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Efficient Breast Cancer Classification using Improved Artificial Immune Recognize System with Csonn

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Abstract: Breast Cancer is one of the serious problems for the women, which causes many problems like skin irritation, pain, enlargement of the all the part of the breast, redness and nipple discharging. These problems create dangerous problems for the women, so, the proposed paper proposed the Improved Artificial Immnune Recognize System (IAIRS) for classifying and analyzing the cancer from the Adayar Cancer Institute Chennai breast cancer database. Initially the captured breast images are preprocessed and segmented by applying the adaptive mean filter and Fuzzy C-Means clustering approach. Then the various concepts or features are extracted and those features are trained by applying the Cat Swarm Intelligent Optimization with Optimal Brain Damage (OBD) Pruning Neural Networks (CSONN).The training algorithm process the extracted features based on the cat's movements like seeking and tracing mode. Then the selected features are classified by applying the Artificial Immnune Recognize System (AIRS) in which the weights and bias are updated based on the feature training algorithm. Then the performance of the system is evaluated with the help of the performance metrics like, mean square error, sensitivity, specificity and classification accuracy.

Keywords: Breast Cancer, Improved Artificial Immune Recognize System, Cat Swarm Intelligent Optimization, Mean Square Error, Sensitivity, Specificity and Accuracy.

1. INTRODUCTION

Breast Cancer is also called as carcinoma, which is the irregular growth of specified cells of the breast. The carcinoma increases the growth with the help of the lobular carcinoma cell and spreads over the growth via the milk ducts [1]. This carcinoma disease often develops in the women and spread through the tissues and it does not cause any symptoms. But the growth of the cell has some of the signs such as change the size of the breast, lumping, nipple discharge, irritation and dimpling [2]. So, the women may be affected by several types of breast cancers like adenicystic, metaplastic carcinoma, medullary carcinoma, mucinous, papillary and tubular carcinoma [3]. The breast cancer has been tested by using the physical exam, mammogram, clinical breast cancer exam, blood chemistry studies, biopsy studies, ultrasound exam and magnetic resonance image (MRI) [4]. In our proposed system MRI breast image is used to evaluate the breast cancer identification and classification process because it estimates the cancer level with accurate manner. The sample MRI breast image is shown in the following figure 1 [5].

This captured MRI breast image is automatically processed by several image processing and soft computing techniques like, Gaussian filter [6], mean filter [7], Sobel segmentation [8], Canny Segmentation [9], Support Vector Machine [10], Neural Networks [11] and so on. Even though these methods are providing the best classification results. The performance of the system needs to be improved for reducing the error while matching the templates. So, in this paper proposed an effective breast cancer classification approach for identifying the cancer from the captured MRI image. The captured MRI images are preprocessed by

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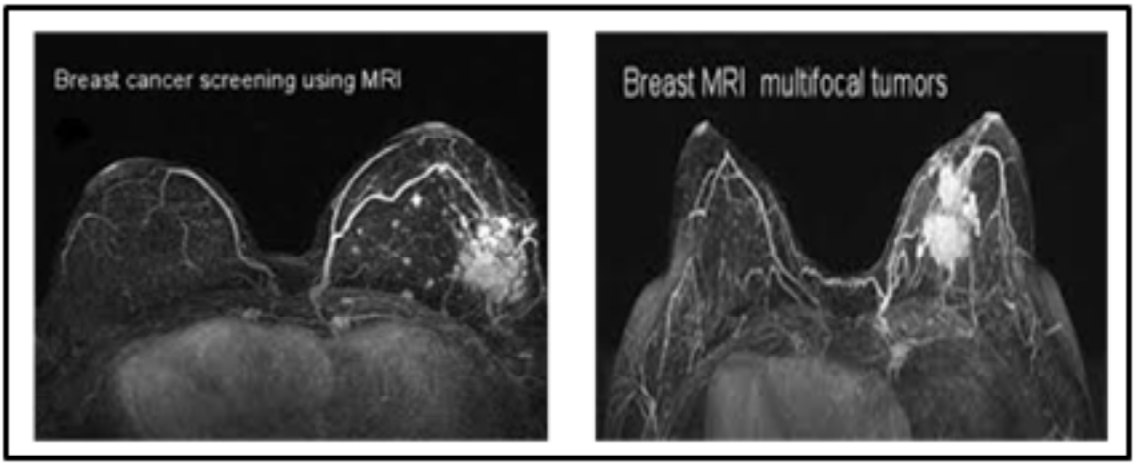

Figure 1: Sample MRI Breast Image

applying the Adaptive Mean filter [12] and the images are segmented by using the Fuzzy C-Means Clustering approach [13]. Then the cancer related concepts are extracted and the features are trained by applying the CSONN based optimization algorithm. Finally the classification is done with the help of the Artificial Immune Recognization System (AIRS) approach. The following section section 2 deals with related works which explains the breast cancer and classify methods, section 3 depicts that the AIRS method and related performance measure, section 4 describes that the CAT algorithm and related applications, section 5 describes that detailed proposed methodology and section 6 describes the comparison between the CSONN and the proposed algorithm.

