Securing Image Data's Using Cellular Automata Techniques

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Abstract: One of the most efficient methods for breast cancer early detection is mammography. It's a new attempt for Securing image data's using cellular automata techniques is presented here. It is done by different stages: first, from the 322 dense mammographic images, originating from the MIAS database we applied these Soft computing techniques like noise removal, segmentation and pectoral muscle extraction, detection of micro calcifications. Finally, the extracted features are fed as input to the Cellular Automata Technique and are classified into different rules. The results are analyzed using MATLAB for Soft Computing Techniques. Securing Image Data's and Detection of Survival for Breast Cancer in Mammogram using Cellular Automata Technique is experimented using Java.

I. Introduction

In recent years, extensive research methods for data security in image had been done by various researchers. Great attention has been paid to maintain and to store the data's in the systems. Great attention has been paid to secure the data's in image from different methods, which has become the most exciting topic of data security in image. Especially, the security of data's in image using cellular automata has attracted considerable attention. The idea for data security in image came from the several models, such as Langton's Ant, Bitozoa - Artificial Life, John Conway's game of life. Since the cellular automaton model is conceptually simpler and can be easily implemented on computers for numerical investigations, it has become a particularly interesting choice for the most scholars. Yang et al [1] proposed a new cellular automata model to data security in image. It is difficult to access real medical images for experimentation due to privacy issue. The proposed makes use of the data collection obtained from Mammographic Image Analysis Society (MIAS) [2]. Before implementing the Cellular Automata techniques Image pre-processing techniques are necessary, in order to find the orientation of the mammogram, to remove the noise and to enhance the quality of the image. It can be done in four stages: first, the preprocessing stage deals with noise removal, and normalized image. Second stage, segmentation and pectoral muscle extraction. Third stage consists of the detection of micro calcifications. Finally, the extracted features are fed as input to the Cellular Automata Technique and are classified into different rules. The given classification approach is applied to a database of 322 dense mammographic images, originating from the MIAS database. The results are analyzed using MATLAB for a first three stages. The final stage is the Detection of Survival for Breast Cancer in Mammogram using Cellular Automata Technique is experimented using Java.

II. Related Work

Vega-Corona et al. (2003) was used a method for detecting MCs in digitized mammograms. The method consists of image enhancement by adaptive histogram equalization to improve the visibility of MCs with respect to the background, processing by multistate wavelets and gray-level statistical techniques for feature extraction, clustering by the k-means algorithm for MC detection and, finally, using feature selection and a classifier based on a general regression neural network (GRNN) and multilayer perception (MLP) to classify MCs.

D'Elia .C (2004) was used a method for allowing the diagnosis of a breast cancer at a very early stage. A method designed for this task as described. The mammograms are firstly segmented by means of the tree

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structured Markov random field algorithm which extracts the elementary homogeneous regions of interest on the image. Such regions are then submitted to a further analysis (based both on heuristic rules and support vector classification) in order to reduce the false positives. The approach has been successfully tested on a standard database of 40 mammographic images, publicly available.

H. Osta, R. Qahwaji, and S. Ipson (UK) (2008) investigate wavelet-based feature extraction from mammogram images and efficient dimensionality reduction techniques. The aim of this study is to compare the classification accuracy performance of two sets of features using radial-basis-functions neural network (RBFNN) and support vector machines (SVM). The two sets of features used in this study are extracted from region of interest. The first set is extracted from wavelet decomposition and the second is a reduced obtained by applying the minimal-redundancy-maximal relevance criterion (mrmr) to the first set. It is found that SVM performs much better than RBFNN and achieves outstanding results reaching an accuracy of 89.3%.

Wiselin Jiji .G (2010) used a new classification approach for detection of micro calcification clusters in digital mammograms. In this method micro calcification detection is done in two stages. In the first stage, features are extracted to discriminate between textures representing clusters of micro calcifications and texture representing normal tissue. The original mammogram image is decomposed using wavelet decomposition and Gabor features are extracted from the original image Region of Interest (ROI). In the second stage, the ability of these features in detecting micro calcification is done using Back propagation Neural Network (BPNN). The classification approach is applied to a database of 322 dense mammographic images, originating from the MIAS database. A recognition score of 84.[illegible]% was achieved for this approach.

