Breast Density Classification Using Histogram-Based Features

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Abstract — *The risk of having cancer in dense breast on mammogram is higher compared to those who have less. This is due to presence of glandular cells in the breast parenchyma. Therefore, it is important for radiologists to pay more attention to denser breasts in order to detect abnormalities. Denser breast has tendency to hide breast lesions and therefore reduces the sensitivity of the radiologists to diagnose the condition. The aim of this paper is to explore a novel quantitative method to categorize breast density by using digital mammogram images. The suggested method works based on the statistical parameters including kurtosis, skewness, median and mean. The system evaluated 180 mammogram images and it was found to be 92.8% accurate with a strong correlation between the system and radiologists' estimation (K=0.87, p=0.0001).*

Keywords — Breast Density, Mammogram, BIRADS, Histogram, Image Processing

I. Introduction

There are some risk factors, which increases the chance of breast cancer in women. This includes positive family history, positive BRCAI and BRCAII genetic factor, exposure to radiation, diet, obesity and late menopause [1, 19, 26]. The breast consists of different tissues such as fat, epithelial, and stromal tissues. These tissues normally categorized into two groups, fatty and glandular as seen on mammogram. The glandular tissue is directly related to breast density [15] and women who are in the highest quartile of mammographic density have 4 to 6 times higher chance of having breast cancer than women of similar age who are in the lowest quartile [16].

The other important risk factor of breast cancer is breast density. Denser breast on mammograms is associated with higher rise of breast cancer than those with fatty breast [15]. Mammograms with dense breast poses difficulty for the radiologist to interpret the image because masses may be hidden behind the tissues [5]. Upon evaluating a mammogram, commonly the first step that the radiologist comments is on the breast density. In 1970s, Wolfe developed a systematic category for breast density [16]. Based on the percentage of glandular cells of whole breast area, 4 Wolfe pattern categories were developed which includes N1, P1, P2 and DY [10]. The N1 pattern corresponds to breast that is almost completely fat; the P1 and P2 patterns correspond to breasts in which the ducts are increasingly prominent; and the DY pattern corresponds to breasts that show diffuse and extensive nodular density [9]. This can also be percentage of density as shown in Table I [21].

In addition, there are other definitions for categories of breast density based on the amount of fat and the size of the area encompassed by the tissue [12, 17]:

Grade 1: Having no areas of tissue that could obscure cancer.

Grade 2: Having at least one area of tissue that could obscure cancer.

Grade 3: Having tissue that can obscure cancer in 50% to 75% of the breast.

Grade 4: Having tissue that can obscure cancer in >75% of the breast.

The American College of Radiology developed the Breast Imaging Reporting and Data System (BI-RADS) in 1992 to assist and standardize interpretation and reporting of mammograms [7]. Based on this system the breast density categorized in 4 classes (Table I) [2, 8]:

TABLE I
BIRADS BASED ON PERCENTAGE OF DENSITY AND ACR

BIRADS categories	Percentage	ACR
BIRADS I	Less than 25% dense	Almost entirely fatty
BIRADS II	25 to 50% dense	Scattered fibroglandular tissue
BIRADS III	50 to 75% dense	Heterogeneously dense
BIRADS IV	More than 75% dense	Extremely dense

The main aim of this paper is to suggest a new method to categorize breast density.

II. Background

In 2006, Jamal et al [12] developed a semi automatic system for breast density classification. However, the user should determine the pectoral muscle area and glandular cell area manually through the image histogram. The system initially removes pectoral muscle area and count the number of glandular density. Finally, to obtain density percentage, the number of glandular density is divided by the total number of pixels. They used the following criteria under Tabar categories to determine breast density:

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Category I: Less than 25% dense
Category II: 25 to 50% dense
Category III: 50 to 75% dense
Category IV: More than 75% dense

Zhou et al. [27] developed an automated tool to determine breast density. Three steps include breast region segmentation, adaptive dynamic range compression, and rule-based classification is used in this system. The rule based system was used to classify breast density into four categories.

In the other research Oliver et al. [23] suggested an automatic classification of breast density. The fuzzy C-means, kNN, and ID3 algorithms are used in this system. The method which they suggested is based on the integration of texture and gray level information. They reported that the system could classify 47% correctly when the combination of kNN and ID3 were used. The researchers stated that each of above methods, kNN and ID3 alone, obtained less correct classification than the combination of them.

