A Review of Breast Cancer Detection in Medical Images

Yao Lu†, Jia-Yu Li†, Yu-Ting Su†, ✉An-An Liu*†
† *School of Electrical and Information Engineering*, *Tianjin University*, Tianjin, China

***Abstract*—Breast cancer is a malignant tumor that occurs in the glandular epithelium of the breast. It is considered to be one of the most common cancers affecting women in the world. However, there is not an effective way to cure breast cancer yet, the key to reducing the risk of death is the early detection and diagnosis of breast cancer. Accurate diagnosis of breast cancer normally requires analysis of medical images of different modalities. There is a great need of automated system that could analyze these images accurately and rapidly. In this paper, we introduce some commonly used medical imaging methods for diagnosis of breast cancer, and based on them we investigate some recently proposed approaches for breast cancer detection with computer vision and machine learning techniques. Finally, we compare and analyze the detection performance of different methods on histological images and mammograph images respectively.**

***Index Terms*—Breast Cancer Detection, Histological Image, Mammograph Image, Ultrasound Image, Machine Learning**

I. Introduction

Breast cancer is a malignant tumor that occurs in the glandular epithelium of the breast. Sometimes, the process of cell growth goes wrong. New cells form even the body doesn't need them and old or damaged cells do not die as they should. When this occurs, a build up of cells often forms a mass of tissue called a lump, growth, or tumor. Its onset is often related to heredity, and the incidence of breast cancer is higher among women between the ages of 40 and 60 or around the menopause. Breast cancer is considered to be the most common cancer around the world, and is considered to be one of the major reasons of an increased death rate among women.

The etiology of breast cancer is not yet fully understood, but earlier diagnosis of breast cancer through periodic screening could improve the chance of recovery. A variety of enhancement techniques are used to provide rich look of mammogram image to detect breast cancer easily. The efficient way to improve early detection accuracy is to combine different imaging methods such as x-ray (mammography), ultrasound and magnetic resonance imaging (MRI) jointly.

However, detection on large amounts of medical images with human labors requires a lot of time, and the accuracy is not well guaranteed even for experts. Therefore a rapid and accurate automated diagnosis system for breast cancer disease is greatly needed.

Corresponding author: An-An Liu (anan0422@gmail.com)

A. Challenges

Automated detection system in medical images has the following challenges: 1. The detection of masses from mammograms and ultrasonic images is considered to be a challenging problem due to their large variation in shape, size, boundary and texture. In histology analysis, the biological structures and textures in both metastatic regions and background have large variations. 2. Due to the image acquisition process, there may be low signal to noise ratio compared to the surrounding breast tissue.

B. Organization

The paper is organized as follows: In Section II we introduce the commonly used imaging methods for breast cancer detection in medical applications and some widely used dataset for detection performance evaluation . In Section III, we introduce some recently proposed works for breast cancer detection problems. In Section IV, we introduce the commonly used metrics to evaluate detection problem, and discuss the performance of some previously introduced detection methods. Finally in Section V, we give a conclusion based on our previous reviews.

II. Dataset

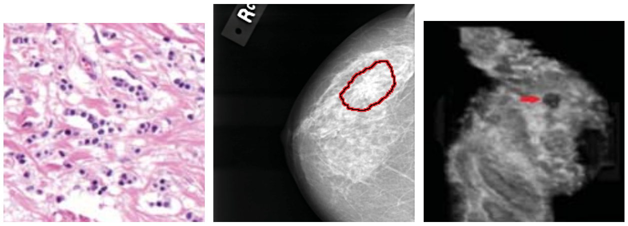
The diagnosis of breast cancer requires different imaging methods such as histological imaging, x-ray (mammography) imaging and ultrasound imaging. In order to better diagnose breast cancer diseases, the most effective way is to combine the detection results of these three imaging modalities. In this section, we introduce some widely used dataset for assessing the accuracy of breast cancer detection in these imaging modalities.

A. Histological Image.

Metastasis detection in sentinel lymph node from histopathological analysis plays an important role in the assessment of the extent of cancer spread for breast cancer staging. In this section we introduce some histological image datasets. They are broadly used for the evaluation of breast cancer detection accuracy using computer vision techniques.

