UDC 004.352.243

EXTRACTION OF INFORMATIVE FEATURES IN MAMMOGRAPHY IMAGES BASED ON THE LBP METHOD

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Abstract. *Mammography is crucial for early identification and screening of breast cancer. Mammogram images can identify and classify anomalies and explain breast tissue, as well as other useful information. A technique for obtaining informative signs to lower false positives in the detection of breast tumor areas is investigated in this research work. The key problem in this investigation is differentiating the area of the breast tumor from the area of normal tissue. This issue was resolved by using the LBP approach to extract informative characters from the region of interest (ROI) in the mammography images provided in the international mini-MIAS image dataset.*

Keywords: *mammograms, breast cancer, features, image processing, feature extraction, feature selection.*

I. INTRODUCTION

Medical image analysis. Medical images represent physical characteristics measured from the human body and are different from ordinary photographs. Therefore, in the analysis of medical images, it is necessary to rely on certain methods and follow the medical references. Artificial intelligence has been used in medicine since the 1980s, and medical applications based on artificial intelligence are constantly expanding. Currently, medical image analysis has become a branch of artificial intelligence. There are various types of medical imaging, including radiography, magnetic resonance imaging, ultrasound, nuclear imaging, optical microscopy, and others [1]. X-ray imaging uses electromagnetic waves with wavelengths longer than the visible spectrum to produce a diagnostically meaningful image. Fluoroscopy and angiography, computed tomography (CT), and mammography are types of radiography.

*Mammogram images***.** A mammogram is a diagnostic image that displays breast tissue using a low-dose x-ray technique. Digital mammography and screen-film mammography are the two different methods of mammogram imaging. Traditional analog mammography films are used in screen-film mammography (SFM). Labels and markers are typically present in the SFM background and should be eliminated because they are considered noise. Full-field digital mammography (FFDM) is a different term for digital mammograms. Breast cancer can be diagnosed correctly in 83–95 % instances with mammography, which has a high level of accuracy [3]. In most cases, the right and left projections, which are perpendicular to each other, are used to examine the mammary gland. A specialized X-ray equipment called a mammograph is used to perform mammography. Mammography may differentiate between primary and secondary breast tumors [14,15,16].

Informative features in mammogram images. Tissue characteristics play an important role in mammogram analysis and contribute to the correct interpretation and description of breast tissue. The texture elements are called texels, and they provide valuable information about the spatial location and features within the breast tissue. Abnormalities such as swellings, microcalcifications, and structural disturbances often exhibit distinctive textural features. Analysis of textural markers can help identify these abnormalities that may be difficult to detect based on intensity-based markers alone, as well as provide insight into the internal structure and composition of breast tumors [2]. By quantifying textural features such as heterogeneity, complexity, and regularity, radiologists and computer-aided diagnosis (CAD) systems can differentiate between benign and malignant tumors.

II. LITERATURE SURVEY

Tissue analysis increases the ability to classify different types of breast tumors and provides valuable information for diagnosis and treatment planning. Studies have shown correlations between specific texture patterns and histopathological features such as tumor grade, proliferation rate, and molecular subtypes. Texture analysis can aid in risk identification and treatment decisions [4,5,6]. Informative features serve as valuable data for machine learning algorithms and deep learning models, and this type of analysis consists of several types of statistical and structural attributes. Statistical texture symbols are quantitative values that indicate the level of intensity in the image and constitute a vector of symbols. Statistical attributes include first-order statistical values, second-order statistical values, and higher-order statistical values. The first-order statistical values describe the texture features obtained from the image based on histogram, such as mean value, variation, smoothness, third moment, similarity, skewness, kurtosis, and entropy. The second-order statistical values represent texture features obtained from the image based on the GLCM method, such as contrast, correlation, homogeneity, entropy, and energy. High-level statistics describe the SRE, LRE, GLN, RLN, RP, LGRE, and HGRE values obtained by the GLRLM method. In addition, valuable textural informative features can be obtained from the mammographic image based on LBP, Gabor function and Wavelet transforms [7,8,9].

