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A review on data mining techniques for Digital Mammographic Analysis

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Abstract- Medical Data mining is the search for relationships and patterns within the medical data that could provide useful knowledge for effective medical diagnosis. The predictability of disease will become more effective and early detection of disease will aid in increased exposure to required patient care and improved cure rates using computational applications. Review shows that the reasons for feature selection include improvement in performance prediction, reduction in computational requirements, reduction in data storage requirements, reduction in the cost of future measurements and improvement in data or model understanding.

Keywords: Data mining, Digital Mammographic Analysis, clustering , classification, medical image processing

I. INTRODUCTION

Data mining methods have been applied to a variety of medical domains to improve medical diagnosis [25]. Some include predicting breast cancer survivability using data mining techniques [50], application of data mining to discover subtle factors affecting the success, failure of back surgery which led to improvements in care , data mining classification techniques for medical diagnosis decision support in a clinical setting [12] and the techniques of data mining used to search for relationships in a large clinical database [41].Feature selection is the process of identifying and removing as much of the irrelevant and redundant information as possible [37] and is often considered as a necessary preprocess step to analyze these data, as this method can reduce the dimensionality of the datasets and often conducts to better analysis [10]. Data mining has gone into improving the predictive accuracy of the classifiers by applying the techniques of feature selection. Feature selection techniques identify the features that mostly improve the predictive accuracy of the classifiers. Many authors have reported improvement in the performance of the classifier when feature selection algorithms are used [15, 3, 4].Yu and Liu (2003)[21] nothing that attribute evaluation methods are likely to yield subsets with redundant features since these methods do not measure the correlation between features. Subset evaluation methods, in contrast, select feature subsets and rank them based on certain evaluation criteria and hence are more efficient in removing redundant features.

II. MEDICAL IMAGE PROCESSING TECHNIQUES

The proposed techniques involve the following steps: preprocessing for highlighting the Region of Interest (ROI), segmentation to isolate the abnormality and choosing proper simple statistical parameters for describing the abnormality. Though research started from 1970s, still intense research is carried out in these areas in order to obtain a generalized black box for automated breast cancer analysis. Qi et al (2003) proposed an automated asymmetry analysis technique for abnormality detection from breast thermographs. It involved the following steps: Detecting the edges using Canny filter, identifying the left and right body boundary curves and two lower boundaries of the breasts using Hough Transform, identifying the point of intersection of the parabolic curves using segmentation, deriving the Bezier histogram for each segment and computing the curvature from the two histograms. The difference in curvature is used as a measure for abnormality identification. However the success of the proposed technique lies in effective edge detection and segmentation algorithms[35].

Frize et al (2003) proposed an automated breast cancer detection algorithm by implementing Head's methodology. Initially the difference in mean temperature between left and right breasts is determined. .[28] Thermograph is divided into four quadrants namely upper left, upper right, lower left and lower right. For each quadrant, scores are created as 0,5 if the mean temperature difference between the left and right halves is between 0.5 degrees to 1 degree. On the other hand the score is made as 1 if the difference is greater than 1 degree. An index is created by adding the scores for the four quadrants and if the index is greater than 1 then it indicated the presence of the abnormality. Yang et al (2007) analyzed the breast thermographs based on temperature distributions between the left and right breasts. In normal cases, the histograms of the left and right breasts are symmetrical in contrast to asymmetrical histograms in abnormal breasts[2]. Also the temperature distribution curve obeys mathematical normal distribution while it deviates in the case of abnormality. From the analysis, they concluded that 0.5^0 C differences in temperature between the two breasts of the patient can be considered as the threshold to distinguish abnormality from normal breasts Wick et al (2003) proposed imaging software for breast cancer diagnosis from breast thermographs. In the proposed method abnormality was described using three different sets of parameters. That includes first order moments such as mean, skewness and kurtosis, second order statistical parameters namely cooccurrence matrix and parameters such as entropy, energy based on image transformation using wavelet analysis[5]. Tang et al (2008) proposed an automated analysis technique for breast cancer detection based on measuring Localized Temperature Increases (LTI). The proposed technique involved two phases. Initially the suspicious focusregions in breast infrared thermographs are found visually. Later morphological approaches were used to determine the LTI and then decisions were made based on three measures. LTI is calculated as the difference between the pixel temperature

and the corresponding background temperature. The key aspect of this analysis technique lies in determining the background temperature. A proper structuring element such as 'disc' is chosen and the opening at each radius is considered as the approximate background. They found that there is a significant difference between benign and malignant cases in terms of LTI amplitude.[17]