1) MITOS: MITOS [1] is a database that contains histological images for the 2012 ICPR mitosis detection contest. These histological images are acquired by slide scanning. The slides are stained with standard hematoxylin and eosin (H&E) and then scanned by two slide scanners: Aperio Scanscope XT and

978-1-5386-4458-4/18/$31.00 ©2018 IEEE



(a) Histological image (b) Mammograph image (c) Ultrasound image

Fig. 1: Three types of imaging modalities for breast cancer detection in medical applications.

Hamamatsu Nanozoomer 2.0-HT. In each slide, the pathologists selected several frames at $\times 20$ magnification which have been subdivided into four frames at $\times 40$ magnification. There are about 300 mitosis annotated by pathologists in the dataset. Every image contains 2048×2048 pixels covering an area of $512 \times 512 \mu m$ ([2] [3]).

2) MICCAI-AMIDA13: MICCAI-AMIDA13 is a database that contains annotated histology images. Like MITOS dataset, they are acquired by tissue staining (H&E) and scanning (Aperio ScanScope XT scanner). There are 23 patients involved in this dataset. Every image contains $2,048 \times 2,048$ pixels with a resolution of $0.25\mu m$/pixel [4].

3) Camelyon16: Camelyon16 [5] dataset contains 399 whole-slide images from 399 patients in the Netherlands: Radboud University Medical Center (RUMC) and University Medical Center Utrecht (UMCU). RUMC images were produced with a digital slide scanner (Pannoramic 250 Flash II; 3DHISTECH) with a 20× objective lens (specimen-level pixel size, 0.243 $\mu m \times$ 0.243 μm). UMCU images were produced using a digital slide scanner (NanoZoomer-XR Digital slide scanner C12000-01; Hamamatsu Photonics) with a 40× objective lens (specimen-level pixel size, 0.226 $\mu m \times$ 0.226 μm)

B. Mammograph Image.

Mammography is a widely used imaging method for early breast cancer diagnosis. The mammograph images could be used to detect wide variety of suspicious lesions such as masses and micro-clacifications.

1) mini-MIAS: Mini-MIAS is a database that contains digital mammograph images for breast cancer detection. It changes the original images from 50 micron pixel edge to 200 micron pixel edge to reduce the size of images. There are 322 gray-scale mammograms of 161 cases with dimension of 1024 x1024 pixels. Every image has labelled with character of background tissue and class of abnormality. They are available through Pilot European image processing archive (PEIPA), University of ESSEX [6].

2) DDSM: DDSM [7] is a digital mammograph images database for breast cancer diagnosis. It is maintained by University of South Florida. There are 680 mammograms of 172 cases which are manually classified into six possible classes: negative, benign finding, probably benign, suspicious abnormality, highly suggestive of malignancy, and proven malignancy ([8], [9]).

3) INbreast: INbreast [10] is a database that contains high quality full-field digital (FFD) mammograms. There are 410 mammograms of 115 cases which are divided into six possible classes same as DDSM. 116 images of it contain benign or malignant masses, and the rest does not contain any masses. Every image has a detailed lesion annotations. It does not a have a standard train/test split. ([8], [11]).

C. Ultra Sound Image.

Breast ultrasound imaging serves as a complementary modality to mammography for early detection of breast cancers. The 3-D breast ultrasound images dataset used in [12] are generated by two kinds of ABUS systems: the SomoVu automated 3-D breast ultrasound system and the ACUSON S2000 automated breast volume scanning system. The dataset contains 42 images, 7 images of them generated by SomoVu system and others acquired from ACUSON S2000. There are 50 masses (38 malignant and 12 benign lesions) altogether in these images. The mean diameter of the masses which are annotated in the dataset is $10.23mm \pm 5.65mm$. About 80% of masses have diameters less than 15 mm and about 50% of them have diameters less than 7 mm.

