A Novel Approach For Topological Modeling And Classification Of Mammographic Data Using Artificial Neural Network

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Abstract- *Breast cancer is the most mutual type of cancer for women and the second leading cause of cancer related deaths, next to lung cancer. Breast cancer is caused when abnormal tissue in the breast begins to multiply uncontrollably. The advantage is that breast cancer is easy to treat if it is detected early on. Breast tumors can be successfully treated before cancer spreads throughout the body. FCM (Fuzzy C-Means) clustering-based for Fuzzy Rules calculation grouping small scale calcification bunches. The FCM algorithm implements the clustering task for a dataset (MIAS, DDSM). Micro calcifications are minute guarantees of calcium salts inside breast tissue that arise as small shining or bright spots in mammograms. It is very important to perform the evaluation of micro calcification clusters to determine whether they are benign or malignant. In the existing system they used KNN (K-Nearest neighbors). But it has some drawbacks like less accuracy, unwanted parts are also detected. In this project, ANN algorithm is used to overcome the limitations.*

Keywords: Mammogram, Micro-calcification cluster, graphs, classifications, Artificial neural network.

I. INTRODUCTION

Breast cancer is currently the most mutual cancer affecting women worldwide [1]. In European women, it is the leading cause of cancer death, causing one in six of all deaths from cancers [2]. In the U.S., a woman has a 12.15% (about one in eight) risk of unindustrialized breast cancer during her lifetime [3]. Mammography is one of the supreme steadfast and effective methods for detecting breast cancer at its early stages [4]. In the developed countries, population-based mammography screening programs have been implemented [1]. Women are encouraged to participate in regular breast examinations through mammography. In the U.S., annual mammographic screening is recommended for women at normal risk, beginning at age 40 [5]. In the U.K., women aged between 50 and 70 years are invited for breast screening every three years. Early detection methods of breast cancer include screening by mammography and analytic breast examination. Digital mammography is an x-ray analysis of the breasts. In order to improve the prediction accuracy and to reduce the time duration of radiologists interpreting micro calcifications in mammograms, computer-aided diagnosis (CAD) systems have been developed. The shape and morphological features are mainly extracted from individual micro calcifications, such as roughness, size, and shape. Only 20-30% of breast biopsy cases recommended by radiologists turn out to be of malignant nature. It has been shown that computerized detection and classification methods outperform radiologists' detection and classification [3]. Micro calcification detection and segmentation is useful for computerized screening of mammograms and for classification of malignant and benign clusters.

II. RELATED WORKS

An evaluation and comparison of the performance of four different texture and shape feature extraction methods for classification of benign and malignant micro calcifications in mammograms. For 103 regions containing micro calcification clusters, texture and shape features were extracted using four approaches: conventional shape quantifiers; co- occurrence-based method of Haralick; wavelet transformations; and multi wavelet transformations. A shape analysis method to aid radiologists in classifying regions of interest that are difficult to diagnosis.

Two categories of correlated gray- level image structure features are defined for classification of "difficult-to-diagnose" cases. The first category of features includes second order histogram statistics based features representing the global texture and the wavelet decomposition-based features representing the local texture of the micro calcification area of interest. The second category of features represents the first-order gray-level histogram-based statistics of the segmented micro calcification regions and the size, number, and distance features of the segmented micro calcification cluster.

A set of shape factors to measure the roughness of contours of calcifications in mammograms and for use in their classification as malignant or benign. The analysis of mammograms is performed in three stages. First, a region growing technique is used to obtain the contours of calcifications. Then, three measures of shape features, including compactness, moments, and Fourier descriptors are computed for each region.

III. PROPOSED SYSTEM

In the proposed system, is used ANN (Artificial Neural Network) for detecting the breast cancer effectively. ANN is a parallel distributed processor that has a natural tendency for storing experiential knowledge. They provide suitable solutions for the problems. The FCM (Fuzzy C-Means) clustering-based for Fuzzy Rules algorithm classifying micro calcification clusters. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm.

3.1. Read Input Image

The data used in the experiments consist of two datasets that are composed of image patches of different cases. The first dataset was extracted from the MIAS database, containing image patches with the same size of 256*256 pixels. The second dataset was taken from the digital database for screening mammography (DDSM) database containing image patches. Figure 3.1 is the input image taken as RGB color model.