Nurhayati et al (2010) proposed an automated algorithm based on first order moments for abnormality detection in breast thermographs. Initially thermographs were deblurred using Weiner filter, contrast enhancement is done by histogram equalization, abnormality is detected by segmentation and is described using the first order moments namely mean, variance, skewness and kurtosis.[30] Based on these parameters, abnormality detection is achieved. However the performance of the proposed technique can be improved if spectral and structural methods of analysis are performed.Wang et al (2010) proposed an automated algorithm for determining the severity of the abnormality from breast thermographs by using five different parameters. They are IR1, the difference in surface temperature at the lesion site from that at the mirror image site on the collateral breast, IR2, the temperature difference between the lesion site and the rest of the normal breast tissue of the ipsilateral breast, IR3, a combination of 8 various abnormal vascular patterns, IR4, an edge sign or bulge sign backed by heat, indicating loss of smooth contour of part of the breast due to skin retraction or bulging caused by a breast tumor and IR5, the presence of an asymmetric or heterogeneous vascular pattern at and around the lesion site, when the contra lateral breast did not reveal such a pattern. Based on these parameters decision about the severity of the abnormality is made.[47]. Scales et al (2010) proposed three different techniques for detecting the boundaries of the breasts.[26] In the first approach, modified Hough transform was used to detect the boundaries. In the second approach an algorithm used to detect the longest connected edges that are not part of the body boundary, and a third approach involving the density of detected edges in the breast region. They found that the last two methods provided better results in segmenting the edges. They also found that better segmentation techniques such as snake transform can be decided to improve their results.Kapoor et al (2010) proposed an automated computer aided analysis for breast cancer detection from breast thermographs.[33] The proposed algorithm involves the following edge detection by Canny filter, Breast boundaries detection by parabolic Hough transform, feature extraction and asymmetry description using skewness and kurtosis and cumulative histogram. These parameters are then used for diagnosis of cancer regions.

Nurhayati et al (2011) proposed an automated breast cancer classification tool by combining five statistical parameters with the principal Component Analysis(PCA)[30]. Pseudocolor breast thermographs were converted to gray scale thermographs of size 256x256, Five statistical parameters namely mean, variance, entropy, skewness and kurtosis and eigen values, eigen vectors and covariant matrix are calculated. Based on theses parameters decision about the severity of the abnormality was determined. However they found that the performance of the proposed system can be ***improved by using proper image preprocessing techniques***.

Table 1: mammogram analysis

Name	Year	Technique	Findings
Wang	2010	5 different parameters IR1 to IR5	Severity of abnormality
Scales	2010	Boundary approach	Segmentation of edges
kapoor	2010	Canyfilter,Hough transform	Diagnosis of cancer regions
Nurhayati	2011	5 statistical parameters	Severity of abnormality

III. DIGITAL MAMMOGRAPHY PROCESSING TECHNIQUES

Mammography is the screening modality proven to detect breast cancer at early stage and diagnosis of breast cancer in women [29,5,40] The efficiency of mammography is limited in extremely dense breasts where sensitivity to detect cancer maybe as low as 60–70% [8]. Both digital and film mammography use X-rays to produce an image of the breast. [31] provided the overall diagnostic accuracy of digital and film mammography as a means of screening for breast cancer is similar. However, digital mammography performed better than film for pre- and premenopausal women younger than 50 years with dense breasts [32]. In addition, digital mammography allows improvement in image storage and transmission because images can be stored and sent electronically.

Diagnostic mammography is done for women with signs or symptoms of breast cancer. Any sign of cancer should be communicated to the radiologist with the referral for a diagnostic mammogram. Radiologists basically look for two types of patterns in mammography: micro-calcifications and masses [20].Variety of statistical methods is available for mammographic diagnosis of breast cancer [19,34,14,39,9]. Rakowski and Clark[39] utilized multiple logistic regression to select significant correlates of screening mammogram and used classification-tree (CHAID) to combine the significant correlates into exclusive and exhaustive subgroups [39]. In addition, Chhatwal et al. reported that logistic regression model can discriminate between benign and malignant in decision making for the early detection of breast cancer and identify the most important features associated with breast cancer [9].

Moreover, Heine and colleagues show how parametric statistical methods can be useful for in identifying normal tissue in mammograms [14]. Recently, many studies have been made on the problem of breast cancer diagnosing based on digital mammography [44,35]. Some scholars applied data mining techniques to predict diagnossis for digital

mammography [49,25]. Data mining techniques offer precise, accurate, and fast algorithms for such classification using dimensionality reduction, feature extraction, and classification routines. Neural networks have improved accuracy rate for the classification of benign and malignant patterns in digitized mammography [38,48,6]. Recently, the fashionable technique support vector machine (SVM) [22,11] have been applied for mammogram classification and have improved the prediction performance of breast cancer diagnosis.

