International Journal of Applied Engineering & Technology

# CLASSIFICATION OF BREAST CANCER IMPLEMENTING ISLAND DIFFERENTIAL EVOLUTION ALGORITHM USING ART1 NEURAL NETWORK

**S. Vijaya[1*] and Dr. D. Gladis[2]**
[1]Research Scholar, PG and Research Department of Computer Science, Presidency College, University of Madras, Chennai
[2]Principal, Bharathi Women's College, Chennai
[1]vijayapeterraj@gmail.com and [2]gladischristopher@gmail.com
[*]Core Author: vijayapeterraj@gmail.com

## ABSTRACT
*Breast cancer a prominent deceased cause disease among woman has become a social dread. Classification of breast cancer enforce a bigger challenge for researchers and scientists in the medical arena. In modern era, Artificial Neural Network (ANN) has been universally used as a dynamic tool in numerous scientific regions such as pattern recognition, medical diagnosis, machine learning and so on. In recent times neural network has turned out to be a sensible tool in the classification of breast cancer. To overwhelm the disadvantages of ANN and to improve ANN learning Differential Evolution (DE) algorithm has been used. Island model has been proposed to overcome the issues of DE. A change in small proportion of vigilance parameter identifies the condition of better performance This paper discussed about the performance in the classification of breast cancer using Wisconsin Breast Cancer Data (WBCD) implementing Island Differential Evolution algorithm using ART1 neural network.*

*Keywords: Neural Networks, Differential Evolution, Island model, WBCD, Breast Cancer.*

## 1. INTRODUCTION
Breast cancer is the second predominant dead causing disease among women. Timely detection and prompt treatment can bring down the mortality rate [1]. Breast cancer that has become a social distress, makes the researchers, experts and authorities to concentrate and devote in the medical science field [11]. Of late neural networks has become an intelligent tool in the classification of breast cancer due to its ability to depict the behaviour of linear and nonlinear functions. WBCD is extensively used in the diagnosis of breast cancer by the researchers [10]. WBCD is used in analysing the performance of neural networks. The objective of this paper is to propose an approach for classification of breast cancer using Island model based differential evolution algorithm implementing neural network. Select the best individuals, replace worst individuals policy and vigilance parameter improves the performance of the network and increase the accuracy. This paper discuss about the performance measures and accuracy in the classification of breast cancer using WBCD implementing Island model based differential evolution algorithm using ART1 neural network.

## 2 LITERATURE REVIEW
The root cause of cancer in human body is due to the unsystematic development of cells in an organ. Breast cancer, the second largest cancer that ends the human life, affects both genders but women are the predominant victims. Breast cancer cells develops in the tissue of breast, grow, divides by itself, form new cells that accumulate to form as a lump or tumour. Cancer cells infect the nearby breast tissues, form way to lymph nodes, and have a pathway to other parts of the body. Breast cancer as like other diseases has many stages, the early is stage I and the advanced is stage IV where cancer cells spread to other parts of body. Breast cancer is mainly due to anomalies in gene, 5 – 10% owing to hereditary[14], deformities due to aging, 90% due to life style [1].

Htet Thazin Tike Thein and Khin Mo Mo Tun compared the computing time of two different topologies Random and Torous on breast cancer data set and analysed that random topology has less computing time than torus topology in the classification of breast cancer[2].Htet Thazin Tike Thein and Khin Mo Mo Tun compared the accuracy between two migration topologies and analysed that random topology showed correct classification % than torous migration topology. Random topology has better results on convergence time than torus[2].Htet

Thazin Tike Thein with Feed forward neural network system experimented the island model ring topology with migration strategy select the best and replace the worst. The migration interval is integration and to migrate and replace one third of the old population is used. Of the four programs developed Island Differential evolution feed forward neural network(IDENN), Differential evolution feed forward neural network(DENN),Particle Swarm optimization feed forward neural network(PSONN)Genetic algorithm feed forward neural network algorithm.(GANN), IDENN has higher classification accuracy of 99.01%, lower convergence time of 103 sec and lower learning iteration 200[3].Htet Thazin Tike Thein and Khin Mo Mo Tun tested the Breast cancer data set with Migration based differential evolution (MBDE) neural network classifier and the highest accuracy rate is 100% obtained by selecting the migration strategy of select the best and replace the worst[4].Htet Thazin Tike Thein and Khin Mo Mo Tun experimented the island model with best select and worst replace migration policy and four different migration topologies . The islands used are identical (i.e) islands with same parameters. The migration interval, iteration and to migrate one third of the old population are used. The results are analysed based on the convergence rate and classification performance.Medical data set is used to implement Migration based Differential Evolution system which shows higher accuracy and has reduced computing time for breast cancer dataset . Fully connected and Torus topology gives better result than Ring and Random topology[5].Omar and Eman proposed a hybrid classification algorithm using Differential Evolution and Least Square - Support Vector Mechanism in the classification of Breast Cancer and has obtained an accuracy of 99.75%[7].

