Classifying lesions in mammograms using artificial neural network

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Abstract— In this paper, we propose a computer-aided diagnostic (CAD) system for breast images based on a statistical characterization combined to a classifier method. In the module of computer-aided detection (CADe), the co-ocurrences matrix was applied to the whole of image, while in the module of computer-aided identification (CADx), the same matrix was calculated only for the region of interest (ROI). For the both modules, the features are passed as inputs to the Learning Vector Quantization neural network (LVQ-NN) in order to classify the images in first module at normal or abnormal cases and at benign or malign cases in the second module.

Our system was tested by using two samples of breast images composed respectively of two known bases of mammographic images namely: Digital Database for Screening Mammography (DDSM)[19] and mini-MIAS base generated by Mammographic Image Analysis Society[20].

A correct classification rate of 85.71% has been achieved by the CADe module and of 84.61% has been realized by the CADx module.

Keywords— Breast images, Computer-aided diagnostic - CAD, Co-occurrences matrix, Learning Vector Quantization - LVQ

I. Introduction

Medical images play a vital role in the diagnosis of patients. However, the phenomenal explosion of image collections in number and in size has made effective use of medical images a challenge for experts in the field. Therefore, the automatic annotation of medical images, being a recommended solution to this challenge, is very important in part because it has become very expensive to carry out a manual annotation of images. On the other hand, it is very difficult for a user to express the content of the image with low-level descriptors when performing a non-text query using the color or texture while preferring instead textual queries.

Automatic annotation of images being the process that affects, without human intervention, meaningful words to an image by taking into account its content, stir up a lot of interest in way that it enables the indexing, searching and understanding a large collection of images. However, the annotation of images is a difficult task for two reasons: the first reason is related to what is called the semantic gap because it is tedious to extract semantically meaningful entities based only on the low levels descriptors. The second reason concerns the shortage of correspondence between keywords and image regions in the learning level [1].

The diagnostic mammographic image on the cancer disease is an application area well known for automatic annotation. In fact, experts in the field emit the need for a diagnostic support system especially after the profusion of breast cancer disease and the need for screening companions who justly can generate a huge amount of images using mammography technique.

In mammographic diagnosis, classification of Benign and malignant cases is the most important process in the breast cancer diagnosis because it helps in the detection of disease at an early stage, which can help save lives. However, breast abnormalities are often camouflaged by different breast tissue structures. That is, radiologists tasks consisting of correctly classify suspicious areas (Benign or malignant) in mammographic images become tedious. In the early stage, the visual indications are subtle and varied in appearance, thus making the diagnosis difficult and problematic even for specialists. Indeed, a benign lesion is often difficult to differentiate from cancer, and therefore, a cancer may be falsely interpreted as a benign case. Although, clinically the differentiation between a benign lesion and malignant is difficult [2].

So even if screening mammography combined, possibly breast ultrasound is recommended by experts in the field to find lesions in a beginning stage, the interpretation of mammograms is variable by nature, because mammograms are read by human.

In order to give more chance of success in screening, it is important to detect lesions early in the disease course. This fact is possible according to several studies achieved by Droamin et al. [3], Birdwell et al. [4], Brem [5], Dean and Ilvento [6], Freer and Ulissey [7], Morton et al. [8], which shown that the use of computer-aided diagnostic in the interpretation of mammography screening may increase the cancer detection rate at an early stage compared to radiologists.

Thus, systems CAD (Computer-Aided Diagnosis) are being developed in order to overcome some limitations of mammography. Two different types of CAD systems are under development [2]: computer-aided detection (CADe) that can be used to assist radiologists to find breast cancer on a mammogram, and computer-aided identification (CADx) that can be used to assist radiologists to decide whether a lesion is benign or malignant. However, it should be noted here that CAD refers to the entire field and includes both CADe and CADx.

