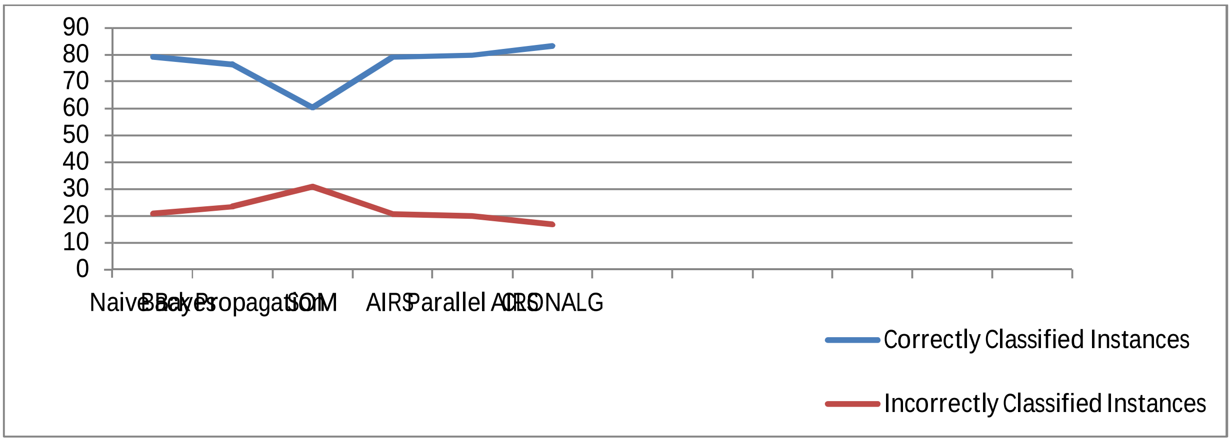
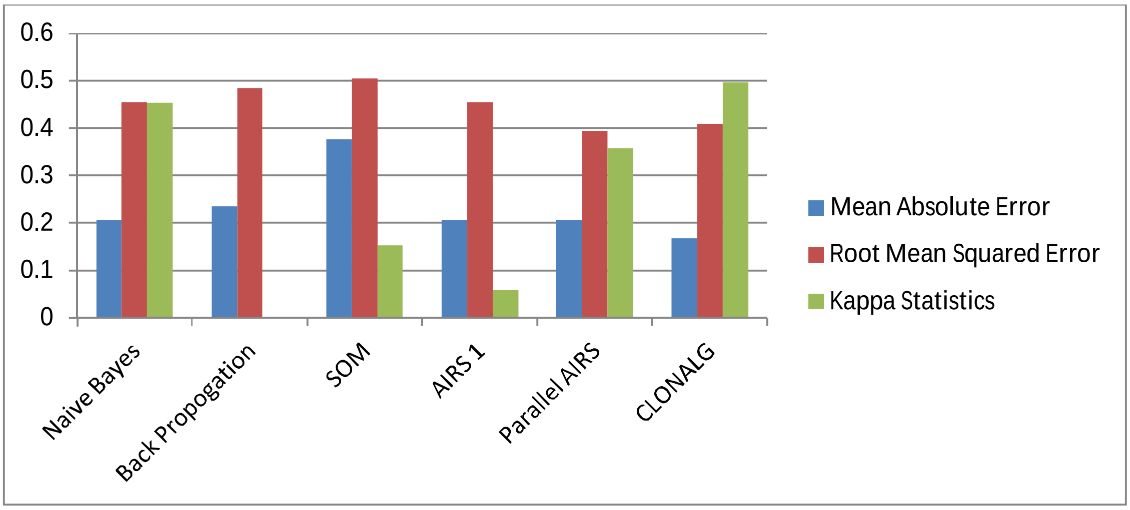


Figure 6.2 : Comparison between Parameters used in the Algorithm



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5. CONCLUSION

This paper explored various soft computing classification techniques along with other AIS algorithms. A comparative study of various algorithms gives a possible idea of enhancing AIS algorithms like AIRS, parallel AIRS and CLONALG for achieving better accuracy in classification.

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7. APPENDIX A (Questionnaire)

Motor Skills

- Does the child have problems with small or large motor co-ordination?

Cognitive Skills

- Does the child explore the environment? If so, how?
- How does the child problem-solve?
- How does the child transition from one activity to another?
- What activities hold the child’s attention?
- How long is the child’s attention span?

Language Skills

- Can the child follow directions?
- Does the child communicate with words?

Social Skills

- Does the child make eye contact?
- Will the child play with other children or does he/she prefer to play alone?

Psychological Development

- What is the child’s reaction to physical contact?
- Whether the child aggressive? (hit, kick, bite, spit, throw objects or verbally lash out at others)
- How does the child express emotions such as fear, anger, frustration and sadness?
- What is the child’s frustration level? What does he/she do when frustrated?