IV. DATA MINING TECHNIQUES FOR MAMMOGRAPHY PROCESSING

data mining techniques widely used for developing computer aided diagnosis are bayesian network [7,43], naivesbayes classifier [23], genetic algorithm [27], artificial neural network [27][13][23][24], associative classification [16][18][45]. Many hybrid approaches are also used to accurately diagnose mammographic findings. In [41] genetic algorithm is hybridized with neural network to classify Wisconsin breast cancer data. In [13] classification based on multiple association rule and neural network are hybridized to create CMARwNN model for classifying mammographic mass data. Association rule mining discovers various relations that data share between them. An association rule is a relationship of the form X →Y , where X and Y are disjoint itemsets i.e., X IY = φ . The support and confidence of the rule are defined as, Support (X →Y) = P(X UY) and Confidence X

(. X →Y) = P Y

The association rule mining task consists of extracting all rules with support and confidence greater than or equal to user-specified thresholds. Classification is the process of finding a model by analyzing a set of training data, such that the model can be used to predict the class of previously unseen records as accurately as possible. Associative classification is an integration of association rule mining and classification. In this process association rules are generated and analyzed for use in classification. Classification based on association (CBA) is the earliest and simplest algorithm for associative classification [46]. Let D be a training dataset with n attributes A AAn , ,.....1 2 and | m =| D instances. The dataset also has a class attribute { , ,..... } C = C1 C2 Cr. An item is described by an attribute Ai and a value $_{ij}$a denoted as (,) $_{ij}$i A a , where j ≤ m . An item set is a set consisting of items in the training set (,),.....(,) A a_{ii} 1 A a_ik_i, where k ≤ m . A rule r in associative classification is of the form r = (A ,a_{ii} 1),.....(A ,a_ik_i),C where the rule antecedent is a conjunction of items (,),.....(,) A aii 1 A aiki and consequent is the associated class label C . The occurrence of a rule r is the number of instances in D that match the itemset of r . For a given rule r , the support count is the number of instances in D that match the itemsets of r , and belong to the class label C of r . Thus the confidence of a rule r is the percentage of the instances in D satisfying the rule antecedent that also have the class label.The strength of the class association rule (CAR) is measured using support and confidence threshold. CBA generates the complete set of CAR's for classifying new instances. In the classification process, if more than one rule fit a certain cases then CBA will classify the class from the rule with the highest confidence. If the confidences are same then the rule having the highest support will be used to classify the case. CBA saves a default class to deal with the case when no CARs can classify.

CMAR is an associative classification method that performs classification based on multiple association rules. It consists of two steps rule generation and classification. In the rule generation step, CMAR finds the complete set of rules using FP1-growth algorithm [42] in the form R : X →C , where X is a pattern in the training dataset and C is the class label satisfying the minimum confidence and support threshold. Once a rule is generated, it is stored in a CR-tree. CR-tree is a prefix tree data structure which store and retrieve rules efficiently and prune rules based on confidence, correlation and database coverage. Whenever a rule is inserted into the CR-tree, it prunes all rules and only selects subsets of high quality rule for classification.

V. DIGITAL MAMMOGRAPHIC ANALYSIS

Digital mammogram and tumor detection process determined by using artificial neural network. The back propagation neural network is applied to determine whether the given mammogram is suspicious for cancer.The detection of abnormalities on Mammogram is determined Using Frame Texture Classification Method. The sparse approximation as a feature extraction method for Texture Classification. It is a new approach for detecting abnormalities on digital mammogram.A multi resolution pattern recognition approach transforms the data of the images in a wavelet basis, and then using special sets of the coefficients as the features tailored towards separating each of those classes. In addition, another important factor that influences the success of classification methods is working in a team with medical specialists, which is desirable but often not achievable. The consequences of errors in detection or classification are costly. Mammography alone cannot prove that a suspicious area is malignant or benign. To decide that, the tissue has to be removed for examination using breast biopsy techniques. A false positive detection may cause an unnecessary biopsy. Statistics show that only 20-30 percentages of breast biopsy cases are proved cancerous. In a false negative detection, an actual tumor remains undetected that could lead to higher costs or even to the cost of a human life. Here is the trade-off that appears in developing a classification system that could directly affect human life [21].

VI. CONCLUSION

Digital mammograms are among the most difficult medical images to be read due to their low contrast and differences in the types of tissues. Important visual clues of breast cancer include preliminary signs of masses and calcification clusters. Unfortunately, in the early stages of breast cancer, these signs are very subtle and varied in appearance, making diagnosis difficult, challenging even for specialists. This is the main reason for the development of classification systems to assist specialists in medical institutions. Due to the significance of an automated image categorization to help physicians and radiologists, much research in the field of

medical images classification has been done recently. With all this effort, there is still no widely used method to classify medical images. This is due to the fact that the medical domain requires high accuracy and especially the rate of false negatives to be very low. In the process are adopting rapid changes based on the technology development therefore 3D approaches to be reviewed for the further process of the research.

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