2. RELATED WORKS

Breast cancer is a dangerous disease which is mostly affected to the women. Many researchers discuss the automatic detection of the breast cancer in the captured MRI images. *Ahmed et al [14]* proposed that the Multimodal Markov Random framework for automatically detecting the tumors in the breast. The tumor related features are extracted by applying the condition mutual information dependency criteria and the features are related to the proposed framework. From the dependency, the related features are mapped by using the support vector machine. Thus the proposed system classifies the breast cancer with high and low risk factors when compared to the existing systems. *YasmeenMourice George et al., [15]*proposed an automatic breast cancer detection system by using the cytological images. The false positive rate feature present in the cytological image is processed by applying the Otsu'sThresholding approach. Then the tumor related part is segmented by using the watershed transform and the twelve different features are extracted by the Hough transform. Finally the classification is performed with the help of the different classifiers such as support vector machine, multilayer perceptron, backpropagation neural networks and probabilistic neural networks. Thus the author evaluates the performance of the system with 92 breast cytological images and the error rate performance metrics.

*Krawczyk et al., [16]*uses the themography based breast cancer detection process. The image is captured by using the sensitive camera and the features are extracted by bilateral symmetries. From the extracted feature the tumors are classified by applying two different stages. In the first stage, the cancer related decision is carried out by weighted based evolutionary algorithm. During the second stage, the features are classified by using the neural networks. Then the performance of the proposed system is compared with the canonical classification approach. *Magna et al., [17]*detecting the breast cancer by applying the screening digital mammography based captured breast cancer image. The proposed system uses the two different database, namely, 32 pair MLO projection based mammographic image and 30 mini MIAS mammography database. The captured images are classified by applying the Adaptive Artificial

Immune System classifier. Thus the performance of the proposed system is compared with the several convolution methods.

*YanfeiZhon et al., [18]*developing the adaptive artificial antibody based neural networks to classify the breast cancer. The author uses the supervised classification method for analyzing the extracted features by applying three different steps like, clone, mutation, and selection. The performance of the proposed system is compared with the different algorithms like Gaussian Maximum Likelihood, Minimum distance, Back-propagation Neural Networks. Thus the proposed system classifies the breast cancer with highest accuracy. *IlyesJenhani et al., [19]*discusses the various works based on the Artificial Immune Recognize System (AIRS). This algorithm wieldy used to develop the real time application problems with accurate manner because it takes the important parameter while processing the features. The performance of the proposed system is evaluated with the help of the UCI database and taking thenumRepAg parameter to achieve better performance.

3. ABOUT ARTIFICIAL IMMUNE RECOGNIZE SYSTEM

Artificial Immune RecognizeSystem (AIRS) [21] is one of the supervised learning algorithm, which works based on the biologically inspired immune characteristics. This AIRS has widely used to process the set of features and helps to perform the classification and pattern recognition problems. The AIS has following characteristics such as, self regulation, performance, Generalization and Parameter Stability. This characteristic is used to produce the high classification accuracy while performing the particular recognition process. Then the AIRS system detects the harmful antigens from the collection of organs via the B cell and T cell. This cell matches the antigens by using the shape-space parameter while detecting the harmful antigens. This AIRS system uses the some of the parameters while detecting and matching the cells during the pattern recognition process. First parameter is, Affinity Threshold Scaler which is used to detect the similarity between the recognized cells and the specified antigen cell. The second parameter is, clonal rate used to determine the number clonal during the refinement stage also identify the best matching memory while creating the cell pooling. Third parameter is Hypermutation Rate used to create the mutated clone matching memory via the clonal rate and cell stimulation process. The fourth parameter is simulation parameters and the related threshold values which are used to identify the classification parameters. The AIS parameters and the characteristics are used to classify the features by using the three different ways which are mentioned as follows,

- Artificial Immune Recognize System
- Parallel Artificial Immune Recognize System
- Clonal Algorithm

3.1. Artificial Immune Recognize System (AIRS)

The Artificial Immune Recognize Systemcategories the memory cells by doing the dataset training process. The function of the AIRS block diagram is shown in the following figure 2.