The following methods are used to extract textural features in mammogram analysis:

I. First-order statistical features. The histogram function is often used in texture analysis to identify first-order statistical features. A histogram is a graphical representation of the intensity distribution in an image. Based on the histogram of the image, it is possible to determine how many pixels correspond to each intensity. The first-order statistical measure does not take into account pixel-neighbor relationships. Basic statistics such as variance are measured from the original image values [12]. These types of informative symbols include informative values such as mean value, variation, smoothness, third moment, similarity, skewness, kurtosis, and entropy. We take the image as a function $f(x, y)$ here x and y are spatial variables, $x = 0,1,2,..., N-1$ and $y = 0,1,2,..., M-1$. The function $f(x, y)$ can take discrete values $i = 0,1,2,..., G-1$, where G is the total number of intensity levels of the image. The number of pixels with a given intensity in the entire image is represented by an image histogram:

$$h(i) = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} \delta(f(x, y), i) \quad (1)$$

here, $\delta(i, j)-$ Kronecker delta function: $\delta(i,j) = \begin{cases} 1, & j = i, \\ 0, & j \neq i. \end{cases}$.

A histogram consists of clear and simple statistical information in an image. The ratio of $h(i)$to the number of pixels in the image is called the density of the intensity distribution:

$$p(i) = \frac{h(i)}{NM}; i = 0,1,2,\ldots,G-1 \quad (2)$$

here, N and M are the number of columns and rows of the image.

Informative features that can be extracted from the histogram of a given image are given in Table 1.

Table 1. Histogram-based informative symbols and their mathematical expression.

Informative features	Mathematical expressions
Mean- a measure of the average intensity level in an image.	$\mu = \sum_{i=0}^{G-1} ip(i)$
Variance- a quality representing the change of the intensity level around the average value.	$\sigma^2 = \sum_{i=0}^{G-1} (1-\mu)^2 p(i)$
Skewness- an indicator of symmetry, that is, if the histogram of the image is symmetrical to the average value, the value of the skewness is zero, and if it is above the average value, it has a positive value, and if it is below it, it has a negative value.	$\mu_3 = \sigma^{-3} \sum_{i=0}^{G-1} (i-\mu)^3 p(i)$
Kurtosis- a measure of the flatness of the histogram.	$\mu_4 = \sigma^{-4} \sum_{i=0}^{G-1} (i-\mu)^4 p(i) - 3$
Entropy- a measure of similarity of the histogram.	$H = -\sum_{i=0}^{G-1} p(i) \log_2 [p(i)]^2$
Energy	$E = \sum_{i=0}^{G-1} [p(i)]^2$

II. Second-order statistical features. These features include informative features extracted based on the GLCM method. GLCM (Grey-level co-occurrence matrix) is one of the most widely used methods in texture analysis. This method consists of a function of angle and distance in the neighborhood of pixels [10,11]. Various statistical measures can be obtained from GLCM, such as contrast, energy, entropy, uniformity, correlation, shade, and prominence. These measurements determine the relationship between pixel intensities and provide information about the texture features of the image. Based on this method, G^2 elements can be calculated, which is too many for texture analysis. Therefore, reduced texture features can be calculated based on this method [7]. In practice, 14 texture features proposed by Haralick are used (Haralick's texture features) and they are labeled f_1 to f_{14}. Let image I be given, if its dimensions are $N \times N$:

$$P(i,j)=\sum_{i=1}^{N}\sum_{j=1}^{N}\begin{cases}1, & I(x,y)=i, I(x+\Delta_x, y+\Delta_y)=j \\ 0, & otherwise\end{cases} \quad (3)$$

Equation (3), $P(i,j)$ is the joint distribution of joint intensities i and j in the given interval (Δ_x, Δ_y) of the image, x and y are spatial coordinates in the image. Given (Δ_x, Δ_y) interval describes distance d and angle θ between pixel $I(x,y)$ and its neighbors. In Figure 1, the GLCM matrix depicts the gray level value of any two adjacent pixels in the image along the specified path and direction.