## 3. DATASET

### 3.1 Wisconsin Breast Cancer Data (WBCD)

The data set for classification of Breast cancer is WBCD obtained from university of Wisconsin[1]. It has 699 instances where each instance illustrates nine attributes as given below [1]. Of these 458 instances are Benign and 241 instances are Malignant. Table 2 provides the attribute information of WBCD with values ranging from 0 – 10.

***Table 1.****Features of breast cancer (WBCD)*

| No | 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 |
| 6 | Bare nuclei | 1 – 10 |
| 7 | Bland chromatin | 1 – 10 |
| 8 | Normal nucleoli | 1 – 10 |
| 9 | Mitosis | 1 – 10 |
| 10 | Class | 2 for benign and 4 for malignant |

Researchers assessed WBCD in the classification of breast cancer using neural networks.

### 3.2 Data Pre-processing

Data pre-processing is the first and foremost step used for preparing the data for further process. Many types of processing are performed on raw data. It was performed on task to discover quality data with the help of knowledge algorithms. In real world data is messy and dirty. The data pre-processing technique prepares the data without noisy, incomplete and inconsistent.

#### 3.2.1 Replacing the missing values

WBCD has missing values and are replaced by median value given by

$median = \frac{size(n+1)}{2}$ where n is the number of features [1].

### 3.2.2 Data Normalization

Data normalization an important pre-processing step is to improve the performance of the neural network. Normalization scales the data in a range of 0 – 1 and is done for each attribute. The min-max normalization is used to normalize the data [10] and is given by

$$v' = \frac{v - \min_A}{\max_A - \min_A}(new\_\max_A - new\_\min_A) + new\_\min_A$$

were

A is the instance of the input data

$v'$ is the new value

$\max$ and $\min$ are the minimum and maximum value of the instance

The normalized data is scaled to binary values and are given as input to the neural network.

## 4. DIFFERENTIAL EVOLUTION ALGORITHM

Differential Evolution (DE) algorithm is a simple heuristic evolutionary algorithm used to optimize the ANN model's N dimensional input space and functions like selection process; the weakest solutions are eliminated while stronger, more viable options are retained and re-evaluated in the next evolution.

DE has been used successfully in solving problems of large input space. For searching the solution space of an optimization problem DE enforces the continued existence of the fittest and genetic propagation of characteristic principles of biological evolution. The principle features of DE are, it requires only scalar values, does not requires second and/or first order derivatives of the objective function, capable to handle nonlinear and noisy functions, perform global search and are more likely to arrive at a near global optimum, do not impose preconditions such as smoothness, differentiability and continuity[2].

DE is an improved version of genetic algorithm, exceptionally simple evolution approach. Faster and robust at numerical optimization, it uses floating point numbers and non-uniform crossover and tournament selection operations to create new solution [2] Its main advantages are: simple structure, ease of use, speed and robustness [2].DE is similar to Genetic Algorithm in principle.

## 5. ISLAND MODEL

In the island model approach every individual island performs a standard chronological evolutionary algorithm. The migration process assures the communication between sub-population. Some randomly selected individuals (migration size) migrate from one island into another after every certain number of generations (migrations interval) depending upon a communication topology (migration topology).[2] The two fundamental and most susceptible factors of island model strategy are migration size that specify the number of individuals migrating and controls the quantitative aspect of migration and migration interval indicate the migration frequency[2].

### 5.1 Migration Topology

The migration topology depicts which islands send individuals to which islands. There are many topologies like random topology, torus topology, ring topology and so on [5].

### 5.2 Migration Policy

The migration policy consists of two parts

1st part: selection of individuals, which migrates to another island.