3.1.1 Initialization

Initialization is the first step in the AIRS recognition process, in which the data have been prepared by making the normalization process. The normalization process reduces the value of the features within the range [0,1] which is done as follows,

$$normalized\ value = normalized\ value, \frac{1}{\sqrt{n}} \tag{1}$$

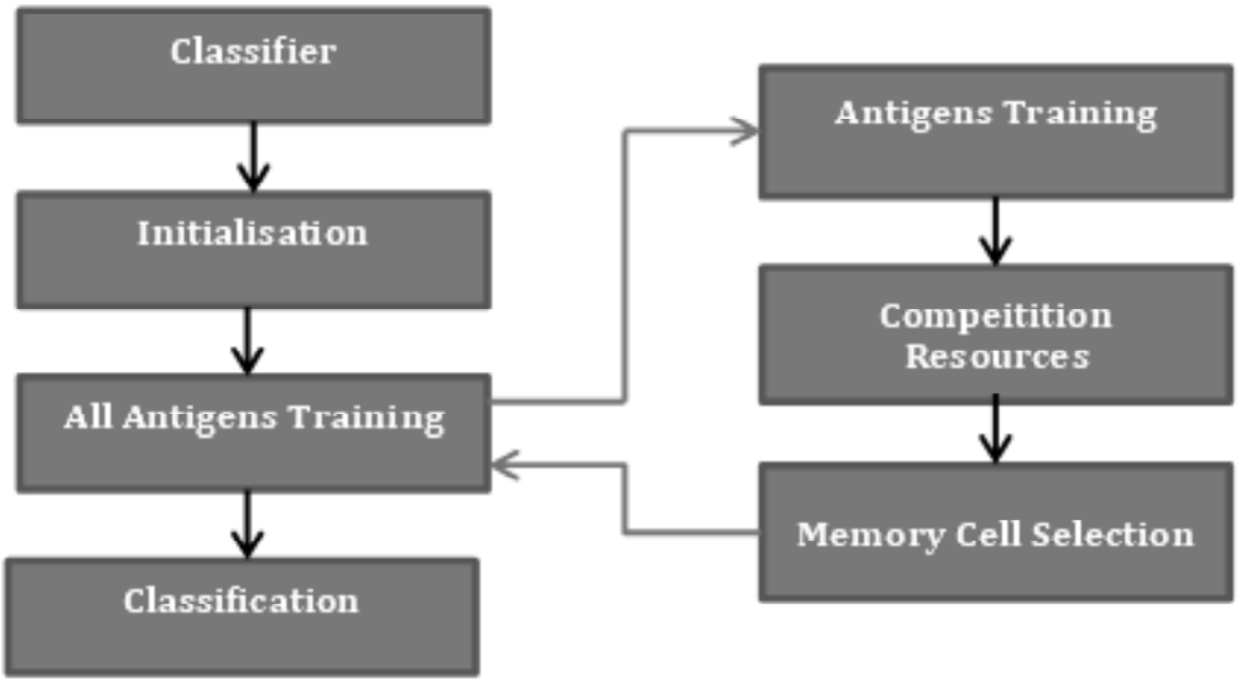

Figure 2: Block diagram for the Artificial Immune Recognize System

After normalizing the process, the distance between the feature is calculated by Euclidean Distance as follows,

$$distance = \sqrt{\sum_{i=1}^{n} (v1_i - v2_i)^2} \tag{2}$$

Where $v1$ and $v2$ represented as the two values which is need to be measured the affinity value that is measured as follows,

$$affinity = \frac{(distance)}{(maximum\ distance)} \tag{3}$$

The maximum distance is calculated as follows,

$$maximum\ distance = \sqrt{\sum_{i=1}^{n} r_i^2} \tag{4}$$

Where *r* is the data range of the attribute *i*.

3.1.2. Antigen Training

The next step is an antigen training process which is used to create the memory pool for simulating and recognize the cells. Each antigen has own memory cell that is visible at one time in the memory pool which is calculated by using the simulation value. The simulation value is measured by the affinity value as follows,

$$simulation\ value = 1 - affinity \tag{5}$$

From the calculated simulation value the maximum value is selected as the best memory cell. During the training process, the best mutated clone value is shown as follows,

$$num\ Clones = stimulation.\ clonal\ Rate.\ hypermutation\ Rate \tag{6}$$

Where, simulation is the best match between the memory cell, clonal rate and hyper mutation rate is the user parameter.