Our approach to the annotation of mammographic images concerns these both types of CAD. CADe that we propose allows a semi-automatic detection of abnormalities that may exist on a mammogram. After an automatic image classification of an image as representing an abnormal case, the expert fixes the location of abnormalities. The CADx that we propose allows deciding if an abnormality detected on the mammography is malignant or benign by analyzing the region of interest.

In the following, we will describe the main work done in this research field.

II. Related work

In a recent study conducted by Yassin et al. [8], it was listed over 150 references dedicated to breast cancer computer-aided detection and classification of microcalcifications including machine learning techniques.

Helwana et al. [9], proposed an automated classification of breast tissue using two machine learning techniques: Feedforward neural network using the backpropagation learning algorithm (BPNN) and radial basis function network (RBFN). By applying their system on a sample of 106 images, they obtained an accuracy rate of 93.39% with BPNN and 94.33% with RBFN.

Magna et al. [10], used a version of Artificial Immune Network - adapted by theirs self and called AI2NET- to discriminate between normal and asymmetric mammograms. They extracted structural similarity indices as features descriptors and applied a compression to data with PCA analysis. By testing their system to a sample of 188 images formed from DDSM and mini-MIAS databases, they obtained an accuracy rate of 90%.

In [11], Casti et al. defined 24 similarity features by applying the following steps: semi-variogram analysis, oriented components extraction, and 2D cross-correlation analysis in both spatial and wavelet domains. These features were tested on a sample of 188 images constituted from DDSM and MIAS Bases applying standard classification algorithms. An accuracy rate of 82% was obtained.

Eltoukhy et al. [12], proposed a breast cancer diagnostic method for mammographic images by transforming these images into a large vector coefficients through a multi-resolution representation by using wavelet or curvelets method. A matrix was constructed by placing wavelet or curvelets coefficients of each image in a line of the vector, where the number of lines is the number of images and the number of columns is the number of coefficients. The feature extraction is based on the statistical method t-test, which classifies the features according to their ability to differentiate between classes. Then, a dynamic threshold is applied to optimize the number of features, which can lead to maximum efficiency in terms of classification. Finally, the SVM method is applied to classify normal and abnormal tissue and differentiate between malignant and benign tumors. The classification accuracy rate achieved by the proposed method using wavelet coefficients is of 95.84% for normal versus abnormal; while the rate of 96.56% is obtained when determining whether the tumor is benign or malignant. Using curvelet coefficients, the classification accuracy rate reached 95.98% to classify between normal and abnormal and 97.30% to determine whether the tumor is benign or malignant.

In [13], Wei et al have proposed a system diagnosis of breast cancer by the classification of microcalcifications based on research by content. In a first step, they achieved a content-based research to find the similar mammographic images by using a similarity measure based learning. The main idea of the concept of similarity used in this proposal and introduced by the same authors in [14], is to consider the similarity as a function of relevant features in images, and therefore using a machine learning in order to model the concept of similarity using the SVM method on a set of training images defined by experts. In the second stage, they proceed to the application of the classification compared to the resulting images of content-based research carried in the first stage i.e. a classification guided by research. The classification is based on an adapted SVM (Ada-SVM) where the decision function is adapted according to the behavior of the SVM on neighboring images of the request image. The proposed system was applied to a mammographic images database collected by the Department of Radiology of the University of Chicago. The base consists of 200 different mammographic images of 104 cases (46 malignant and 58 Benign). For the characterization of images, 12 descriptors based on the geometric distribution of microcalcifications were selected. Using the adaptive SVM has improved the classification performance from 78% to 82%.

Verma et al. [15] have proposed a system based on a soft cluster neural network (SCNN) used to classify suspicious areas on mammographic images. The idea of cluster is based on the fact that in a classification problem, each class can have more than a software cluster. This requires the integration of a mechanism that improves the ability of generalization in the neural network by specifying more the relationship between the input and outputs of characterization classes (benign or malignant). The proposed system was tested on the DDSM database and achieved an accuracy rate of 93%.

