A Review of Medical Imaging in Breast Cancer Detection

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ABSTRACT

With the rapid development of the computer science and artificial intelligence, medical imaging technologies based on deep learning are playing an increasingly important role in medical services. In addition, breast cancer is one of the most threatening tumor diseases for women's health, with a high mortality rate among female cancers. Consequently, the use of medical imaging technologies for breast cancer diagnosis can contribute to the medical field. This article discusses the detection of breast cancer using medical imaging technology to extract lesion characteristics and labeling, which can provide valuable help for people.

KEYWORDS

Medical images; Breast cancer; Deep learning; Artificial intelligence

DOI: 10.47297/taposatWSP2633-456918.20230402

1 Introduction

Medical image processing uses mathematical methods and computers as modern information processing tools, with the help of various medical imaging tools, according to the actual needs and processing technology to visualize the resulting images. The objects of medical image processing are mainly radiology images, CT images, MRI images, ultrasound images, PET images and SPECT images. With the help of medical image processing technology, medical personnel can diagnose diseases more accurately and quickly, provide better medical services for patients, and make medical technology more intelligent. With the continuous progress of modern science and technology, medical image processing technology is also improving. Breast cancer is an uncontrolled proliferation of epithelial cells in the breast under the influence of various carcinogenic factors. In terms of incidence, it ranks first among malignant tumors in women, while it is less common in men. There are currently four internationally recognized molecular typologies for breast cancer: luminal A, luminal B, HER-2 and triple negative breast cancer (TNBC). This paper will provide a brief overview of medical image processing and image-based lesion detection and labeling for breast cancer.

2 Literature Review

In 1993, Berg et al. validated a recently proposed temporal resolution method to improve medical imaging based on transmittance as an important example of diode laser emitters[1].In 2008, Takeda et al. described a generation of CdSe nanoparticles conjugated to an anti-HER2 monoclonal antibody (trastuzumab) [quantum dots (QDs)] generation and achieved unique in vivo molecular imaging of breast cancer cells[2]. One of these methods, breast tomography, has finally been introduced into the clinic for routine use and has the potential to replace mammography in the future. 2013, a paper by Secopoulos et al. reviewed the extensive research done during the development of mammotome synthesis reviewed and focused on the medical and physical aspects of this imaging method[3,4];

in 2017, Mehdy et al, analyzed the recently published literature, paying particular attention to the methods and current state of NN technology in medical imaging[5]. In 2018, the goal of Mambou et al. was to compare and study multiple breast cancer detection methods using powerful computer vision techniques and deep learning models[6]. In some medical fields, each of these methods is essential. In 2021, Houssein et al. were scheduled to present a review showing new applications of machine learning and deep learning techniques for breast cancer detection and classification and an overview of advances in this area [7].

3 Digital Image Acquisition

Digital breast tomosynthesis (DBT) is an X-ray mammography technique that reconstructs a tomographic image of the breast into multiple low-dose projections by moving an X-ray tube in an arc within a limited angular range [8]. It consists of a frame, a computer system and a monitor.

The image acquisition process is as follows: first, a compression plate is used to apply some pressure to the somites, such as the breast or cervix, to make the breast tissue as flat as possible, thus reducing the effect of overlapping breast tissue on the image results. Second, an X-ray source is used to generate X-rays at a certain angle with a high voltage generator, and the attenuated signal is projected through the transparent layer of the breast or cervix into the detector. Similarly, as the rotating scanning frame is rotated along a certain arc, the X-ray source repeatedly acquires multiple projections over a limited range of angles. Finally, the acquired multiple projections are reconstructed using a reconstruction algorithm within the computer system to produce a three-dimensional image of the breast tissue, which is viewed on an image monitor [9] (see Figure 1).

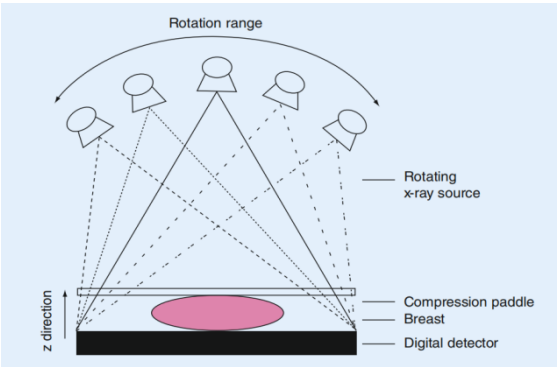

Figure 1. Typical digital breast tomosynthesis system [10]

4 Medical Image Preprocessing

(1) Image segmentation

Image segmentation is a commonly used digital image processing method in some target detection research projects for segmenting and extracting desired regions in an image and is commonly used in the preprocessing stage of image target detection and to improve the detection accuracy of the model. This paper uses the image segmentation methods of pixel thresholding segmentation and edge detection segmentation. Pixel thresholding segmentation can be performed by selecting single or multiple thresholds in the gray level, and is a necessary image preprocessing step before image classification and feature extraction. Edge detection segmentation is mainly used

to detect edge points in the image for marking segmentation, which can maximize the integrity of the image [11]. (See Figure 2) Its specific processing flow; (See Figure 3) The final rendering.