3.1.3. Competition Resources

The next process is a competition resource identification process in which the simulation value is used to determine the limited antigen resource value. During the resource estimation process, the antigen pools are normalized and the limited resources are allocated to each antigens presents in the memory pool. Finally the Pruning process is performed by eliminating the unwanted or low simulation values from the memory pool. If the memory pool having the best antigens, then the mutated clone has been generated as follows,

$$num\ Clones = stim \times clonal\ Rate \tag{7}$$

The related resource values are calculated as follows,

$$resource = norm\ Stim \times clonal\ Rate \tag{8}$$

After estimating the antigens limited resource then the optimized cell has been selected by a memory cell selection process which is discussed as follows.

3.1.4. Memory Cell Selection

The next process is a memory cell selection which is selected based on the maximum simulation score of the memory pool value. This selection process is done by comparing the original cell value with the existing calculated cell value. This estimation used to identify the best matching score with the help of the cutoff value. The cutoff value is calculated as follows,

$$cut\ Off = affinity\ Threshold \times affinity\ Threshold\ Scalar \tag{9}$$

where, *affinityThreshold* is the initialized parameter value and *affinityThresholdScalar*is the user defined parameter value. Finally the selected value is used to classify the cell during the pattern recognition process.

3.2. Parallel Artificial Immune Recognize System

The AIRSnaturally exploit in two ways such as distributed and parallel manner while making the antigens training. The parallel Artificial Immune Recognize System is the simple process which is similar to the AIRS classification system. The classification process takes the following steps while doing the training and the antigen classification process.

Step 1: Input parameter and related antigens are initialized

Step 2: The data set is divided into the number of desired processing partition running in the AIRS.

Step 3: These partitions are allocated to the memory pools

Step 4: Then calculate the affinity value of the memory cells which is used in the classification process.

3.3. Clonal

The clonalbased Artificial Immune System is one of the best pattern recognition process. The algorithm selects the antibody based on their affinity values rather than matching the antigen patterns. The selected antibodies are directly proportional to the affinity value and the hyper mutation rate is inversely proportional to the affinity value. During clonal process, the low affinity value is replaced by the randomly generated antibody values. The Clonal algorithm follows the steps during the classification process.

Step 1: Initialize the individuals in random.

Step 2: Determine the Affinity value of the each individual in the population.

Step 3: Select the highest affinity value and then generate the copy of the individuals.

Step 4: Mutate the generated copy of individuals which is proportional to the greatest affinity value.

Step 5: Add the mutated value to the individuals and reselect the individuals for storing in the memory.

Based on the above discussed training and classification process, the proposed system uses the AIRS system to identify and classify the breast cancer from the captured MRI image.

4. PROPOSED STUDY OF THE BREAST CANCER

Breast melanoma develops in the breast cell which causes critical drawback to the ladies that result in dying.So, the proposed system creates the automatic breast cancer detection approach by using the MRI breast image. The proposed algorithm works in two different stages. In stage 1 the captured images are processed by applying the image preprocessing, segmentation, feature extraction and feature training process. The classification is performed in the stage 2 and the proposed system block diagram is shown in the figure 3.