J. Subash Chandra Bose, K. R. Shankar Kumar and M. Karnan P (2012) developed an Detection of Microcalcification in Mammograms using Soft Computing Techniques. The statistical features are extracted by decomposing the mammogram images into different frequency sub-bands using wavelet transform. The ability of these features in classifying breast tissue is done using an Artificial Neural Network (ANN)). The classification approach is applied to a database of 322 dense mammographic images, originating from the MIAS database.

II. Problem Statement

We explore a variation of Conway's Game of Life where there are three kinds of cells – two kinds of live cells "good cells and bad cells") and dead cells. A bad cell is one of that tends to destroy its neighboring; a good cell is one that helps neighboring to Survive. Our main aim is to study the sufficient conditioned, i.e, Cellular Automata rules that enable good cells to win over bad cells and vice versa. "Winning "in our context is closely associated with survival. Good cells (benign cells) are said to win if more number of good cells survive (compared to bad ones) after several iterations and vice versa. Cellular Automata techniques act as a data Abstraction which hides the other attributes of data present in the Medical Image. H. Li et al. (1995) [5] was used a Markov random field (MRF) model based method consists of the detection of tumors is performed in two steps: segmentation and classification. In segmentation, first regions of interest extracted from the images by adaptive thresholding. A further reliable segmentation achieved by a MRF model-based method. In classification, the MRF segmented regions classified into tumor and normal by a fuzzy binary decision tree based on a series of radiographic, density-related features.

III. Proposed Method

For the Medical Image first we are applying the processes of soft computing. The features are extracted from the image using Discrete Wavelet Transforms. The features values are then converted as macro's (say for example in C or C++ #define - Defines a preprocessor macro). This values or variables contain all the information about the features is fed input as cellular automata technique as shown in the figure 1.

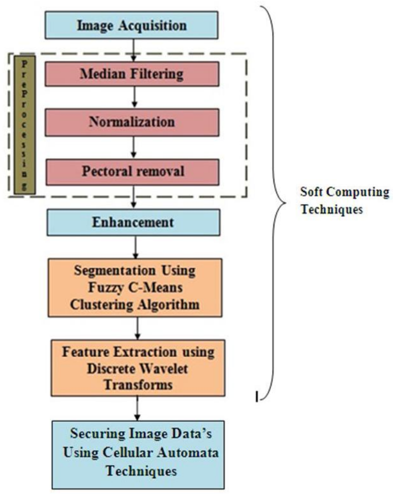

Figure 1. Flowchart of the proposed method

IV. A. Cellular Automata

The Features extracted from the DWT is given as input to the cellular automata. Here various rules are defined is explained below.

Dead cells are represented as gray in color = 0
Good are represented as White in color = 1
Bad cells are represented as Black in color = 2

Neutral cells are represented as Black in color = 3

Neighbors = Up, Down, Left, Right

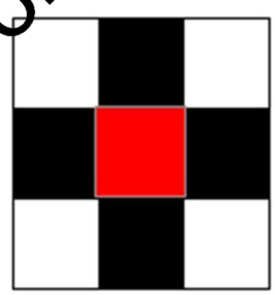

Figure 2. 3x3 grids taken from some finite no of grids.

The next state of the red cell depends upon their neighbor's cells which represented as black in color. A feature extracted from the DWT is converted as variables or numeric values using macro functions. Assume that number of colors is m and number of the neighbors is n the m^n rules to be defined. If all the cells are dead cells then the matrix is formed as 00000, the next state of i^{th} cell is depends upon its neighboring cells.00100, 01234, 40132, etc.

Possible cases for neighbors are
All four neighbours may be good (or) >=3 neighbours are good.
Possible initial configuration
Number of Good cells = Bad cells

Number of Good cells > Bad cells
Number of Good cells < Bad cells

I am exploring for different ratios between Good cells and Bad cells
Good cells/Bad Cells

The initial pattern constitutes the current state of the system. The next state is created by applying the above rules simultaneously to every cell in the current state, survival and destruction happens simultaneously. The rules continue to be applied repeatedly to create further generations.

