A Review of Breast Cancer Histopathological Image Classification

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Abstract. Breast Cancer (BC) is the most common malignant tumor for women in the world. Histopathological examination serves as basis for breast cancer diagnosis. Due to the low accuracy of histopathological images through manual judgment, the classification of histopathological images of breast cancer has become a research hotspot in the field of medical image processing. Accurate classification of images can help doctors to properly diagnoses and improve the survival rate of patients. This paper reviews the existing works on histopathological image classification of breast cancer and analysis the advantages and disadvantages of related algorithms. Findings of the histopathological image classification of the Breast Cancer study are drawn, and the possible future directions are also discussed.

1. Introduction

Breast Cancer (BC) is the most common malignant tumor for women in the world. Taking about the statistics on women cancer globally in 2018 [1], breast cancer ranks first for both the new incidence rate (24.2%) and mortality rate (15%). It is one of the greatest health enemies of ladies. In developing countries, most women diagnosed with BC cannot survive because it was discovered too late. Early discovery can greatly reduce the mortality of BC. Therefore, accurate BC detection and early diagnosis have become the key to preventing BC.

Detection and diagnosis of BC can be accomplished by medical imaging techniques such as diagnostic mammograms (X-rays), magnetic resonance imaging, ultrasound, and thermography [2]. Imaging for cancer screening has been introduced for more than forty years [3]. However, to determine whether a cancer is present or not, tissue biopsy is the best way to reach an accurate diagnosis. Among the biopsy techniques, the most common options are fine needle aspiration, core needle biopsy, vacuum-assisted, and surgical biopsy. The procedure involves collecting samples of cells or tissue, which are subsequently fixed across a glass microscope slide for staining and microscopic examination. Diagnosis from a histopathology image is thus the best practice in diagnosing almost all types of cancer, including BC [4]. The final BC diagnosis is carried out by pathologists to perform grading and analysis the stages through applying visual inspection of the histological samples under magnifying glasses.

Due to the uniqueness of breast cancer histopathology images, the fundamental idea of the early research is to pretreatment and segment BC histopathology images first, and then perform feature
extraction and classification. With the increasing maturity of deep learning methods, lately, more and more studies have applied deep learning methods to automatically classify BC histopathological images. This article reviews the traditional classification methods of manually extracting BC histopathological image features and the deep learning methods for automatical breast cancer histopathological image features extracting, and respectively highlights the advantages and disadvantages of the above-mentioned methods. Subsequently, it analyzes the research of combining deep learning and other methods to classify BC histopathological images and wrap up the conclusions and future development trends of BC histopathological image classification research.

2. Breast Cancer Histopathological Image Classification Based on Artificial Feature Extraction and Traditional Machine Learning Algorithms
The traditional classification of breast cancer histopathological images consists of five modules shown in Figure 1 [5]. The most critical module is feature extraction. Some commonly used image feature extraction algorithms have also been applied to the classification of breast cancer histopathological images.

2.1. Artificial feature extraction
Common image features include color features, texture structure, gray-scale distribution, etc. Many researchers have done research on this.

Local Binary Pattern (LBP) is an operator used to describe the texture characteristics of an image. It was first developed by Oulu University’s Ojala proposed [6]. In 2002, Ojala published an article on the LBP operator on PAMI [7], which clearly stated that the multi-resolution, gray scale is not The LBP operator with degeneration, rotation invariance, and equivalent pattern improvement. Guo et al. [8] proposed a Completed Local Binary Pattern (CLBP) operator which is different from the traditional LBP operator. It has three descriptors, namely CLBP-M, CLBP-S, CLBP-C, these three descriptors can be fused in the form of histograms in series, parallel or series-parallel, which significantly improves the classification of texture features. Use the extracted texture features as the classifier Input to distinguish benign and malignant images of breast cancer.

2.2. Machine learning algorithm
In the classification of early BC histopathological images, researchers have done a large number of research and made many important research progresses.

Kowal et al. [9] used adaptive threshold technology and Gaussian mixture clustering to analysis breast cancer tissues. The cell nucleus in the pathological image is segmented, the accuracy rate on 500 BC histopathological images is between 92% to 98%. Because most of the nucleus segmentation
algorithms cannot perform well on high-resolution BC histopathological images in the work, Filipczuk et al. [10] used the circular Hough Transform method to estimate the position of the cell nucleus and proposed a breast cancer diagnosis system based on fine-needle biopsy histopathological image analysis to distinguish the histopathological images of BC as malignant or benign. Four classifiers trained with 25-dimensional feature vectors have an accuracy of 98% on a data set composed of 737 images. George et al. [11] not only used circular Hough transforms to detect histopathological images of breast cancer cell nucleus position in, also used fuzzy C-means clustering and Otsu threshold method to remove the noise in the image, using several machine learning models, such as support vector machine and neural network, obtained on a database composed of 92 images 76% to 94% accuracy rate. Aim at improving the algorithm robustness, Wang et al. [12] proposed a method of using a computer-aided diagnosis system to analyse breast cancer histopathological images, which uses multi-scale regional growth the method combined with wavelet transform is used to detect and segment the nucleus of the region of interest in the image, and then use the SVM algorithm to classify 68 BC histopathological images, with an accuracy rate of 96.19%. Osareh et al. [13] combined with recent Methods such as K-Nearest Neighbourhood (KNN), Probabilistic Neural Network (PNN) and Support Vector Machine (SVM), are used to diagnose BC to distinguish malignant and benign breast tumors.