In 2008, a novel method suggested by Oliver et al. [24]. Their suggested method, three steps were employed for breast density classification include segmentation of fatty and dense area, identify morphological texture in the different areas, and finally using Baysian combination of classifiers. In the first step, combination of gray levels and fuzzy C means algorithem has been used to identify and explore the fatty tissue and glandular tissue. The fuzzy functions are described by Bezdek [3] a long time ago and many researchers used this method for detection of breast cancer and pattern recognition [20, 25]. In the second step the co-occurrence filters employed to extract the features inside the fatty and non-fatty tissues. Finally they used decision tree classification to classify breast density. The results showed that their method reached to 66% correct classification of breast density while when they used a combination with the Bayesian classifier then the correct classification increased to 75% [24].

Many other researchers investigated on the breast density classification. The previous researches are emphasized on the histogram information but recent researches are more focused on the other methods such as texture.

An automated determination method was developed for breast density classification in 1998 [14]. The researcher investigated on relation between breast density and breast cancer risk. The pectoral muscle is detected using Hough transform. Then, the whole breast area divided based on the distance from the skin. To evaluate the suggested method, 615 digitized mammograms were examined and 67% agreement between system and radiologist estimation was obtained. In the other side, the other method suggested to classify breast tissue [4]. In this method, the Minkowski function was employed and the performance of the system was evaluated using 512 by 512 pixels images. The system could classify 66% of cases correctly.

III. METHODOLOGY

A. Mathematical Background

In statistics, kurtosis refers to the measure of peak of the distribution of a real-valued random variable. Kurtosis in a histogram is related to the height of the histogram. The higher histogram shows that more pixels are concentrated in a small area and there are fewer amounts of pixels in the other area. On the other hand, when the pixels spread along X axis, it is not so high in the histogram. The kurtosis is computed based on the following equation (1):

$$Kurtosis = \frac{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^4}{\left(N-1\right)s^4} \qquad (1)$$

Where $\bar{x}$ is the mean, 's' is the standard deviation, and 'N' is the number of data. Since the kurtosis of standard normal distribution equals 3, some sources used the following equation (2):

$$Kurtosis = \frac{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^4}{\left(N-1\right)s^4} - 3 \qquad (2)$$

With this definition positive kurtosis indicates a peaked distribution and negative kurtosis indicates a flat distribution [22].

In statistics, skewness is a measure of asymmetry of distribution of a random variable. When there is a bell shape and symmetric distribution, the distribution is normal and its skewness is zero. When the left tail is longer and the mass of distribution is concentrated on the right side, it is called left-skewed distribution and skewness is negative. On the other hand, when the right tail is longer and the mass of distribution is concentrated on the left side, it is called right-skewed distribution and skewness is positive [11].

The skewness is calculated based on the following equation (3):

$$Skewness = \frac{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^3}{\left(N-1\right)s^3} \qquad (3)$$

Where $\bar{x}$ is the mean, 's' is the standard deviation, and 'N' is the number of data [22]. In a balanced (normal) distribution, the mean, mode, and median are equal. In a skewed distribution, the mean is farther out in the long tail than median [11, 13].

B. Extracted Rules

In the first step histogram of different breast density categories were extracted. A function design for this purpose removes all values of background (0) and draws the histogram based on the breast area (the non-zero pixels). The general shape of the histograms showed that the kurtosis and skewness of the histograms in different breast density categories were different. This is shown in Figure 1.

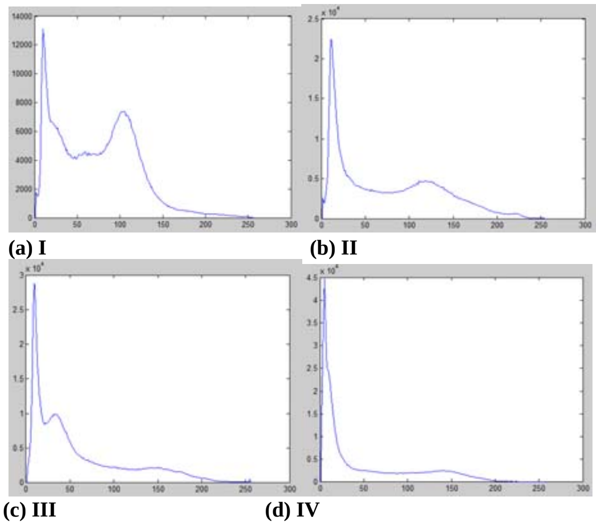

Fig 1. Histogram of the Images based on BIRADS

Four statistical parameters, kurtosis, skewness, mean, and median were computed. 300 images were selected to explore and make rules. Based on the observations, the difference of median and mean is the best criteria for breast density estimation; however, when there are some lesions, some error may appear. For the BIRADS I the difference of median and mean is positive and less than 0.02. The difference between these two statistical parameters decreases up to -0.1 when the breast density increased, the other criteria is the ratio of kurtosis to skewness. In BIRADS 4 this ratio is less than 2 and is increased up to more than 4 when the breast density is decreased.