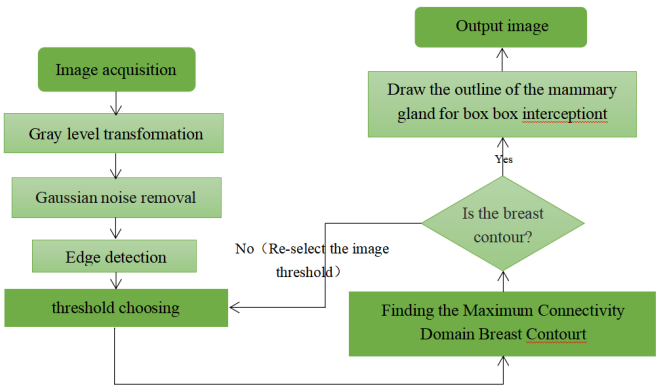

Figure 2. Flow chart of image segmentation processing

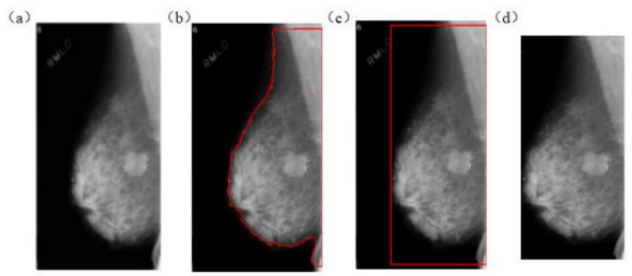

Figure 3. Segmentation effect of breast X-ray image: (a) original breast image; (b) Breast contour; (c) Box interception; (d) Breast extraction [11]

(2) Image contrast enhancement

Post-processing makes the modeled object more three-dimensional and realistic. In digital image processing technology, the image histogram algorithm can be implemented by counting the number of pixel appearances in the image. According to the image histogram principle, it can be said that the X axis is fixed and represents the gray value of the image in the value range [0, 255], and that the value of the Y axis corresponds to the number of appearances of the same gray value in the image, which makes it possible to obtain the distribution of pixels in the image using the image histogram algorithm. The image histogram algorithm can be used to find the distribution of pixels in an image. Moreover, the trend of the pixel distribution of an image is invariant when the image is panned, zoomed, rotated, etc. Therefore, the image histogram algorithm is often used in digital image processing, such as image smoothing, image segmentation, image binarization, and so on. In the process of image contrast enhancement, histogram equalization (CLAHE) algorithm is usually used, which equalizes the gray values of the image and can improve the image contrast [11].

In this paper, the histogram equalization algorithm is mainly used to enhance the image contrast. Its main role is to widen the gray range of the image, which belongs to a kind of nonlinear image stretching, which will make the transformed image gray level probability distribution uniform. In the process of image denoising, median filtering technology is introduced, using this nonlinear denoising method, it is very effective in removing impulse noise and does not cause the loss of edge features of the breast image, so the median filtering technology is usually used to complete the image denoising process when doing contrast enhancement of the image [11].

5 Detection of Lesions

(1) Feature extraction of lesions

1) Geometric feature extraction

The geometric features of a lesion are a key determinant of whether it is benign or malignant, and lesions in certain areas of the breast tend to produce geometric changes. In general, the geometric features of benign lesions are well-defined, nearly circular, and have smooth edges, while the geometric features of malignant lesions have unclear boundaries, rough edges, and irregular shapes. In this paper, we mainly extract nine dimensional features: the maximum cross-sectional radius of the lesion, the average radial length of the lesion, the standard deviation of the radial length of the lesion, the surface area, volume, roughness, roughness, duty cycle, roundness, and confidence ratio [12]. The specific equations are as follows:

a.Maximum section radius:

$$R = max\left(\sqrt{(x_j - x_0)^2 + (y_j - y_0)^2}\right)$$

Where (x_j, y_j) is denoted as the coordinates of any point located on the lesion area, and (x_0, y_0) is the center of mass of the lesion region center of mass of the region.