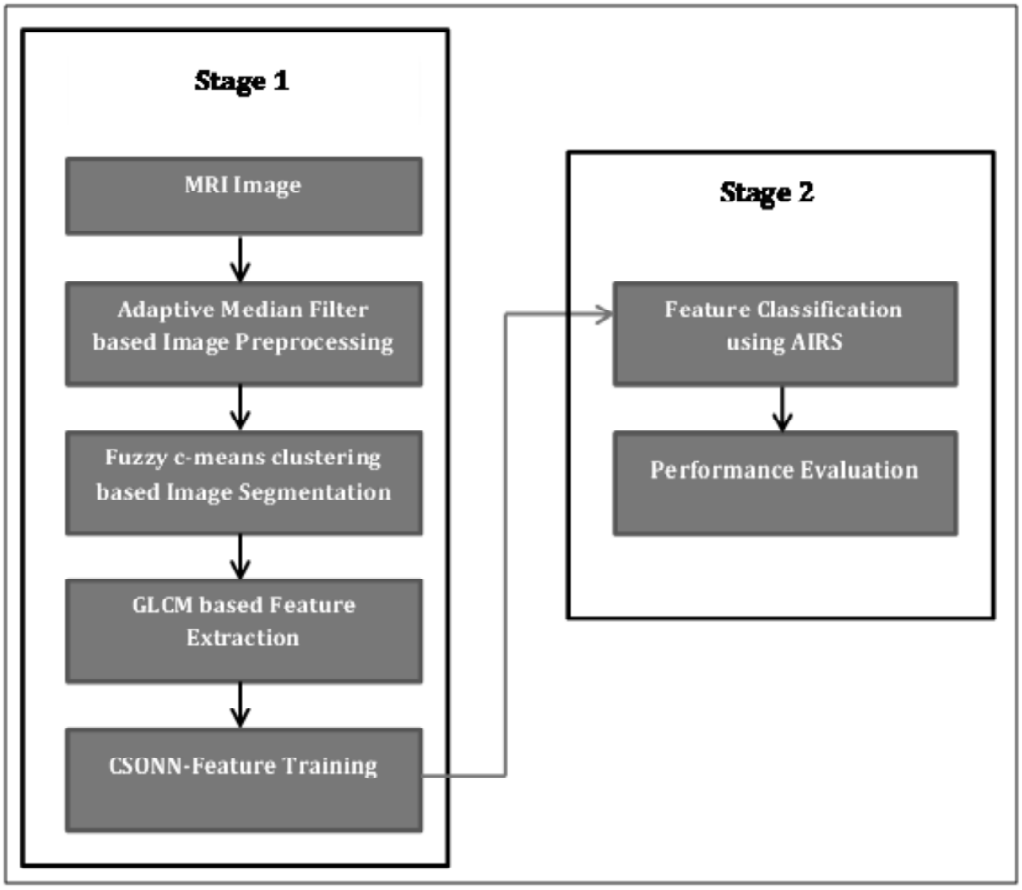

Figure 3: Proposed System Block Diagram

4.1. Breast Cancer Classification Stage 1

The steps and procedure of the stage 1 process are explained as follows,

4.1.1. Image Preprocessing

The captured MRI image has some of the impulse noise which reduces the performance of the system during the classification process. So, the impulse noise has been removed by applying the adaptive mean filter. The adaptive mean filter [22] alternate the window size depending on the noise presents in the input image. Initially the pixels are ranked according to the brightness value and the median value is calculated. If the pixel is corrupted by any noise, that pixel has been replaced by the calculated median value. Thus the noise removal process eliminates the noise without losing the quality of the image. This noise removed image is used for further classification process.

4.1.2. Image Segmentation

Image segmentation [23] is the process of dividing the images into small groups which is used to detect the affected part with accurate manner. The preprocessed image has noise free pixels which depends on the particular cluster. So, each pixel threshold and cluster center value is calculated based on the objective function. The objective function is defined as follows,

$$Im_{FCM} = \sum_{k=1}^{n} \sum_{i=}^{c} \left(v_{ik}\right)^{q} d^{2}\left(x_{k}, v_{i}\right) \tag{10}$$

Where, $x = \{x_1, x_2, x_3, ,,,, x_n\} \subseteq R$; *Image data set*

n = *number of items*

c = *number of clusters*; $2 \leq c < n$

v_{ik} = *degree of membership of* x_k *in* i^{th} *cluster*

q = *weight for the member*

v_i = *center of the cluster i*

$d^2\ (x_k, v_i)$ = *distance between object and cluster center*

The calculated objective function is used to determine the cluster heads and membership value. This process is continuously changing their center while segmenting the input image. This approach is repeated until it satisfies the special threshold. The segmentation is continued based on image brightness, vicinity of the pixels which is used to establish the elements of the segmented picture.

4.1.3. Feature Extraction

Feature Extraction [24] is the process of extracting the breast cancer related useful information. The breast cancer related features are extracted by applying the Gray Level Co-occurrence Matrix (GLCM) because it focuses on color,shape, texture related measure while retrieving the feature. These measures are important in the feature extraction because the breast cancer is identified based on the swelling, pain, irritation and redness attributes and so on. Thus the breast cancer related features such as contrast,color,energy,correlation,entropy,shape,texture,dissimilarity, intensity and homogeneity values are calculated as follows in the table 1.

The extracted features are used to train the network, which is used during the feature classification process.

4.1.4. Feature Training

The next step is feature training which has reduced the error rate while making the breast cancer classification process. So, the proposed system uses the Cat Swarm Intelligent Optimization with Optimal Brain Damage (OBD) Pruning Neural Networks (CSONN) algorithm for feature training process. The Cat Swarm Intelligent Optimization (CSO) [25] algorithm used for optimization that works based on the cat behavior. The cat has seeking and tracing behavior that is used to train the extracted feature. In the seeking mode the cat watches all the activities in the rest position with the help of the memory pool, the dimension of the particular range, dimension change and self position attributes. Based on the attributes dimension and position of the attribute is evaluated by ranking process. The rank of the attribute is estimated using the fitness value. The fitness function reduces the error rate that improves the performance of the system. In the tracing mode, the cat changes their position value by the next best attribute value. The combined optimized feature training algorithm is explained by using the following algorithm.