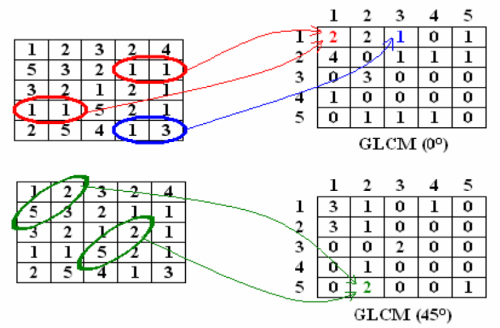

Fig.1. GLCM matrix.

Table 2. Informative features obtained based on GLCM and their mathematical expression.

Informative features	Mathematical expressions
Energy (f_1)	$f_1=\sum_{i,j=0}^{N-1}(P(i,j))^2$ where is element (i,j) of the normalized symmetric GLCM, N is the number of gray levels.
Entropy (f_2)	$f_2=\sum_{i,j=0}^{N-1}-\ln(P(i,j))P(i,j)$
Contrast (f_3)	$f_3=\sum_{i,j=0}^{N-1}P_{ij}(i-j)^2$
Homogeneity (f_4)	$f_4=\sum_{i,j=0}^{N-1}\frac{P_{i,j}}{1+(i-j)^2}$
Correlation (f_5)	$f_5=\sum_{i,j=0}^{N-1}P_{i,j}\frac{(i-\mu)(j-\mu)}{\sigma^2}$ where μ is the mean the mean GLCM and is calculated as: $\mu=\sum_{i,j=0}^{N-1}iP_{ij}$
Shade (f_6)	$f_6=\mathrm{sgn}(A)\lvert A\rvert^{1/3}$, where $sgn(x)=\begin{cases}x<0 \ for \ x=-1\\ x=0 \ for \ x=0;\\ x>0 \ for \ x=1\end{cases}$ and A is calculated as follow $A=\sum_{i,j=0}^{N-1}\frac{(i+j-2\mu)^3 p_{ij}}{\sigma^3\left(\sqrt{2(1+f_5)}\right)^5}$, f_5- Correlation
Prominence (f_7)	$f_7=\mathrm{sgn}(B)\lvert B\rvert^{1/4}$, where $B=\sum_{i,j=0}^{N-1}\frac{(i+j-2\mu)^4 p_{ij}}{4\sigma^4(1+f_5)^5}$, f_5- Correlation

Informative features obtained based on the GLCM method are described in Table 2.

III. High-order statistical features. Gray-Level Run-Length Matrix (GLRLM): GLRLM analyzes the lengths and frequencies of consecutive pixels with the same intensity value. It captures the spatial distribution of similar gray-level runs in different directions and provides symbols such as SRE, LRE, GLN, RLN, LGRE, HGRE. Run-length is the location of a set of pixels with a certain intensity in one line [13]. Run length statistics are calculated by counting the number of runs of a given length (from 1 to n) at each gray level. Run length is expressed based on g_l, r_l, θ, where g_l - gray level, r_l - run length, θ -direction. In the run length matrix, pixels with the same gray level are searched along the given θ -direction in the image, and a two-dimensional matrix is constructed. Based on GLRLM, 6 texture features are extracted. Let $P(i,j)$ be an image matrix designed for extracting GLRLM features. The texture features extracted based on the GLRLM method are shown in Table 3.

Table 3. Informative features and their mathematical expression based on GLRLM.