2nd part: choose which individuals are replaced by the newly obtained individuals.

The migration policy decides the migration of individuals between islands based on topology.

There are four migration policies [3]

Select the best individuals replace worst individuals.

Select random individuals replace worst individuals.

Select the best individuals replace random individuals.

Select random individuals replace random individuals.

### 5.3 Migration Interval

Migration has to take place so as to dispense information among islands about excellent individuals. This can be done either synchronously, every nth generation or asynchronously, non-periodically. It is generally accepted that more frequent migration leads to higher selection pressure and therefore a more rapidly convergence. But at all times with higher selection pressure comes the susceptibility to get stuck in local optima. Various migration intervals can be experimented to find the best solution for the neural network training [3].

### 5.4 Migration Size

An important factor is the number of individuals which are exchanged. The migration size has to be tailored to the size of a subpopulation of an island. A very small percentage of migration leads to the influence of the exchange to be negligible. Too much of migration of individuals, take over the existing population, leading to a diminish of the global diversity[2].

## 6. NEURAL NETWORKS

### 6.1 Learning Methods

ANN works through the optimized weight values. Attaining the optimized weight values by using some methodology is called learning, that tries to teach the network how to obtain the desired output when the corresponding input is given. The trained neutral network, after completing the learning process, using the updated optimal weights, should be able to produce the output with desired accuracy corresponding to an input pattern.

A variety of neural networks is applied in classification, pattern matching, pattern completion, optimization, data mining, time series modelling and many more.

### 6.2 ART1 Neural Network

The ART1 model is unsupervised in nature and consists of :

- F1 layer or the comparison field(where the inputs are processed)
- F2 layer or the recognition field (which consists of the clustering units)
- The Reset Module (that acts as a control mechanism)

The F1 layer accepts the inputs and performs some processing and transfers it to the F2 layer that best matches with the classification factor. There exist two sets of weighted interconnection for controlling the degree of similarity between the units in the F1 and the F2 layer. The F2 layer is a competitive layer. The cluster unit with the large net input becomes the candidate to learn the input pattern first and the rest F2 units are ignored. The reset unit makes the decision whether or not the cluster unit is allowed to learn the input pattern depending on how similar its top-down weight vector is to the input vector and to the decision. This is called the vigilance test. Thus that the vigilance parameter helps to incorporate new memories or new information. Higher vigilance produces more detailed memories, lower vigilance produces more general memories. Weight update during resonance occurs rapidly in ART1.

Step 1: Initialization

Initialize bottom up weights W(t) and top down weights V(t). Initialize vigilance parameter $\rho$ ( $0 < \rho < 1$)

Step 2: repeat the steps 3 to 8 for all input vectors $I_H$, presented to F1 layer.

Step 3: choose input pattern vector

Step 4: compute input Y for each node in F2

Step 5: select winning neuron k from step 4

If an indecision tie is noted then perform vigilance test

else go to step 6.

Step 6: compute activation in F1

Step 7: calculate similarity between activation in F1 and input.

Step 8: test similarity with vigilance parameter.

If similarity is true

Temporarily disable node k.

Update top down weights

Update bottom up weights

Update weight matrix w(t) and

v(t) for next input vector

If done with all input patterns then stop the process

otherwise repeat step 3 to 8 for next input pattern.

*ART1 Neural Network algorithm*

### 6.3 ISLAND DIFFERENTIAL EVOLUTION APPROACH TO NEURAL NETWORK(NO MUTATION)

The major steps of Island Differential Evolution [2]

1. Initialize population: Create a population from randomly chosen object vector with dimensions p*d where P is the number of population and d is the no of weights of the neural network.
2. Evaluate all the candidate solutions inside the population for a specified no of iterations.
3. For each candidate in population select the random population members.
4. Apply crossover
5. Apply selection operations.
6. Select individuals from step 6 according to migration strategy
7. Migrate and replace optimal solution
8. Repeat steps 1 to 8 until stopping criteria is reached.