Mousa et al. [16] proposed a breast cancer diagnosis system based on three steps: pre-processing, feature extraction and classification. Three techniques are used to enhance mammography, namely, i) pruning image, ii) histogram equalization iii) global thresholding and grayscale. Also, features extraction is performed in five steps: i) decomposition of the image using wavelets, ii) extraction of the horizontal, vertical and diagonal coefficients from the wavelets decomposition, iii) normalization is applied to simplify the coefficients by dividing each vector by its maximum value, iv) the energy of each vector is calculated by using the squaring of each element of the vector. These values will be considered as the descriptors that will be used in the classification. v) Finally, a reduction in the characteristic is applied by summing a predetermined number of energy values between them. In the classification stage, the ANFIS technique for Adaptive Neuro-Fuzzy System Inference was applied initially to decide whether mammograms are normal or abnormal. Mammography is considered as abnormal if it contains masses and microcalcifications. If the result of the evaluation of mammography tested is abnormal, it is routed to another classification process that determines whether mammography contains masses and microcalcifications. Finally, the abnormality of mammography is classified as malignant or benign cases. The proposed system was tested with a collection of images taken from MIAS mammographic images database which contains 322 images in three categories: normal, benign and malignant [20].

In [17], L. Zheng et al. have combined several techniques of artificial intelligence with the discrete wavelet transform (DWT) for the detection and classification of masses in mammograms. The techniques of artificial intelligence used in this combination were used as follows: analysis of fractal dimension has served as a pretreatment to determine the approximate location of suspicious areas of the mammograms cancer. The dogs and rabbits algorithm was used to initiate the segmentation of mammography to the LL sub-band of decomposition (DWT) in the third level. Finally, a classification based on decision trees is applied to determine if the ROI is cancerous or not. The authors tested their approach using the mammographic images set: 'Mammographic Image Analysis Society'. The results showed an accuracy rate of 97.3% and a number of false positive of 3.92%.

B. Zheng et al. [18], carried out a comparison between the use of a neural network and Bayesian network in CAD. To do this, they calculated 32 local features and 6 global features. Before passing these features as inputs to the neural network and the Bayesian network, they optimized the number of these characteristics using a genetic algorithm. Thereafter, the neural network and Bayesian network were tested with a mammographic database containing 1557 images. Both networks have reached the same level of performance for the detection of mammogram masses. In conclusion, the authors stated that improving the performance of CADs is more dependent on the optimization of features selection and diversity of the learning database that any classification method. For the both networks, the accuracy rate obtained is 86%.

This paper is organized as follow: First, we present our proposed CAD system. Second, we present the information of the images selected from DDSM and MIAS databases for training and testing. Then, we evaluate our system and discuss the results obtained by its application. Finally, conclusion of this work is given.

III. The proposed approach

The majority of CAD systems proposed in the literature is most to least engineered respecting the phases described in Figure 1 [21]. The preprocessing phase of digitized mammography images is used to remove noise and improve contrast image. The segmentation phase as defined in the literature related to the masses detection such as the localization of the suspicious regions. In characterization phase, the characteristics are extracted and selected to classify different types of lesions that can be found in a mammogram. The characterization is a key phase for detecting masses since the performance of CAD depends more on optimization of the features selection than on the classification method itself. Then, a detection step is performed by applying a CADe system or an identification phase followed by a CADx system by always using the features defined in the previous phase. Finally, a performance evaluation of the CAD system is performed by testing it on one or more image databases known in the domain.

In our case, we will proceed as follows:

1) Preprocessing: no treatment was applied on the images.

2) Segmentation: In order to bring out the contours that exist in images, we opted for applying a canny filter. Therefore, this gives us the means to differentiate between normal and those abnormal images when it is about detection (CADe) and differentiate between malignant and those benign images when it is about identification (CADx).

3) Features extraction of textural characteristics are calculated in a statistical manner by using the co-occurrence matrix. We opted in our approach for the most commonly used attributes namely uniformity, energy, contrast and correlation. These features are extracted from the filtered mammographic image in the case of the CADe system and from the region of interest of the filtered image in the case of CADx system.