Informative features	Mathematical expressions
SRE (Short-run emphasis)	$SRE = \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{P(i,j)}{j^2}$
LRE (Long-run emphasis)	$LRE = \sum_{i=1}^{G}\sum_{j=1}^{R} j^2 P(i,j)$
GLN (Gray-level nonuniformity)	$GLN = \sum_{i=1}^{G}\left(\sum_{j=1}^{R} P(i,j)\right)^2$
RLN (Run-length nonuniformity)	$RLN = \sum_{i=1}^{R}\left(\sum_{j=1}^{G} P(i,j)\right)^2$
LGRE (Low gray level run emphasis)	$LGRE = \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{P(i,j)}{i^2}$
HGRE (High gray level run emphasis)	$HGRE = \sum_{i=1}^{G}\sum_{j=1}^{R} i^2 P(i,j)$

Gabor functions. Gabor functions are a family of linear filters that analyze an image in different frequency and direction channels. They are often used for texture analysis due to their ability to capture fine-scale texture detail and orientation [15]. The results obtained through the Gabor filter provide information about texture directions, frequencies, and local features. The Gabor filter is a sinusoid with a specific frequency and direction, modulated on the basis of a Gaussian convolution.

The two-dimensional Gabor function and its Fourier transform $G(u,v)$ are expressed as follows:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \cdot \cdot exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right] \quad (4)$$

where $j=\sqrt{-1}$ and W is the frequency of the modulated sinusoid.

$$G(u,v) = exp\left\{-\frac{1}{2}\left[\frac{(u-w)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \quad (5)$$

where $\sigma_u = 1/2\pi\sigma_x$, $\sigma_v = 1/2\pi\sigma_y$.

The intensity wave in the mammogram is converted into a probability matrix by the following expression:

$$p(x,y) = \frac{g^2(x,y)}{\iint g^2(x,y)dxdy} \quad (6)$$

(5) the textural features extracted from the existing mammogram based on the function and their mathematical expression are explained in detail in Table 4.

Often we are faced with the task of choosing an optimized set of symbols from a large number of available informative symbols. In such cases, methods such as PCA, RF, DT are used. For example, the PCA method is used to select the most important informative markers for classifying a tumor as dangerous or safe. In this method, components of unrelated input vectors are orthogonalized, resulting in orthogonal components (principal components). Thus, the components with the least variation in the data set are eliminated by the components with the largest variation, and they are prioritized. In order to achieve a good classification result, in many ways, the redundancy must be removed to improve the performance of the classifiers. It is the chosen informative characters and their role in the model that are important than the informative characters. Usually, different combinations of informative characters lead to different results. In addition, the relatively small number of characters used in the classifier can improve the classification efficiency.

Table 4. Informative features obtained on the basis of Gabor functions and their mathematical expression.

Informative features	Mathematical expressions
Contrast	$\iiint\limits_{(x-y)=z} z^2 p(x,y)\,dxdydz$
Second angular momentum	$\iint p^2(x,y)\,dxdy$
Inverse difference momentum	$\iint \frac{p(x,y)}{1+(x-y)^2}\,dxdy$
Entropy	$-\iint p(x,y)\log p(x,y)\,dxdy$
Variation	$\iint (x-y)^2 p(x,y)\,dxdy$
Correlation	$\frac{1}{\sigma_x\sigma_y}\left(\iint p(x,y)\,dxdy-\mu_x\mu_y\right)$ where μ_x,μ_y σ_x and σ_y are the mean value and standard deviation of the marginal probability P_x and P_y

III. METHODOLOGY

Local Binary Pattern (LBP) method. LBP is a simple yet effective way to describe local texture patterns in an image. It compares the intensity values of the central pixel with its surrounding neighbors and encodes the results into binary codes. The distribution of these codes across the image provides information about texture variations and patterns. Fig. 2 describes the working principle of the LBP method graphically.