III. Results & Screenshots

The images are taken from the tests using MIAS database [2, 3]. In MIAS database, there are 208 normal images and 114 abnormal images are there total of 322 images are available. All the images are considered for the classification test. The following figures 3,4,5,6 shows the screenshots for sample images of mdb028.pgm Snapshots

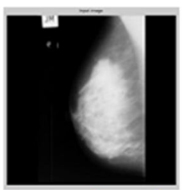
Figure 3: Shows the input image

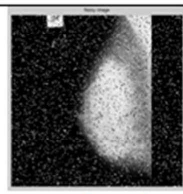
Figure 4: Shows the salt &pepper noise 0.01 %added to input image


Figure 5: Shows the Segmented Image


Figure 6 Shows the detection of micro calcifications (or) segmented tumor

Other screen results between initial state and final state applying Cellular Automata Techniques shown in the figure: 7,8,9,10,11

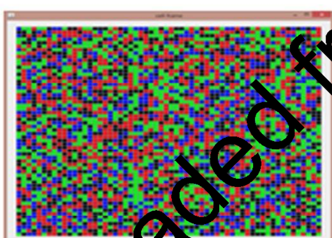
Figure 7: Input State

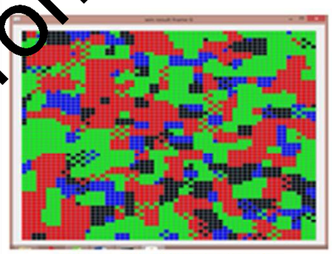
Figure 8: Output State

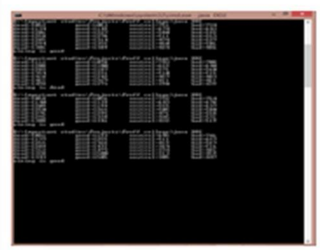
Figure 9: Result State


Figure 10: Comparision between Good/Bad/Dead/Neutral

Figure 11: Results

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IV. Performance and Results

Comparison between various methods for soft computing techniques shown in the table: 1and figure12 [4].

Authors	Methods	Detection Rate
Ferrari and Rangayyan, 2001	Directional Filtering with Gabor wavelets	74.4%
Lau and Bischof, 1991	Asymmetric measures	85.0%
Sallman and Bowyer, 1999	Un wrapping Technique	86.6%
Karnan et al, 2011	Particle Swarm Optimization	96.40%
Subash Chandra Bose et al, 2013	Two dimensional discrete wavelet transforms	97.3%

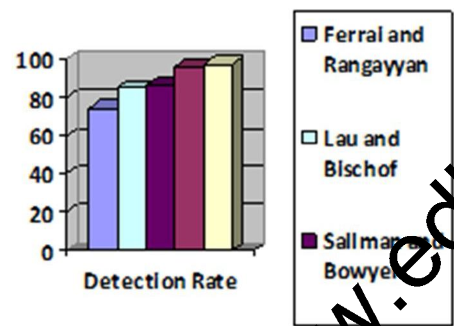

Figure: 12.Comparison between various methods for soft computing techniques shown in the fig

These are the results given by my project and for each rule i tabulated one row as ratio between good cells (benign cells). Bad (Malignant cells) and other row as the winning, according to the above ratio

Rule: 1

Ration Good / Bad/Neutral/Dead	...	4:1	3:1	2:1	1:1	1:2	1:3	1:4	...
Winning	...	G	G	G	G	G	G	D	...

Rule: 2

Ration Good / Bad/Neutral/Dead	...	7:1	6:1	5:1	...	1:1	1:2	1:3	...
Winning	...	G	G	D	...	D	D	D	...

Rule: 3

Ration Good / Bad/Neutral/Dead	...	4:1	3:1	2:1	1:1	1:2	1:3	1:4	...

Winning	...	G	G	N	N	D	B	B	...

Rule: 4

Ration Good / Bad/Neutral/Dead	...	4:1	3:1	2:1	1:1	1:2	1:3	1:4	...
Winning	...	G	N	N	D	D	**B**	B	...

Rule: 5

Ration Good / Bad/Neutral/Dead	...	4:1	3:1	2:1	1:1	1:2	1:3	1:4	...
Winning	...	N	N	D	D	D	B	B	...

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