4) Detection / Identification: for detection in the case of a CADe system, we will pass the features, already calculated from the mammographic image by co-occurrence, in the LVQ classifier in order to decide if the image is normal or abnormal case. In the case where the image is classified as abnormal, the expert marks the location of the region of interest where abnormalities are found.

As for the identification, in the case of a CADx; the characteristics calculated by the co-occurrences method are extracted from the region of interest marked by the expert, and are passed to the same LVQ classifier in order to decide if the detected abnormality is malignant or benign.

5) Evaluation: our approach will be tested on two bases of mammographic images i.e. DDSM [19], and mini-MIAS [20].

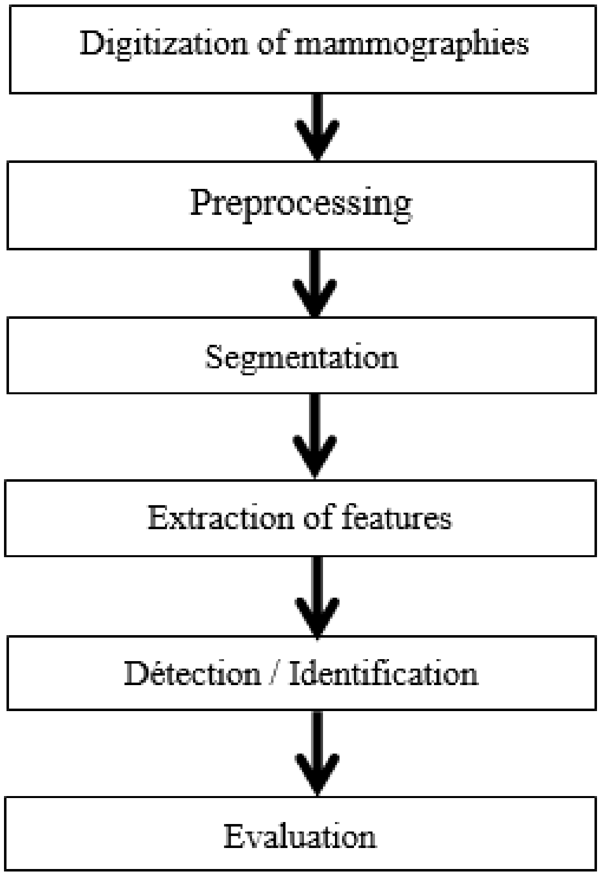


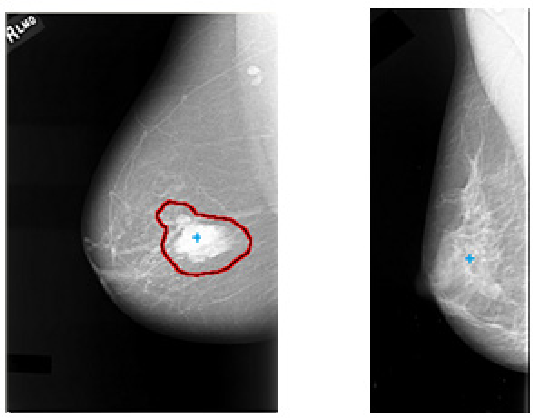
Fig.1. CAD's phases

A. Architecture of the proposed system

A complete annotation system includes two main parts. The first part concerns the classification of images based on the low-level characterization. The second part is to strengthen the system by a semantic layer with a text through user interaction in order to respond to its requests.

Our proposed system being limited to the portion of low-level covers the entire classification chain on mammographic images which generally comprises an abnormality detection step and another step for the identification of those abnormalities.