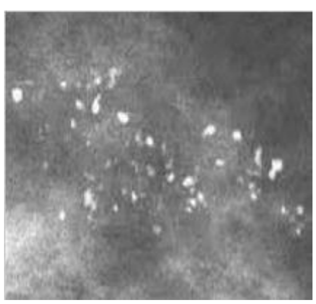


Figure 3.1 Input image

3.2. Preprocessing

Preprocessing phase is needed to improve the image quality and make the segmentation results more accurate. First, remove the unwanted parts in the background of mammogram. The function of mammogram enhancement is to sharpen the edges or boundaries of ROIs (Region of interest), or to boost the contrast between ROIs and background. The morphological top-hat transformation [1] is used for the mammogram image enhancement. In figure 3.2, the digital image processing and mathematical morphology, top-hat transform is an operation that takes small elements and details from given images.

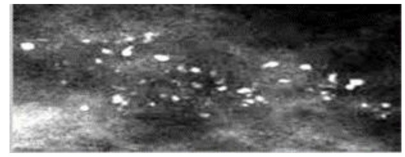


Figure 3.2 preprocessing

3.3. Segmentation and Clustering

Segmentation is the process of confining a ordinal image into numerous segments. For that segmentation algorithm is realistic to the image. There are two altered goals for the segmentation of microcalcifications. One is to obtain the locations of cautious areas to aid radiologists for diagnose. The other is to classify the abnormalities of the breast into benign or malignant. In figure 3.3 (a), it separate microcalcification which occur in breast.

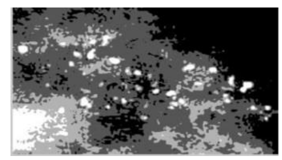


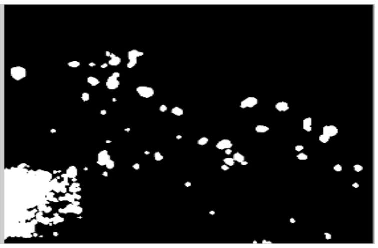
Figure3.3 (a) Segmentation

The Fuzzy C-Means clustering algorithm (FCM) introduces the fuzziness for the belongingness of each object and can retain more information of the data set than the Hard K-Means Clustering algorithm (HCM). The main limitation of the FCM algorithm is noise sensitivity to noises. In figure 3.3(b), it shows how clustering is formed inside the breast by grouping microcalcification. Microcalcification consists of calcium crystals.

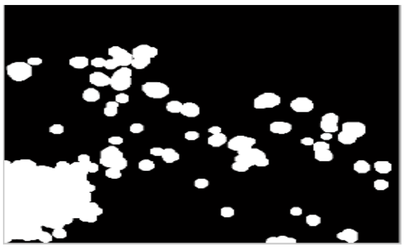
Figure 3.3 (b) Clustering

3.4. Dilation

The scale increases dilation absorbs nearby pixels into individual microcalcifications. Therefore the connectivity between microcalcifications within the cluster is varied by the multi scale dilation that increases the connectivity which will be higher for dense distribution and lower for wide distribution is shown in figure 3.4.



Dilation 1



Dilation 2

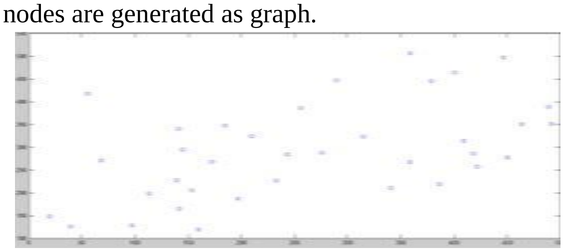
Figure 3.4 Dilation 1&2

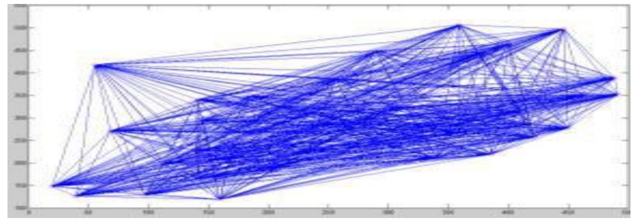
3.6. Graph Generation

The topology of micro calcification clusters is represented in graphical form. It is generated to the spatial connectivity relationship between microcalcification with in the clusters. In a micro calcification graph, each node serve as an individual micro calcification, and an edge is connected between the nodes if the micro calcifications are connected. The connectivity of the micro calcification cluster increases from small to large scales and the corresponding micro calcification graph becomes denser and denser and more edges are created in graph.