Table 1
GLCM related Features and Formule

Features	*Related Formula*
Entropy	$\sum_{i,j=0}^{n-1} -\ln(P_{ij})P_{ij}$
Correlation	$\sum_{i,j=0}^{n-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2}$
Energy	$\sum_{i,j=0}^{n-1} \left(P_{ij}\right)^2$
Contrast	$\sum_{i,j=0}^{n-1} P_{ij}(i-j)^2$
Homogeneity	$\sum_{i,j=0}^{n-1} \frac{P(i,j)}{1+(i-j)^2}$
Dissimilarity	$\sum_{i,j=0}^{n-1} \lvert i-j \rvert P(i,j)$

Feature Training using CSONN

Step 1: Choose the Neural Network for feature training process

Step 2: CSO optimization algorithm based Neural Network has been trained by applying the following fitness value

$$fitnes\ (aij) = \frac{1}{(1+a_{ij})}$$

From the fitness value the attributes are updates their position using the following condition

$$P_i = \frac{\left|FS_i - FS_b\right|}{FS_{\max} - FS_{\min}}$$

where $0 < i < j$, *for minimize: let* $FS_b = FS_{max,}$ FS_i *and* FS_b *is the Fitness* function of each attributes

Step 3: Calculate the Diagonal Element of the Hessian Matix

Step 4: Estimate the salience parameter for the network.

Step 5: Remove the connection between the poor weights and reduce the structure and size of the networks with optimized features.

Step 6: Retrain the Neural Network

Step 7: Continue the process until to reach the stop condition

Step 8: Output the best Pruned Neural Network applies to the Fuzzy Cognitive Map

Step 9: IF then rules are used to classify the incoming concepts or attributes by using the condition.

Then the trained features are fed into the stage 2 for classifying the breast cancer from the MRI image which is explained in the following section.

4.2. Breast Cancer Classification Stage 2

The next stage is a breast cancer classification in which the trained features are fed into the Artificial Immune Recognize System [26] to achieve the greatest classification accuracy. In the initialization stage the trained feature and the related mutate, clone parameters and simulated parameters are determined for choosing the best matching cells. The trained features are normalized by eqn(1) and the affinity value is estimated by eqn(3) based on the eqn (4). After estimating the affinity value, the simulation value is calculated to perform the antigens training. The completion of the training process leads to conduct the competition between the cells present in the memory pool. The competition process selects the best matching score antigen that applies to the parallel AIRS process which is similar to the AIRS classification process. Then mutated clonal process is implemented to generate the copy of the antigens. The copy of the antigens used to match the train the features with the incoming new features with effective manner. The mutated clonal cells consist of the best matching score and the affinity value that is used during the comparison process. The comparison is done by based on the shape-space parameter. Then the algorithm of the proposed classification system is shown as follows,

Pseudocode for AIRS classification

Input: Trained Features, Clone rate, Mutate rate, Affinity Value and simulation rate
Output: Cell Memory
Cell memory← *Initialize the memory pool* (Trained Feature)
For each $Trained\ Feature_i \in Trained\ Feature$ do
Stimulate (Cell memory, Trained Feature)
Cell best ← *Get most stimulated (Trained Feature, Cell memory)*
If *Cell best* ≠ *Trained Feature* then
    Cell memory ← *Createnew memory cell (Trained Features)*
Else
Clone new ← *cell best * clone rate * mutate rate*
Cell clone ← *cell best*
For *i* to *clones num*do
Cell clones ← *clone and mutate (cell best)*
End
While *Average Simulation (cell clone)* ≤ *simulation threshold* do
Foreach$cell_i \in$ *Cell clones* do
    Cell clones ← *Clone and Mutate* ($Cell_i$)
End
Stimulate (Cell clones, Trained Features)
Reducepool to maximum resource (Cell clones, resource)
End
$Cell_c$← *Get most stimulated (Trai*ned Feature, Cell Clones)
If $Cell_c > Cell_c$ then
Cell memory ← $Cell_c$
If *Affinity* ($Cell_c$, *Cell best)* ≤ *affinity* then
Deletecell (cell best, cell memory)
End
End
Return *cell memory*

Based on the AIRS system the new features are matched by the template stored in the memory pool. Thus the proposed system classifies the extracted MRI image features by using the shape-space metrics which is done with the help of the Improved Artificial Immune System. Then the performance of the proposed system is discussed in the following section.