C. Classification

MatLab 7.3.0 was used to implement suggested method. It founds some problems to count the pixels and pixel values therefore; these criteria were not suitable to determine breast density. In our suggested method, the statistical parameters of images were used.

D. Evaluation

The Kappa (κ) was used to assess the agreement between two observers, whom have examined the same data, and computed it based on the following equation (4):

$$\kappa = \frac{\Pr(o) - \Pr(e)}{1 - \Pr(e)} \qquad (4)$$

where '*Pr(o)*' is the relative observed agreement among observers, and '*Pr(e)*' is the probability agreement calculated based on the observed data which indicated the probability of each observer randomly selected each category. If there was a complete agreement between observers, the κ will be equal 1, and the value will be less than or equal to 0, if there was no agreement between observers, it has been concluded that they have selected the categories by chance [6]. Landis and Koch [18] prepared criteria to interpret κ coefficient. It is shown in Table II.

TABLE II
CRITERIA FOR INTERPRETATION OF κ

κ	Interpretation
< 0	No agreement
0.0 — 0.20	Slight agreement
0.21 — 0.40	Fair agreement
0.41 — 0.60	Moderate agreement
0.61 — 0.80	Substantial agreement
0.81 — 1.00	Almost perfect agreement

IV. RESULTS AND DISCUSSION

A total of 220 digital mammogram images (Oblique view) were collected from National Cancer Society of Malaysia (NCSM). These images were from BIRADS I to IV. Initially all unnecessary areas were cropped and removed. Then, all images were resized to 1024 by 1024 pixels. Three expert radiologists were determined breast density. The agreement between expert radiologists was computed and 180 images with 100% agreement of radiologists were selected as final evaluation sample (Table III).

TABLE III
RADIOLOGISTS BREAST DENSITY ESTIMATION

BIRADS	Radiologist 1	Radiologist 2	Radiologist 3
1	8	8	8
2	78	78	78
3	81	81	81
4	13	13	13
Total	180	180	180

In the first step the pectoral muscle was removed using region growing method. The side of breast automatically detected based on the mean value of a 5 by 5 mask. This mask concentrate on the left upper corner of the image and the mean value of 0 determine the background side. Based on the side of breast, the seed point is determined to remove pectoral muscle. In the next step statistical parameters were computed while the background with pixel value of 0 is removed. In the final step based on the rules which was extracted from the histograms, the breast density is classified.

In comparison with the radiologists', the results showed that, out of total images (180), in 167 images the suggested method determines correct breast density (92.8%) (Table IV).

TABLE IV
RADIOLOGISTS AND SYSTEM BREAST DENSITY ESTIMATION

BIRADS	Radiologists	System	
		Frequency	Percent
1	8	8	100
2	78	71	91.02
3	81	78	96.3
4	13	10	76.9
Total	180	167	92.8

As shown in Table IV, in BIRADS I all images were categorized correctly by using the system. 91.02% of images in BIRADS II were correctly classified, while in BIRADS III the percentage of correct categorization is 96.3%, and 76.9%

of images in BIRADS IV.

The results showed that the system has good performance in order to breast density clasification. To measure compatibility or agreement between the system results and radiologists' ranks, the Cohen's Kappa Coefficient was calculated. The Kappa (κ) is used to assess agreement between two observers, who examines the same data [6].

Based on the results obtained from the system and the radiologist, the κ was computed and found to be 0.87 (p=0.0001). Based on the criteria [18] and the κ =0.87 obtained from our data, there is an almost perfect agreement between the radiologist and suggested method to categorize breast density.

The performance of our suggested method is higher than complex techniques which are suggested by the previous researchers. The results showed that the performance of the suggested method is almost twice in comparison with the method that suggested by Oliver et al. [23] and more than 25% higher than [24]. The suggested method also has higher performance than the systems that suggested by [4, 12, 14].

V. CONCLUSION

The breast density is an important factor for radiologists for reporting a mammogram image. Dense breast may increase breast cancer risk. In this research, a method was explored to classify or categorize breast density based on the statistical characteristics. Kurtosis, skewness, median, and mean are different statistical parameters, which can be useful to determine breast density. The new system computed these parameters and determines breast density based on the difference between mean and median. The advantage of using this method is it computes based on pixel values, and are independent of pixel intensity. The performance of the system was strong (κ=0.87, p=0.0001) indicating acceptable efficiency. In conclusion, it shows that the breast density could be determined by using quantitative measurements as opposed to the subjective standard method of eye balling from radiologists.

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