b.Mean of the radial length:

$$\mathrm{d}(j) = \frac{1}{n}\sum_{j=1}^{n}\frac{\sqrt{\left(x_j - x_0\right)^2 + \left(y_j - y_0\right)^2}}{2R}$$

c.Standard deviation of the radial length:

$$\sigma = \sqrt{\frac{1}{\mathrm{n}-1}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{d(j)} - \mathrm{u_d})^2}$$

d.Surface area:

$$S = \sum_{i=1}^{n} P(i)$$

$P(i)$ denotes the side length of the breast lesion region in the i th slice, where P is the square formed by the lesion region side length of the square;

e.Volume:

$$V = V_{voxel} \cdot A_{vocel}$$

Here V_{voxel} is the current voxel value, which defaults to 1, and A is the number of pixel points in the current lesion area;

f.Compactness:

$$\mathrm{C_0} = \frac{p^2}{4\pi A}$$

Compactness is analogous to sphericity, where the shape of a lesion is compared to the tightest spherical shape to measure the lesion's shape;

g.Surface roughness:

$$Ra = \frac{\sqrt[4]{\frac{1}{n}\sum_{i=1}^{n}(d(j)-u_d)^4} - \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}(d(j)-u_d)^2}}{u_d}$$

where roughness indicates whether the edges of the current lesion are smooth or not, and a larger current roughness value means that the edges of the current lesion are irregular and burrier.

h.Extent:

$$E_x = \frac{A}{p}$$

The duty cycle reflects the concavity of the lesion;

i.Circularity:

$$C = \frac{4\pi A}{p^2}$$

Roundness is measured by the ratio of the area of the lesion to the area of the square in which the lesion is constructed of the degree of roundness.

2) Texture feature extraction

Texture characteristics are primarily reflected in the homogeneity between a particular pixel point in the image and the points located in the field of this point, and texture characteristics are accompanied by periodic changes that are characteristic of the structural arrangement of the tissue. Texture characteristics are represented by the gray value of a pixel point and the distribution of gray values in the field of that point. Different organs and tissues have different texture characteristics, and the texture characteristics of benign and malignant breast neoplasms vary widely. Analysis of tissue characteristics can effectively distinguish between benign or malignant characteristics of a lesion, thus providing more reliable results in the diagnosis of breast cancer.

The most common algorithm for extracting texture features is the grayscale covariance matrix (GLCM), which uses the distances and angles between the pixel values of a grayscale image to compute a new grayscale covariance matrix. Some statistics of the constructed gray-level co-occurrence matrix are used as texture features of the image. Assuming that an image is of size $\mathrm{m} \times \mathrm{m}$, , the image is in the θ-direction, the step size is λ, and the size of the grayscale covariance matrix is 1x1, the formula for calculating the value of the i th row and the i th column of this matrix is shown below:

$$P(i,j,\lambda,\theta) = \{[(x,y),(x+dx,y+dy)]|f(x+dx,y+dy)=j\}$$

Where (x,y) is the coordinate on each pixel point, and $dx.dy$ are the spatial distance λ and the projection distance of direction θ in the x and y axis directions, respectively. Taking i as the starting point, P is the probability that the gray level is j at spatial distance λ and direction θ.

Pixels in relatively fine textured regions usually have similar gray values and the values in the matrix are mainly located at the main diagonal positions, while image pixels in image regions with relatively coarse texture features have large differences in grayscale, and the matrix values are randomly distributed in various positions of the matrix. In this paper, we calculate contrast, energy, entropy, variance, sum of variance, inverse variance and correlation using the gray scale co-occurrence matrix. The formula for each texture feature is given below:

a.Contrast:

$$\text{Constant} = \sum_{i=1}^{l} \sum_{j=1}^{l} [(i-j)^2 \cdot G(i,j)]$$

In the formula $G(i,j)$ represents the value corresponding to coordinates (i,j) in the grayscale covariance matrix G and the contrast is a measure of the distribution of the values in the matrix with the image texture produces changes as an important parameter. As the contrast value increases, the grooves in the image become deeper and the image becomes sharper as the contrast in the image becomes more pronounced.

b.Energy:

$$\text{Energy} = \sum_{i=1}^{l} \sum_{j=1}^{l} G^2(i,j)$$

Energy is an important indicator of image texture coarseness using the element values of the grayscale covariance matrix. If the element values of the matrices are basically the same, it indicates that the image energy values are relatively small and the image texture is fine; if the element values of the matrices differ significantly, it indicates that the image energy values are large and the image texture is coarse.