III. Methods

A generalized system architecture for breast cancer detection consists the following four parts:

1) Image prepossessing. The imaging artifact and inconsistency caused by different imaging conditions may have great impact in the next steps of detection. It is necessary to remove the variability and artifacts with image prepossessing techniques for better detection performance.
2) Region of Interest (ROI) area segmentation. Since we only care about the relevant areas of the whole slide image during detection, we need to extract the most relevant parts of the image before running detection methods on them.
3) Feature extraction. Raw image data typically has high dimensions, it is difficulty to use them directly for classification. Feature extraction could map raw image data into a feature space with much lower dimensions, which is more relevant to the classification task.
4) Classification. Extracted features are normally fed into one or more classifier to classify the features of ROI regions as positive or negative for detection.

In the following part of this section, we introduce some recently proposed methods for breast cancer detection based on their improvements on the different steps of the detection process.

A. ROI Area Segmentation.

Dhungel *et al*. [8] proposed a cascade of deep learning and random forest classifiers to detect masses in mammograms. They use area morphological scale space for cell segmentation.

Paul *et al.* [3] constructed a Relative Entropy Maximized Scale Space for cell segmentation by area morphological opening and closing and use a edge preserving filter to ensure accuracy. Beura *et al.* [13] applied the conventional cropping operation to select ROI areas from mammograms. Beevi *et al.* [14] proposed a Krill Herd Algorithm-based localized active contour model to segments cell nuclei from background, and then used a multiclassier system based on deep belief network to classify cells into mitotic and non-mitotic groups. Hu *et al.* [15] utilized adaptive thresholding segmentation on multiresolution representation of the mammogram images for suspicious lesion detection. Kozegar *et al.* [12] proposed a two-stage segmentation approach for mass segmentation on 3D automated breast ultrasound images. They first used an adaptive region growing algorithm based on the Gaussian mixture model (GMM) to get a rough estimation of boundary. and then used a geometric edge-based deformable model to get more accurate target region.

B. Feature extraction

Feature extraction of the ROI region plays important role in the detection process. Al-Ayyoub *et al.* [16] applied a Fuzzy C-Means algorithm based on the Single Pass to extract the mammograph images feature They further proposed to use GPU to speed up their algorithm. Albarqouni *et al.* [4] proposed multi-scale CNN AggNet to learn feature from crowd annotation. Xing *et al.* [17] proposed a novel nucleus segmentation method with deep convolutional neural network and selection-based sparse shape model. [6] developed a BCDCNN to detect breast cancer in mammograms, which proved the feasibility of CNN in breast cancer detection. Castro *et al.* [11] further transform the CNN structure into a Fully Convolutional Network (FCN) for mass detection in full mammograms. Shell *et al.* [18] proposed a multi-tiered backpropagation neural networks (BNN) structure to extract feature. The BNN structure consisted of six neural networks and four of them were selected to determine a malignant or benign classification. Carneiro *et al.* [9] used deep learning model to detect breast cancer, which demonstrated that high-level deep learning features can be used in the classification of mammograms and segmentation maps. Lin *et al.* [19] proposed a novel framework based on fully convolutional networks for feature learning. They reconstructed dense predictions to ensure the accuracy of detection. Elmoufidi *et al.* [20] used the multiple-instance learning (MIL) algorithms for feature learning. Hu *et al.* [21] combined the Hidden Markov Tree (HMT) model and the Dual-Tree Complex Wavelet Transform (DTCWT) to extract features of the ROI regions for microcalcification detection on mammograph images.

C. Classification

Almost all models used existing mature classifiers for breast mass classification. Elmoufidi *et al.* [20] used a standard SVM classifier to classify breast cancer as malignant or benign. Beura *et al.* [13] applied the random forest classifier for the benign-malignant mammograms classification. Al-masni *et al.* [22] proposed a YOLO-based CAD system for breast cancer detection, and they used fully connected neural network (FCNN) to classify breast mass.

IV. Experiment and Discussion

In this section we demonstrate the experimental results of some state-of-the-art works on commonly used dataset and give some discussion based on them.

A. Evaluation Metric

Evaluation of the detection methods are commonly based on the calculation of *precision* (Eq. 1) and *recall* (also known as sensitivity, Eq. 2) on the detected results.

Some statistical measures such as F_1 score (Eq.3), Receiver Operating Characteristics (ROC) and its Area Under Curve (AUC) are also commonly used for the evaluation of detection results.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{2}$$

$$\text{F}_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \tag{3}$$

B. Detection Performance

We compare the detection results with state-of-the-art works in Table. I on histological images and in Table. II on mammograph images. Detection results are from their original papers.