5. PERFORMANCE ANALYSIS

Breast cancer is the one of the leading serious disease which affects women in fast. Thus the proposed system developing the automatic breast cancer detection process by using the Adayar Cancer Institute Chennai Database. The performance of the proposed Improved Artificial Immune Recognize system (AIRS) is evaluated with the help of the mean square error, sensitivity, specificity and classification accuracy performance metrics. In this the error rate is minimized by applying the CSONN based feature training process because the optimization algorithm uses the tree structure reduction process and weight optimization process. The proposed approach mean square error value is shown in the table 2.

Table 2
Mean Square Error of Different Classification technique

Classification Technique	*Mean Square Error Value*
BPN	0.89
RBFN	0.789
GRNN	0.934
FCM Without Pruning	0.345
FCM with CSONN	0.0234
Improved AIRS	0.00036

The above table 2 clearly explains that the proposed Improved AIRS approach has low mean square error when compared to the other classifier network. The Figure 5 shows that the proposed Minimum Means Square Error Value.

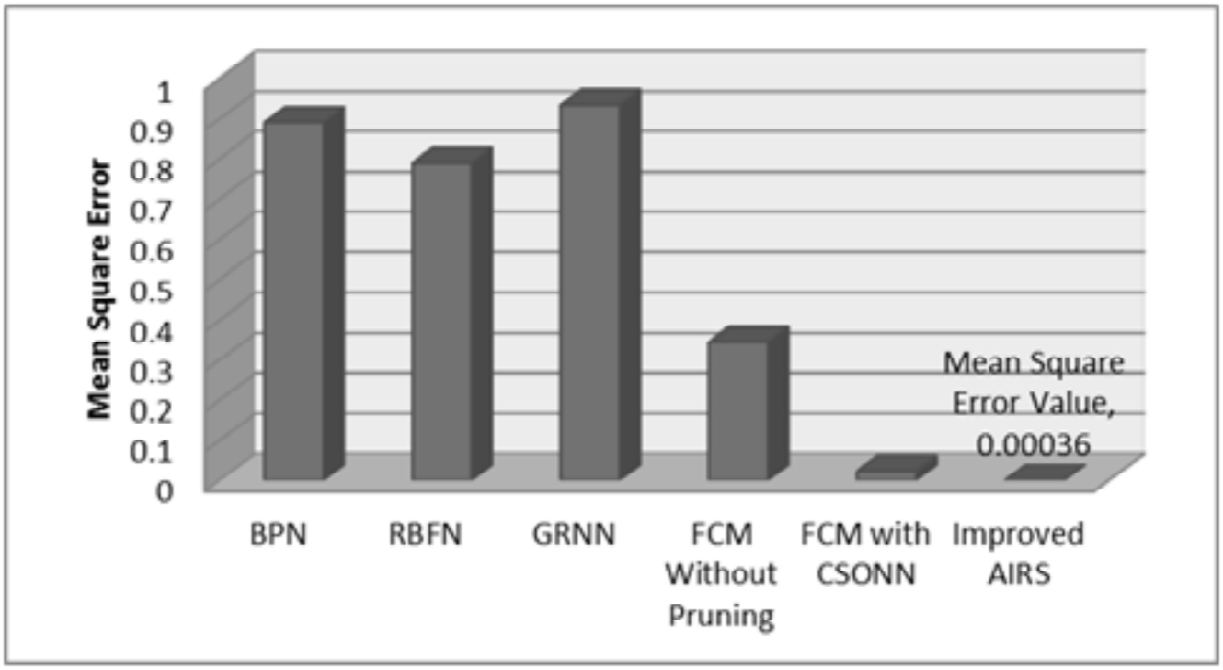

Figure 4: Mean Square Error of Different Classification technique

Then the proposed Improved AIRS classifier, classifies the breast cancer with highest sensitivity and specificity rate because the proposed algorithm consumes minimum mean square error rate. The sensitivity and specificity value is estimated as follows,

$$\text{Sensitivity} = TP/((TP + FN)) \tag{11}$$

$$\text{Specificity} = TN/((TN + FP)) \tag{12}$$

Where, TP = True Positive, TN = True Negative

FP = False Positive, FN = False Negative.

The following Figure 6 shows that the Sensitivity and Specificity value of the proposed system which is compared to the several classification methods such as BPN [28], RBFN [29], GRNN [30].

The above figure used to analyze the accuracy of the proposed classification techniques because it's accepted and rejection rate of the feature is evaluated via the sensitivity and specificity value. So, the classification accuracy of the proposed system is discussed via the table 3.