## 7. RESULT AND DISCUSSIONS

**Performance measures**

Performance measure is a regular measurement of outcomes and results that generates consistent data on the effectiveness and efficiency of programs. The performance of the classifiers can be evaluated as

### 7.1Accuracy

Accuracy, the most used emphatical measure that measures the effectiveness of classification algorithm and approximates how effective the algorithm is calculated as [11]

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

### 7.1.1 Without mutation

The performance of ART1 neural network using island differential evolution is analysed under various inputs. The number of islands chosen for the study diverge from two to ten, and has been reformed frequently so as to find the optimum value. The selection probability indicates the quantum selection of chromosomes from each iteration. Mutation is not implemented The cross over chosen is 0.1 and the selection probability is 0.6. For different combinations of vigilance parameter the network performance is measured and the results are tabulated. It is observed that without mutation the maximum accuracy attained is 84.15%

***Table 2:*** *performance of ART1 with IDE and no mutation*

| Population size | no of islands | % of migration | no of iterations | Crossover | selection probability | Vigilance parameter | Accuracy in % |
|---|---|---|---|---|---|---|---|
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.1 | 84.15 |
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.2 | 65.27 |
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.3 | 65.71 |
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.4 | 65.84 |
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.5 | 66.86 |
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.6 | 67.87 |
| 100 | 2 | 20 | 10 | 0.1 | 0.6 | 0.7 | 68.16 |

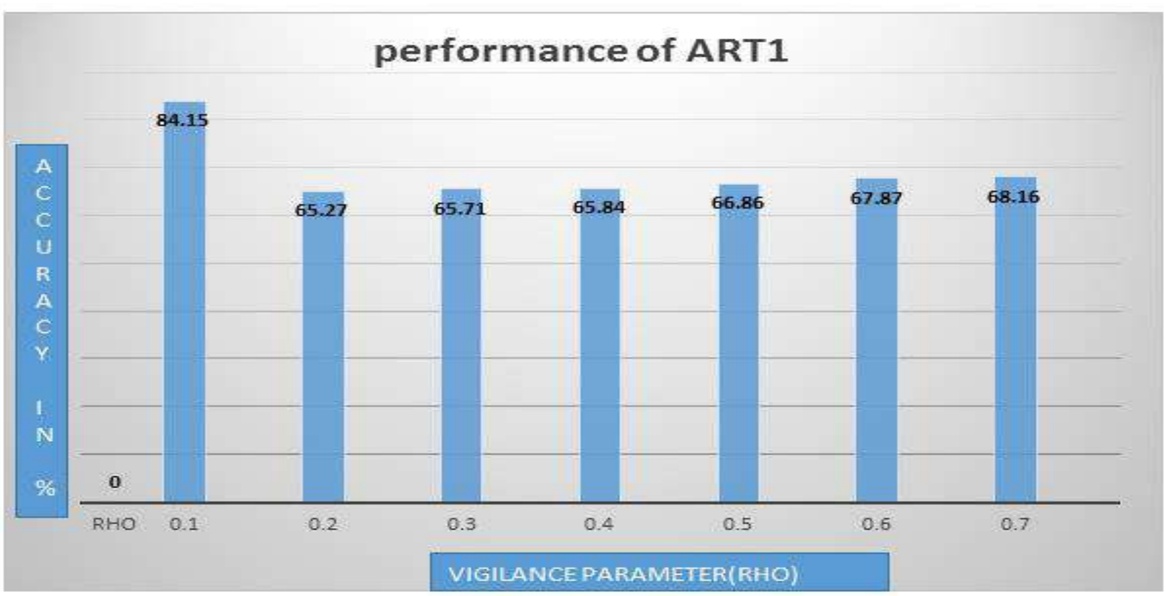


***Figure 2:*** *Performance of ART1 with IDE and no mutation*

### 7.3 With mutation

The performance of ART1 neural network using island differential evolution is studied under various combinations of inputs. Mutation is implemented , cross over chosen is 0.1 and the selection probability is 0.6. For different combinations of vigilance parameter the network performance is measured and the results are tabulated.

It is observed that the maximum accuracy obtained with mutation is 98.33%.

## 8. CONCLUSION AND FUTURE WORK

Island model can get advantages from parallel problem solving and information sharing that lead to faster global search rather than single differential evolution. The training performance of the algorithm will enhance by utilizing the global search power of differential evolution algorithm in conjunction with island model. It is observed that as the vigilance parameter changes the performance changes. The maximum accuracy obtained is 84.15%with out mutation and 98.33% with mutation.