3. Breast Cancer Histopathological Image Classification Based on Deep Learning

After decades of development, deep learning methods have absorbed a lot of knowledge in neurology, statistics, and applied mathematics. Recently, due to the continuous enhancement of computer performance, larger data sets and some new training deep networks Technology has been used in image classification and recognition.

Fabio et al. [14] used the AlexNet network on the BreaKHis dataset to use different fusion block classification probabilities. This method can automatically extract image features and classify, and the accuracy rate is 6% better than traditional Machine Learning algorithms. To explore BreaKHis data Set an algorithm independent of magnification and further improve the accuracy of classification. Bayramoglu et al. [15] first proposed a classification algorithm independent of magnification, to predict malignant tumors a single-task Convolutional Neural Network (CNN) are using, and a multi-task CNN are using at the same time. Predict the magnification of malignant tumors and use deep learning methods to classify BC histopathological images with different magnifications. The accuracy is about 83%. The features encoded by Fisher vectors [16] have good classification potential, Song et al. [17] were inspired by this and proposed a classification model that combines convolutional neural networks and Fisher Vectors, applied it to the BreaKHis dataset to classify BC histopathological images, and the accuracy was further improved. Fisher vectors has two problems that may limit its effect: sudden visual elements and high dimensionality. To solve these problems, Song et al. [18] designed a supervised embedded algorithm with a multilayer neural network model, which will be based on volume the Fisher vectors of the product neural network are transformed into more discriminative feature representations, thereby obtaining a larger discriminant space.

CNN are used in image classification and recognition, object recognition, natural language processing and other fields have been widely used, laying the foundation for the application of convolutional neural networks in breast cancer histopathological images.

4. Breast Cancer Histopathological Image Classification Based on Hybrid Methods.

Current research has shown that the use of deep learning methods to classify breast cancer histopathological images can greatly improve the accuracy of histopathological image classification. However, the lack of vast sample datasets for learning limits the performance of deep learning networks. Hence, scholars try to combine multiple technologies to solve this problem.

4.1. Transfer Learning + Deep Learning
Humans have discovered that if they apply the previously learned knowledge to some new problems, they can solve them quickly or achieve better results. This method is called transfer learning. The difference between traditional machine learning and transfer learning process is shown in the figure 2.

![Diagram showing the difference between traditional machine learning and transfer learning](image)

**Figure 2.** The difference between traditional machine learning and transfer learning process [19].

Spanhol [20] uses the transfer learning method to extract the depth features of a set of breast cancer histopathology images using the weights of the pre-trained BVLC CaffeNet architecture and input them to the classifier, making the accuracy rate reach 83.6%-84.8%. He et al. attempts to avoid the complexity and limitations of manually extracting features, an improved deep learning model is adopted to realize the automatic classification of breast cancer histopathology. Due to the small number of samples in the data set, it uses advanced data enhancement and transfer learning to prevent overfitting during the training process, thereby improving the accuracy of image classification. To solve the problem of excessive training time, Ahmad et al. [21] used AlexNet, GoogleNet and ResNet pre-trained on ImageNet to classify breast cancer histopathological images. This method has reached 85% accuracy, effectively solving the problem of excessive training time and the problem of insufficient training set data.

4.2. **Convolutional Neural Network + Recurrent Neural Network**

Yan et al. [22] has proposed a new hybrid convolution and recurrent neural network for breast cancer histopathological image classification. Based on the richer multi-level feature representation of plaques in histopathological images, the advantages of convolutional neural networks and recurrent neural networks are combined, and the short-term and long-term spatial correlations between plaques are preserved. Experimental results show that the average accuracy rate reaches 91.3% for the four classification tasks. Yao et al. [23] has proposed a new deep learning model that uses two different types of neural networks CNN (DenseNet) and RNN (LSTM), as well as special perceptron attention mechanisms commonly used in the NLP field [24] to unify images features extracted from two different types of networks. It combines the latest switchable normalization method and target dropout regularization technology to improve the performance and robustness of the model. The accuracy of this model on the Bioimaging 2015 dataset is 97.2%.

5. **Conclusion and Future Research**

This research findings on the breast cancer histopathological images classification of this paper are summarized as the following:

- The use of traditional machine learning methods in histopathological images classification of breast cancer requires the assistance of the professional clinical knowledge of pathologists, and the entire feature extraction process requires a lot of time and energy, and the quality of the extracted features is not high, which seriously restricts the traditional Application of machine learning methods in the classification of histopathological images in breast cancer diagnosis.
Deep learning can automatically learn features from numerous images, avoiding the complexity and limitations of manual feature extraction in traditional algorithms.

The absence of various public data sets limits the development of the medical image field. Transfer learning is helpful to resolve this problem, but it is not good enough. More methods should be tried to analyze histopathological images of breast cancer, such as Generative Adversarial Network.

Since different studies are carried out under different data sets, it is impossible to compare the obtained results based on various algorithm setting. Therefore, it is necessary to construct a large public breast cancer histopathology image database for automatic breast cancer image Classification field.

Only focusing on accuracy as an evaluation index cannot objectively reflect the performance of an algorithm. F1 value and Area Under Curve (AUC) can be more practical to evaluate the performance of an algorithm in a more comparatively manner.

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