3.6.1. Benign and Malignant

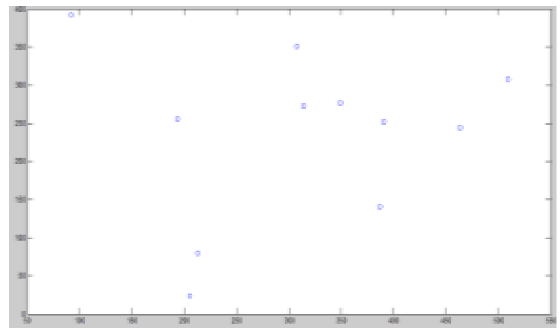
Benign calicifications are generally larger, more rounded, and smaller in number. Malignant calcifications tend to be irregular, numerous, clustered, small, varying in size and shape, angular shaped, and branched in orientation [11]. A reasonable explanation for this observation is that malignant calcifications are smaller in size, and a malignant calcification cluster tends to have more calcification spots and a larger cluster area than a benign one. In figure 3.5 (a) & 3.6 (a), it consider scale as node in dilation process. Figure 3.5 (b) & 3.6 (b), the nodes are generated as graph.





3.5 (a) Node 3.5 (b) Graph

3.6 Figure 3.5. Graph generation for benign



3.6. Graph generation for malignant

3.7. Feature Extraction

Over a range of scales microcalcification graph is a set of graph theoretical features can be extracted to express the topological properties of microcalcification clusters. These features will constitute the feature space for the classification of malignant or benign cluster. Before extracting the topological features of microcalcification clusters, first provide the definitions for general graphs. Use G (V, E) to represent a graph, where V is vertices and E is edge. Use |V| denote the number of vertices in G and |E| denote the number of edges in G, respectively.

3.8 Classification using ANN

The ANN consist of many connected neurons simulating a brain at work. A basic feature which distinguishes an ANN from an algorithmic program is the ability to generalize the knowledge of new data which was not presented during the learning process. Expert systems need to gather actual knowledge of its designated area, whether it is used to check the given input image is benign or malignant.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the classifier models using the multiscale topological feature vectors, a leave-one-out cross- validation (LOOCV) scheme was employed for all datasets.

Table 4.1. Classification results for the three datasets after feature selection

Test data	Cross validation	CA	Az
MIAS (automatic)	Leave-one-out	90%	0.91
MIAS (manual)	Leave-one-out	90%	0.93
DDSM	10-fold	83.9±6.3%	0.90±0.05
MAMMOGRAPHIC DATA	Leave-one-out	93.4%	0.94

ROC analysis was used as the second evaluation approach. The MIAS dataset produced the second best classification results, and moreover, using manual annotations and automatic detections achieved the same performance. For the DDSM dataset, very similar result was shown when using the leave-one-out and ten- fold cross-validation methods, showing a decreased performance in the results when compared to the other datasets. ANN is used to improve the efficiency of breast cancer. To overcome the limitation, use artificial neural network to improve the accuracy, reduce the time complexity.

4.1FEED FORWARD ALGORITHM FOR CREATING NEURAL NETWORK

Step 1: Load the input data.
Step 2: The input and targets specifies the future value A and X. where A is future value, X is variable.
Step 3: Create a neural network using trained data (net 1) and trained parameters
Step 4: Train the neural network using the input, target and the created network

[net 1]=train (net 1,A,X)

Step 5: Save the trained network.
Step 6: Simulate the network for classifying the neural network to find whether the input image is benign or malignant.

V. CONCLUSION

Topological modeling and classification of mammographic data using artificial neural network will be improving the breast cancer neuron analysis. Artificial neural network, is to obtain the repeated breast cancer effectively. It will be improving the accuracy and reducing the time complexity. Cancer ratio will be improved and the error rate is decreased. A set of microcalcification graphs were constructed to describe the topological structure of microcalcification clusters at multiple scales. When analyzing the topology of microcalcification clusters, were extracted eight graph metrics from microcalcification graphs generated at multiple scales, which are number of subgraphs, average vertex degree, maximum vertex degree, average vertex eccentricity, diameter, average clustering coefficient, giant connected component ratio, and percentage of isolated points. The resulting eight graph feature sets were aggregated and constituted the multiscale topological feature vector, which has been used to classify microcalcification clusters into malignant and benign. The topology modeling is an important tool for microcalcification analysis not only because of the improved classification accuracy but also because the topological measures can be linked to clinical understanding.

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