We have observed that the regions of interested (ROI) in images of abnormal cases (Fig. 2a) are often more intense than the (ROI) in the images of normal cases (Fig. 2b).



a) b)

Fig.2. Example of a) a pathological region and b) a normal case

The application of the canny filter to a region containing abnormalities (Figure 3.a) and on a region in center of the normal case (Fig. 3.b), confirm our observations. As seen in Figure 3, the region (a) has less of contours when the region (b) has more of contours.

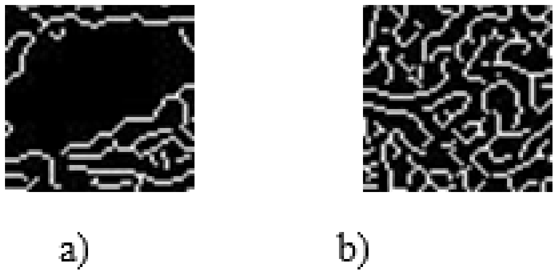


Fig.3. Application of canny filter on a) the pathological region and

b) a center region of a normal case.

Based on these findings we thought that the information related to the distribution of points in the region of interest (ROI) can be an effective means to discriminate abnormal and normal cases for CADe and malignant or benign cases for CADx. Indeed, this has led us to choose the co-occurrence matrix as a method of extracting the descriptors image by opting for the most commonly used attributes of the co-occurrences matrix. Finally, to classify them, the LVQ-NN was used as the classifier to decide in the step of detecting if the image is abnormal or normal case. In case where the image is classified as abnormal, the classifier decides in the identification step if the image is benign or malignant.

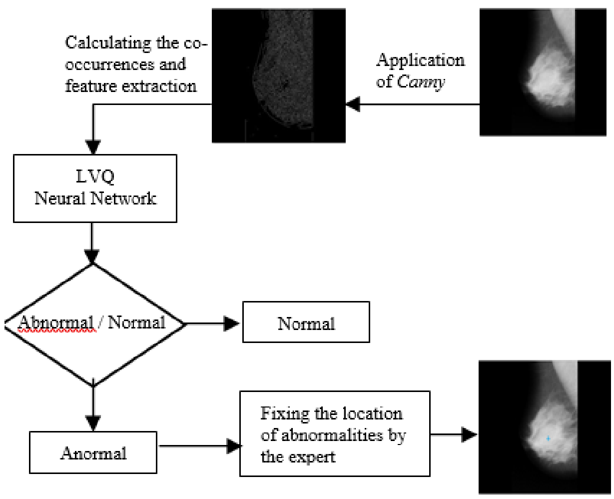


Fig.4. Scheme of proposed CADe

Therefore, as shown schematically in the Figure 4, we designed our CADe as follows:

1) Applying the Canny filter to on the mammographic image.

2) Calculating the co-occurrence matrix of the filtered image and extracting its features by calculating the four attributes of the matrix: homogeneity, energy, contrast and correlation. Setting the matrix has been experimentally set to the angle (theta = 0) and the distance (d = 1).

3) Giving the characteristics as inputs to LVQ – NN in order to decide if the image is normal or abnormal case.

4) In the abnormal case, the expert fixed the location of the anomaly.

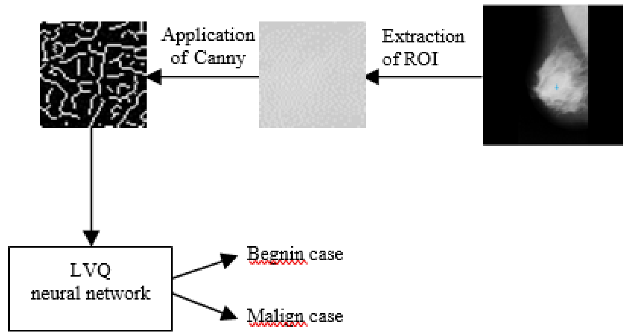


Fig.5. Scheme of proposed CADx

Subsequently, our proposed CADx takes the relay at CADe starting from the annotated image in abnormal case. The CADx follows the following steps (Fig. 5):

1) Extracting the ROI of 50x50 pixels.