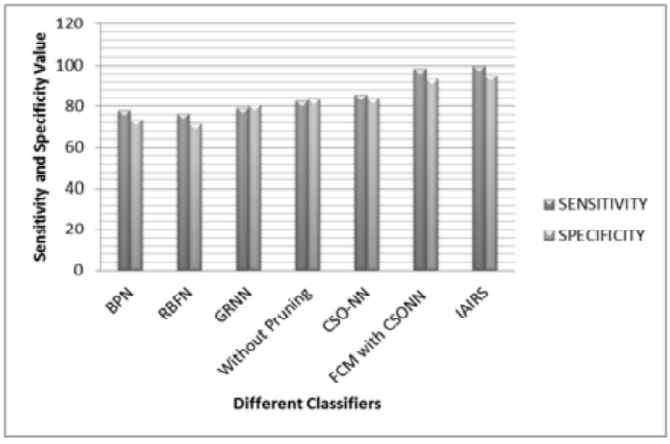

Figure 5:Sensitivity and Specificity of Different Classification technique

Table 3
Classification Accuracy for Different Classification Techniques

S. No.	*Classification Techniques*	*Classification Accuracy (%)*
1	BPN	71
2	RBFN	85
3	GRNN	82.2
4	FCM Without Pruning	85.6
5	FCM with CSO	98.3
6	Improved AIRS	99.64

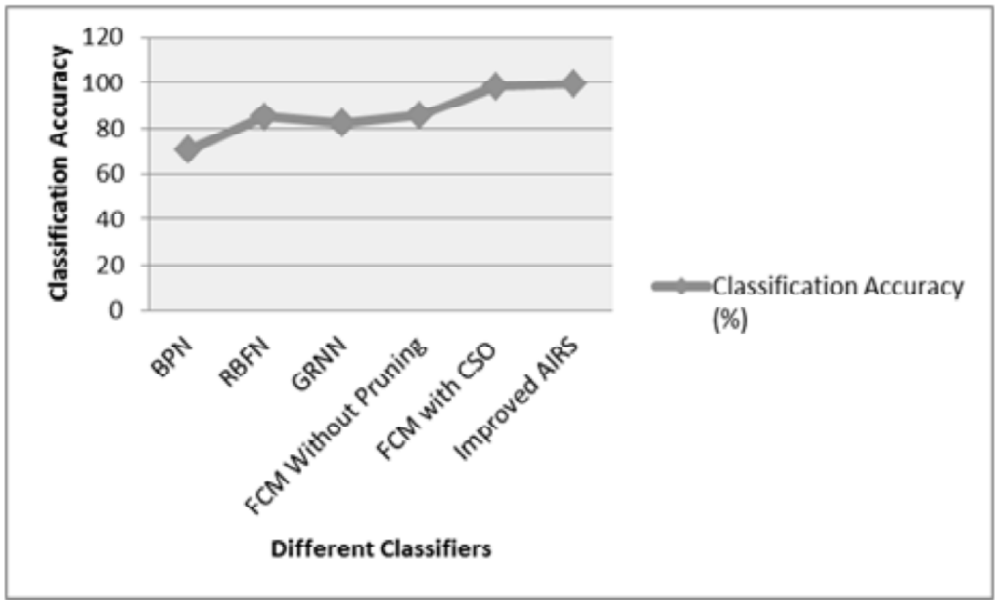

Figure 6:Classification Accuracy of Different Classification technique

The above results describes that the proposed improved Artificial Immune Recognize System achieves the better classification accuracy with 99.64% than compared to the existing methods BPN,RBFN,GRNN, FCM without Pruning, and CSO-NN approach. Thus the proposed system classifies the breast cancer using the MRI image with CSONN trained features. The trained features are helping to minimize the error rate while matching and improves the classification accuracy.

6. CONCLUSION

In this paper the breast cancer classification is performed by using the Adayar Cancer Institute Database MRI image. The captured image is processed in two different stages, which produces the highest classification accuracy. In stage 1 the captured images are preprocessed and the affected part is segmented by applying the Adaptive Mean Filter and the Fuzzy C-means Clustering process. Then the GLCM features are extracted and the features are trained by applying the CSONN approach. The CSONN approach trains the feature based on the cat behavior and the features are fed into the stage 2. In stage 2 the classification is performed by applying the Artificial Immune Recognize System, which matches the cell based on the affinity value and simulation value. Then the performance of the proposed system is analyzed with the help of the experimental results and discussion.

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