The performance of the network can be analysed by using different medical data sets. The migration policies, migration size, migration interval , migration topology and vigilance parameter can be varied and the performance of the network can be analysed.

## REFERENCES

[1]. S.Vijaya, Dr.D.Gladis,"An approach for breast cancer classification using neural networks" Intl journal of data mining techniques and applications, vol:2, issue 5, pages 114-117, ISSN:2278-2419,December 2016.

[2] HtetThazinTikeThein and Khin Mo MoTun.,"An approach for breast cancer diagnosis classification using neural network", Advanced Computing:An International Journal (ACU),Vol.6, No.1, January 2015.

[3] HtetThazinTikeThein,"Island Model based Differential Evolution Algorithm for neural network training",Vol.3,Issue 1 ,No 7,ISSN: 2322-5157, January 2014.

[4] HtetThazinTikeThein and Khin Mo MoTun.,"Medical Diagnosis Classification using Migration based Differential Evolution Algorithm",Computer Science and Information Technology(CS&IT),CSCP,DOI:10.5121/csit 2014.41313,pg 153 – 163, 2014.

[5] HtetThazinTikeThein and Khin Mo MoTun.,"An Analysis of Migration in the Island Model on Feed Forward Neural Network",Global Journal of Advance Research, Vol-1,Issue-2, Page no 222-231, ISSN: 2394-5788, 30 December 2014

[6] ZbigniewSkolicki and Kenneth De jong," The influence of migration sizes and intervals on island models",in proceedings othe Genetic and Evolutionary Computation Conference(GECCO-2005), ACM press, 2001.

[7] Omar S. Soliman and EmanAboEIHamd ," Classification of Breast Cancer using Differential Evolution and Least Squares Support Vector Machine",International journal of E merging Trends and Technology in Computer Science,Vol 3, Issue 2,page no 155 – 161, March- April 2014..

[8] K.V. Prince and RM. Storn"Differential Evolution – A simple and efficient heuristic for global optimization over continuous spaces",Inter national Journal of Global Optimization, vol. 11 no 4, page no 341 – 359, December 1997.

[9] K.V. Prince, R.M Storn and J.A Lampinen, " Differential Evolution – A Practical Approach to Global Optimization", Berlin, Germany, SpringerVerlag 2005.

[10] S.Vijaya and Dr D. Gladis," Classification of Breast Cancer, using ART1 Neural Network", Mathematical Sciences International Research Journal, vol 7 Special issue 3,ISSN 2278 – 8697, 2018 ( UGC India approved journal JrNo 43832.)

[11] S.Vijaya and Dr. D. Gladis, "Breast Cancer classification using ART1 neural network with Improved F-Score feature reduction" ,International Journal of Pure and Applied Mathematics, ISSN1314-3395 Scopus Indexed, Online version, http//www.acadpubl.edu/hub/special issue, Volume 119 No 16 365-381, July 2018.

[12] Chandra PrasetyoUtomo, AsnKardiana, RikaYuliwulandari.: Breast cancer diagnosis using artificial neural networks with extreme learning techniques, Intl journal of advanced research in artificial intelligence, vol.3. No. 7, 2014.

[13] AhmetMert,NiyaziKilic, ErdemBilgili and Aydin Akan: Breast cancer detection with reduced feature set, Hindawi Publishing corporation , Computational and Mathematical Methods in Medicine, volume 2015, Article ID 265138, 11 pages.

[14] Yixiao Feng,[a,b] Mia Spezia,[b] Shifeng Huang,[a,b] Chengfu Yuan,[b,c] Zongyue Zeng,[b,d] Linghuan Zhang,[b,e] Xiaojuan Ji,[b,e] Wei Liu,[a,b] Bo Huang,[b,d,f] Wenping Luo,[b,g] Bo Liu,[a,b] Yan Lei,[a,b] Scott Du,[b,h] Akhila Vuppalapati,[b,h] Hue H. Luu,[b] Rex C. Haydon,[b] Tong-Chuan He,[b] and Guosheng Ren[a,*], "Breast cancer development and progression: Risk factors, cancer stem cells, signaling pathways, genomics, and molecular pathogenesis", Published online 2018 May 12. doi: 10.1016/j.gendis.2018.05.001. Genes Dis. 2018 Jun; 5(2): 77–106. PMCID: PMC6147049, PMID: 30258937.