From the results in the tables we could tell that deep learning based methods have achieved good results for detection on both image modalities, specially the ScanNet has achieved comparable accuracy with human performance on histological images. However, some classical classification approaches still could achieve impressive result, such as the Adaboost + Random Forest classifier in [13] for mammograph images. This result demonstrates that transitional classifiers and hand-crafted features still have potential for detection problem in medical images, which contains relatively less annotated data due to the higher requirement for expertise.

V. Conclusion

In this paper we introduce some commonly used medical imaging methods for breast cancer detection problems, and review some recently proposed methods to solve the detection problem in each imaging modality. We summarize the general detection process as follows: 1. image prepossessing to remove artifacts and variance, 2. ROI area segmentation to extract candidates for further detection, 3. feature extraction and 4. classification. At last, we compare the detection performance of these methods in a relatively uniform format.

VI. Acknowledgment

This work was supported in part by the National Natural Science Foundation of China (61772359, 61472275, 61872267, 61502337).

TABLE I: Detection performance on some proposed methods for histological images.

Method	dataset	Precision (%)	Recall (%)	F_2 score (%)	AUC
AggNet [4]	AMIDA13	44.1	42.4	43.3	-
DBN-MCS [14]	MITOS [1]	62.50	93.75	75.0	-
Random Forest [3]	MITOS [1]	82.6	66.0	73.4	-
ScanNet [19]	Camelyon16 [5]	-	-	-	96.69
Human [19]	Camelyon16 [5]	-	-	-	96.6

TABLE II: Detection performance on some proposed methods for mammograph images.

Method	dataset	Precision (%)	Recall (%)	F_2 score (%)	AUC
Adaboost+RF [13]	MIAS	-	-	98.0	99.8
K-NN [13]	MIAS	-	-	77.1	80.3
SVM [13]	MIAS	-	-	60.3	68.2
CNN [6]	MIAS	70.5	82.7	76.1	-
Adaboost+RF [13]	DDSM	-	-	98.8	99.9
K-NN [13]	DDSM	-	-	88.3	89.5
SVM [13]	DDSM	-	-	68.4	76.0
YOLO based [22]	DDSM	80.6	93.20	86.4	87.74
Multi-View CNN [9]	DDSM	-	-	-	91
Multi-View CNN [9]	INbreast	-	-	-	87

REFERENCES

[1] L. Roux, D. Racoceanu, F. Capron, J. Calvo, E. Attieh, G. Le Naour, and A. Gloaguen, "Mitos & atypia," *Image Pervasive Access Lab (IPAL), Agency Sci., Technol. & Res. Inst. Infocom Res., Singapore, Tech. Rep*, vol. 1, 2014.

[2] A. Giusti, C. Caccia, D. C. Cireşari, J. Schmidhuber, and L. M. Gambardella, "A comparison of algorithms and humans for mitosis detection," in *Biomedical Imaging (ISBI), 2014 IEEE 11th International Symposium on*. IEEE, 2014, pp. 1360–1363.

[3] A. Paul and D. P. Mukherjee, "Mitosis detection for invasive breast cancer grading in histopathological images," *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 4041–4054, 2015.

[4] S. Albarqouni, C. Baur, F. Achilles, V. Belagiannis, S. Demirci, and N. Navab, "Aggnet: deep learning from crowds for mitosis detection in breast cancer histology images," *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1313–1321, 2016.

[5] B. E. Bejnordi, M. Veta, P. J. van Diest, B. van Ginneken, N. Karssemeijer, G. Litjens, J. A. van der Laak, M. Hermsen, Q. F. Manson, M. Balkenhol *et al.*, "Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer," *Jama*, vol. 318, no. 22, pp. 2199–2210, 2017.

[6] Y. Tan, K. Sim, and F. Ting, "Breast cancer detection using convolutional neural networks for mammogram imaging system," in *Robotics, Automation and Sciences (ICORAS), 2017 International Conference on*. IEEE, 2017, pp. 1–5.