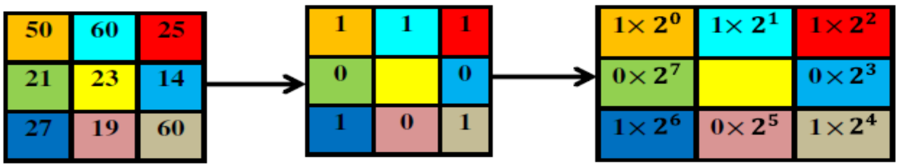

Fig. 2. LBP method.

$$LBP^{P,R}(x_c,y_c)=\sum_{i=0}^{P-1} s\left(g_i^{P,R}-g_c\right)2^i \qquad (7)$$

$$s(x)=\begin{cases}1, & if \quad x\ge 0\\ 0, & if \quad x<0\end{cases} \qquad (8)$$

where P is an integer value, we take P as 8 bits, so the maximum value of different binary patterns is $256(2^8)$, c - center pixel, g_c - center pixel gray level value, g_i the value of the gray level of the corresponding pixel, R -the distance between the central pixel and its neighboring pixel, x_c, y_c - the coordinate of the central pixel.

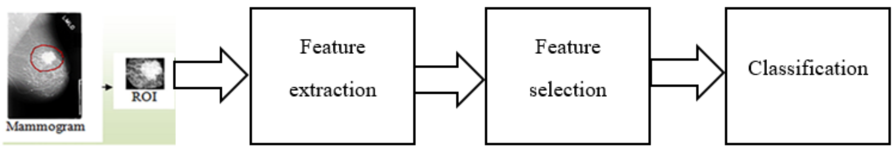

Fig. 3. Algorithm diagram for CAD systems.

The development of CAD, i.e. computer aided detection and diagnosis systems, forms the issues of development or improvement of artificial intelligence, computer vision, machine learning and image processing methods and algorithms suitable for a given problem. Figure 3 shows a general scheme for CAD systems, including steps such as informational features obtained from regions of interest (ROIs) in mammography images, their sorting and classification. In the diagram above, the area of interest is first extracted from the mammographic image, and then informative features are extracted based on various methods. In this research work, we calculated informative features such as energy, contrast, and correlation using the LBP method. In general, the informative signs extracted in some literature are sorted [7] and classified based on various methods, and sometimes the informative signs are directly classified.

IV. EXPERIMENTAL RESULTS

In this paper, we obtained mammographic images for research from the mini-MIAS international image collection. This image collection contains a total of 322 mammography images, of which 209 are of healthy women, 51 are of women diagnosed with malignant tumors, and 62 are of women diagnosed with benign tumors.

Fig. 4. Mammography images from the Mini-MIAS image collection.
a) abnormal image, b) normal image.

Table 5. Informative features were calculated based on the LBP method from mammograms with asymmetric structure.

ROI size	Contrast	Homogeneity	Correlation	Energy
10×10	0.0012	0.0635	1.0678	0.0041
	0.0009	0.0832	1.0908	0.0070
	0.0013	0.0348	1.0361	0.0011
	0.0043	0.0114	1.0115	0.0001
	0.0014	0.0670	1.0706	0.0043
20×20	0.0015	0.0550	1.0060	0.0029
	0.0009	0.0280	1.0290	0.0079
	0.0014	0.0540	1.0570	0.0030
	0.0067	0.0102	1.0102	0.0001
	0.0008	0.0602	1.0639	0.0037
30×30	0.0010	0.0562	1.0582	0.0028
	0.0004	0.0430	1.0050	0.0017
	0.0005	0.0326	1.0033	0.0019
	0.0009	0.0482	1.0507	0.0032
	0.0008	0.0345	1.0506	0.0002

Figure 4 shows samples from the Mini-MIAS international image collection. Images are scaled down to 200 microns, so each image is 1024×1024 pixels. Tissues in mammography images are classified according to the presence of sebaceous glands, dense glands, and fat, as well as asymmetric, certain shape disorders, and calcifications. Healthy cases in the Mini-MIAS set were manually identified.