c.Entropy:

$$\text{Entropy} = -\sum_{i=1}^{l} \sum_{j=1}^{l} G(i,j) \cdot \log_{10} G(i,j)$$

Entropy is an important measure of the amount of information stored in an image, and it can give an idea of the complexity of an image's texture. If an image has no texture, its entropy is zero, meaning that the higher the entropy value, the more complex the image.

d.Variance:

$$\sigma^2 = -\sum_{i=1}^{l} \sum_{j=1}^{l} (i-a)^2 \cdot G(i,j)$$

Where a is the mean of $G(i,j)$.

e.Sum of Variance:

$$S_{\sigma^2} = \sum_{k=2}^{2l} (k-\sigma^2) \sum_{i=1}^{l} \sum_{j=1}^{l} G(i,j), k = 2,3,\ldots,2l$$

Both variance and sum of squares reflect the size of the period of the image texture, when the value of the variance and sum of squares of the image is more larger, the larger the period of the image texture.

f.Inverse Difference Moment:

$$I = \frac{\sum_{i=1}^{l} \sum_{j=1}^{l} G(i,j)}{[1+(i-j)^2]}$$

Inverse Variance is a measure of the degree of local variation in the texture of an image. If the texture is uniform across multiple regions of the image, the texture changes slowly and the inverse variance value is large; if the texture is irregular, the texture changes significantly and the inverse variance value is small.

g.Correlation:

$$u_1 = \sum_{i=1}^{l} i \sum_{j=1}^{l} G(i,j)\,,\ u_2 = \sum_{i=1}^{l} j \sum_{j=1}^{l} G(i,j)\,,$$

$$\sigma_1 = \sum_{i=1}^{l} (i-u_1)^2 \sum_{j=1}^{l} G(i,j)\,,\ \sigma_2 = \sum_{i=1}^{l} (j-u_1)^2 \sum_{j=1}^{l} G(i,j)\,,$$

$$\text{Correlation} = \sum_{i=1}^{l} \sum_{j=1}^{l} \frac{[i \cdot j \cdot G(i,j) - u_1 \cdot u_2]}{(\sigma_1 \cdot \sigma_2)}$$

Where u_1 and u_2 represent the mean of $\sum_{j=1}^{l} G(i,j)$ and $\sum_{i=1}^{l} G(i,j)$ respectively, and $\sigma 1$ and $\sigma 2$ represent the variance of $\sum_{j=1}^{l} G(i,j)$ and $\sum_{i=1}^{l} G(i,j)$ respectively. Correlation is used to indicate the similarity of the row (column) orientation of the matrix elements, and if the elements have almost the same row orientation, then the correlation value of the row elements will be larger, and vice versa. Therefore, when the correlation value of an image changes in a certain direction, it is possible to determine the direction of the current texture.

(2) Marker of lesions

For a volume of DBT images, lesions may not appear on every image, and their morphology and size often change on different tomographic images, so it requires specialized knowledge and skills to correctly distinguish the lesion area in the gland. The lesion annotation software used by doctors is an open source software called VGG Image Annotator, which not only provides multiple annotation methods for doctors to choose from, but is also simple to use, making it easy for doctors to annotate lesions. Doctors first open the DBT image they want to annotate in the annotation software, wait for the program to finish loading the image to mark the shape of the lesion on the image of the case, and then export the annotation information after completing the annotation [13]. (See Figure 4 for details) The final result.

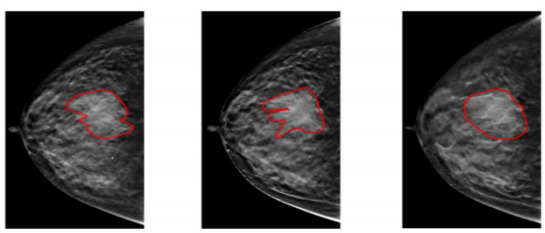

Figure 4. Image labeling; (a) slice labeling of the first appearance of the lesion; (b) slice labeling of the largest lesion; (c) slice labeling of the last appearance of the lesion [13]

6 Conclusion

With the development of digital image technology, determining diseases through medical images plays an extremely important role in medical diagnosis. Deep Learning and Reinforcement Learning are relatively tight combinations of machine learning algorithms and breast cancer image processing and have achieved considerable results. Grayscale conversion, target segmentation, feature extraction and labeling of lesions in breast cancer images using artificial intelligence greatly improves the efficiency of doctors and promotes the development of the medical industry.

About the Author

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