[7] M. Heath, K. Bowyer, D. Kopans, R. Moore, and P. Kegelmeyer, "The digital database for screening mammography," *Digital mammography*, pp. 431–434, 2000.

[8] N. Dhungel, G. Carneiro, and A. P. Bradley, "Automated mass detection in mammograms using cascaded deep learning and random forests," in *Digital Image Computing: Techniques and Applications (DICTA), 2015 International Conference on*. IEEE, 2015, pp. 1–8.

[9] G. Carneiro, J. Nascimento, and A. P. Bradley, "Automated analysis of unregistered multi-view mammograms with deep learning," *IEEE transactions on medical imaging*, vol. 36, no. 11, pp. 2355–2365, 2017.

[10] I. C. Moreira, I. Amaral, I. Domingues, A. Cardoso, M. J. Cardoso, and J. S. Cardoso, "Inbreast: toward a full-field digital mammographic database," *Academic radiology*, vol. 19, no. 2, pp. 236–248, 2012.

[11] E. Castro, J. S. Cardoso, and J. C. Pereira, "Elastic deformations for data augmentation in breast cancer mass detection," in *Biomedical & Health Informatics (BHI), 2018 IEEE EMBS International Conference on*. IEEE, 2018, pp. 230–234.

[12] E. Kozegar, M. Soryani, H. Behnam, M. Salamati, and T. Tan, "Mass segmentation in automated 3-d breast ultrasound using adaptive region growing and supervised edge-based deformable model," *IEEE Transactions on Medical Imaging*, 2017.

[13] S. Beura, B. Majhi, R. Dash, and S. Roy, "Classification of mammogram using two-dimensional discrete orthonormal s-transform for breast cancer detection," *Healthcare technology letters*, vol. 2, no. 3, pp. 46–51, 2015.

[14] K. S. Beevi, M. S. Nair, and G. Bindu, "A multi-classifier system for automatic mitosis detection in breast histopathology images using deep belief networks," *IEEE journal of translational engineering in health and medicine*, vol. 5, pp. 1–11, 2017.

[15] K. Hu, X. Gao, and F. Li, "Detection of suspicious lesions by adaptive thresholding based on multiresolution analysis in mammograms," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 2, pp. 462–472, 2011.

[16] M. Al-Ayyoub, S. M. AlZu'bi, Y. Jararweh, and M. A. Alsmirat, "A gpu-based breast cancer detection system using single pass fuzzy c-means clustering algorithm," in *Multimedia Computing and Systems (ICMCS), 2016 5th International Conference on*. IEEE, 2016, pp. 650–654.

[17] F. Xing, Y. Xie, and L. Yang, "An automatic learning-based framework for robust nucleus segmentation," *IEEE transactions on medical imaging*, vol. 35, no. 2, pp. 550–566, 2016.

[18] J. Shell and W. D. Gregory, "Efficient cancer detection using multiple neural networks," *IEEE journal of translational engineering in health and medicine*, vol. 5, pp. 1–7, 2017.

[19] H. Lin, H. Chen, Q. Dou, L. Wang, J. Qin, and P.-A. Heng, "Scannet: A fast and dense scanning framework for metastastic breast cancer detection from whole-slide image," in *Applications of Computer Vision (WACV), 2018 IEEE Winter Conference on*. IEEE, 2018, pp. 539–546.

[20] A. Elmoufidi, K. El Fahssi, S. Jai-andaloussi, A. Sekkaki, Q. Gwenole, and M. Lamard, "Anomaly classification in digital mammography based on multiple-instance learning," *IET Image Processing*, 2017.

[21] K. Hu, W. Yang, and X. Gao, "Microcalcification diagnosis in digital mammography using extreme learning machine based on hidden markov tree model of dual-tree complex wavelet transform," *Expert Systems with Applications*, vol. 86, pp. 135–144, 2017.

[22] M. Al-Masni, M. Al-Antari, J. Park, G. Gi, T. Kim, P. Rivera, E. Valarezo, S.-M. Han, and T.-S. Kim, "Detection and classification of the breast abnormalities in digital mammograms via regional convolutional neural network," in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*. IEEE, 2017, pp. 1230–1233.