According to the smallest tumor area in the mammogram, the regions of interest (ROIs) were taken in 3 different sizes, i.e. 10×10, 20×20, 30×30. Energy, homogeneity, contrast, and correlation informative features were calculated for these regions of interest (ROIs) using the LBP method. Table 5 shows the values of the informative markers calculated for the regions of interest (ROIs) with dimensions 10×10, 20×20, and 30×30 obtained from 5 mammographic images with an asymmetric structure.

V. CONCLUSION

In this article, the LBP method is used to obtain the informative signs that are often used in mammogram analysis. The methods for extracting informative features analyzed above have strengths and limitations, and the choice of technique depends on specific research or clinical goals. In addition, researchers often combine multiple texture features or combine them with other image features to increase the accuracy and robustness of texture-based analysis in mammography. By combining texture features with other image features such as shape, intensity, and spatial information, more sophisticated, accurate classification and segmentation models can be developed for breast cancer diagnosis. The aim is to analyze and compare different informative feature extraction methods, their advantages, limitations, and their applicability in increasing the accuracy of breast cancer diagnosis. In conclusion, informative features in mammogram analysis provide important information for tumor detection, characterization, prediction of tumor behavior, and treatment monitoring. They increase the diagnostic capabilities of radiologists and contribute to more accurate and reliable diagnosis of breast cancer, ultimately improving patient outcomes.

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Поступила в редакцию 3.10.2023

Citation: *Abdieva Kh.S., Yusupov O.R.* 2023. Extraction of informative features in mammography images based on the lbp method. *International Journal of Theoretical and Applied Issues of Digital Technologies*. 4(6): 75-82.

ИЗВЛЕЧЕНИЕ ИНФОРМАТИВНЫХ ПРИЗНАКОВ ИЗ МАММОГРАФИЧЕСКИХ ИЗОБРАЖЕНИЙ НА ОСНОВЕ МЕТОДА LBP

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Аннотация. *Маммография имеет решающее значение для раннего выявления и скрининга рака молочной железы. Изображения маммограммы могут идентифицировать и классифицировать аномалии и объяснить состояние ткани молочной железы, а также предоставить другую полезную информацию. В данной научной работе исследована методика получения информативных признаков для снижения ложноположительных результатов при выявлении участков опухоли молочной железы. Ключевой проблемой в этом исследовании является дифференциация области опухоли молочной железы от области нормальной ткани. Эта проблема была решена с помощью подхода LBP для извлечения информативных символов из области интереса (ROI) на маммографических изображениях, представленных в международном наборе данных изображений mini-MIAS.*

Ключевые слова: *маммограммы, рак молочной железы, особенности, обработка изображений, извлечение признаков, выбор признаков.*

LBP USULI ASOSIDA MAMMOGRAFIYA TASVIRLARIDAN INFORMATIV BELGILARNI AJRATIB OLISH

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Annotatsiya. *Mammografiya tekshiruvi ko'krak bezi saratonini erta bosqichda aniqlash va skrining uchun juda muhimdir. Mammogramma tasvirlari anomaliyalarni aniqlash va tasniflash, ko'krak to'qimalari va boshqa foydali ma'lumotlarni tushuntirish uchun ishlatilishi mumkin. Ushbu tadqiqot ishida ko'krak o'smalari sohalarini aniqlashda noto'g'ri pozitivlarni kamaytirish uchun informativ belgilarni ajratib olish usuli o'rganilgan. Ushbu tadqiqotning asosiy muammosi ko'krak o'smasi sohasini oddiy to'qimalar sohasidan farqlashdir. Ushbu muammo xalqaro mini-MIAS tasvirlar to'plamida taqdim etilgan mammografiya tasvirlarida qiziqilgan sohadan (ROI-region of interest) informativ belgilarni ajratib olish uchun LBP yondashuvidan foydalangan holda hal qilindi.*

Kalit so'zlar: *mammogrammalar, ko'krak bezi saratoni, informativ belgilar, tasvirni qayta ishlash, belgilarni ajratib olish, belgilarni tanlash.*