2) Applying the Canny filter on the ROI. The application of the canny filter has a major impact on performance's results as we will see in the results section.

3) Calculating the co-occurrence matrix for the filtered region and extract its characteristics with the same attributes calculated in step (ii).

4) Giving the characteristics of the ROI as inputs to LVQ-NN in order to classify the image in a benign or malignant case.

IV. Results and discussion

In order to evaluate our approach, we chose to test it by using two samples of images from two databases of mammographic images i.e. DDSM and mini-MIAS. The DDSM sample is formed with 80 images and the MIAS sample is composed with 75 images.

The DDSM sample is equally divided between normal images (Fig.2.b) and abnormal images (Fig.2.a) including abnormalities areas with 20 malignant and 20 benign.

While the MIAS sample is divided into 21 normal images and 54 abnormal images including abnormalities areas with 29 malignant and 25 benign.

A. CADe

After calculating the co-occurrences matrix for all images of both samples, we calculated for each image the four attributes of the co-occurrences matrix namely uniformity, energy, contrast and correlation. Then, these attributes were passed as inputs to LVQ-NN. The setting for the calculation of the co-occurrences matrix and the LVQ has been experimentally set to the following values: theta = 0, distance = 1 for the calculation of the co-occurrence matrix and the number of twenty hidden neurons (20) for the LVQ.

Table I, presents the results obtained by applying our CADe to the DDSM and MIAS samples.

It is shown in Table I that our approach has given acceptable results for classifying images into abnormal and normal cases in particular by using the combination of the uniformity or contrast attributes of the co-occurrences matrix with the LVQ-NN.

TABLE I. PRECISION (CADE: CO-OCCURRENCES + LVQ) APPLIED TO THE SAMPLE OF DDSM AND MIAS BASES

method / Sample	Uniformity + LVQ	Energy + LVQ	Contrast + LVQ	Correlation + LVQ
DDSM	72.5%	78.75%	72.5%	72.5%
MIAS	85.71%	80.95%	85.71%	61.90%

B. CADx

We have tested our proposed CADx system with the images representing the abnormal cases from the DDSM and MIAS samples utilized in CADe.

The first sample was composed of 40 images labeled as abnormal cases in DDSM sample and the second sample consists of 54 images labeled as abnormal in MIAS sample

TABLE II. PRECISION (CADX: CO-OCCURRENCES + LVQ) APPLIED TO THE SAMPLES OF MIAS AND DDSM BASES

method / Sample	Uniformity + LVQ	Energy + LVQ	Contrast + LVQ	Correlation + LVQ
DDSM sample	80%	80%	70%	80%
MIAS sample	55.5%	55.5%	55.5%	55.5%

TABLE III. PRECISION (CADX: ATTRIBUTES COMBINATION OF CO-OCCURRENCES + LVQ) APPLIED TO THE SAMPLES OF MIAS AND DDSM DATABASES

method / sample	(Energy, Contrast) + LVQ	(Homogeneity,Energy, Correlation) + LVQ
DDSM sample	53.84%	84.61%
MIAS sample	83.88%	50%

In Table II and III, we can see that the results obtained by applying of our CADx with attributes combination of the co-occurrences matrix to the both samples are much better compared to those obtained by the CADx with single attributes of the co-occurrences matrix.

V. CONCLUSIONS

In this paper, we have proposed a computer-assisted diagnostic (CAD) for breast images composed of two modules. The first module is computer-assisted detection (CADe) process, which classify the images at normal or abnormal cases by applying the co-occurrences matrix on the whole image and its attributes i.e uniformity, energy, contrast and correlation are calculated and passed as inputs to the LVQ-NN. As output of the CADe, the ROI of abnormal image will be marked by expert. Hence, the second module consists of a computer-assisted identification (CADx) system. This module in its turn try to classify the abnormal image as benign or malign case by applying this time the co-occurrences matrix only on the ROI and its attributes are also passed as inputs to the same LVQ-NN.

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