Research on Image Classification of Pathology Based on Deep Learning

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Abstract: Histopathological image classification based on in-depth study is one of the significant methods for diagnosing diseases. Pathology image information is complex, diverse, and has a large number of features, which leads to difficult classification and low diagnostic accuracy. Building computer-aided diagnostic tools using image processing and artificial intelligence techniques can dramatically improve pathologists' productivity and reduce error rates. The classification methods for histopathological images mainly included the traditional machine learning methods based on manual feature extraction and deep learning-based pathology image classification methods. The classification accuracy of principal component analysis (PCA), random forest (RF), and support vector machine (SVM) in the traditional machine learning methods were 99.05%, 88%, and 80-85%, respectively. In the deep learning method, the classification accuracy of the convolutional neural network GoogleNet, AlexNet, and deep residual network ResNet is 91%, 99.74%, and 97.4%, respectively. Compared with the shortcomings of traditional classification methods of pathological images, the histopathology image classification methods of deep learning have obvious advantages, but there is also over-dependence on data labeling, feature extraction, and algorithm models, which need to be improved and improved in the future.

Keywords: Disease Diagnosis; Histopathological Images; Deep Learning; Image Classification

1. Introduction

For the diagnosis of most cancer diseases, histopathology—which examines disease symptoms through microscopic tissue structure observation—is regarded as the gold standard [1] and an important basis for accurate classification of pathological images [2-4]. In general, a patient's tissue specimen is stained with a special color to highlight components of interest in the tissue, such as glands, lymphocytes, cancer nuclei, etc [5]. It is an essential part of disease grading and diagnosis that the pathologist looks under a microscope at the features of the tissue structure. However, this approach is labor intensive, and diagnostic findings are affected by cognitive diversity caused by the absence of quantitative analysis [6]. Whole Slide Image (WSI) scanners can scan tissue images and preserve the results as digital pathology images thanks to advancements in digital pathology technology. Digital pathology image information is complex, diverse, and has a great deal of features, which leads to difficult classification and low diagnostic accuracy. The development of computer-aided diagnostic tools through image processing and artificial intelligence has the potential to significantly increase pathologists' productivity and decrease their error rate. Histopathological image classification based on in-depth study is one of the significant methods for diagnosing diseases. Histopathological image classification based on in-depth learning has good clinical application significance and prospects. Currently, the classification of histopathological images falls into two main groups: the traditional machine learning methods based on manual feature extraction and deep learning-based pathology image classification methods.

2. Traditional Machine Learning Classification of Pathological Images

2.1 Exploration of Pathological Image Classification by Traditional Machine Learning

With the advancement of artificial intelligence technology in recent years, especially in the field of machine learning, a significant amount of study has been done on the classification of histopathological images. Traditional machine learning algorithms use classification models such as Gaussian Mixture Model (GMM), Principal Component Analysis (PCA), K-means, Random Forest (RF), and Support Vector Machines (SVM). In 2016, Wang et al. [7] used SVM to classify pathological images of breast cancer, reaching a 96.19% accuracy rate, with 93.33% specificity and 99.05% sensitivity, respectively. An image processing technique was presented by Zhang et al. [8] based on an ensemble model of principal component analysis to classify pathological breast cancer images, validating the effectiveness of their method on two different datasets with an accuracy of up to 88%. Spanhol et al. [9] introduced the Breast Cancer Histopathological Image Dataset (BreaKHis) in 2016, which includes benign and malignant images. They used random forest (RF) for classification, achieving accuracy between 80% and 85%, indicating there is still room for improvement. Traditional machine learning algorithms applied to the classification of pathological images have significant limitations, as they struggle to adapt to the diverse variations of pathological diseases and exhibit poor generalization ability.

2.2 Problems in Traditional Machine Learning Pathological Image Classification

Compared to CT, MRI, ultrasound images, etc., it is relatively difficult and cumbersome to obtain pathological images. Although WSI technology has emerged, pathological images contain a large amount of information, and differences in tissue types, cell types, staining materials, and the unevenness of image backgrounds will all have a serious impact on the identification and classification of pathological images and the robustness of classification algorithms [10]. The classification of pathological images faces various challenges: (1) Difficulty in obtaining pathological datasets, lack of substantial, publicly available annotated datasets. (2) The lack of authoritative pathological experts and the immaturity of automatic labeling technology. Pathological slice images need to be carefully labeled by pathological experts before they can be used for data analysis, and currently, automatic labeling technology is still immature. (3) The subjectivity of pathological expert judgment criteria directly affects the results of image classification.

3. Deep Learning for Pathological Image Classification

3.1 Convolutional Neural Networks for Pathological Image Classification

Convolutional Neural Networks utilize their end-to-end learning mechanism to input images into the network, where each layer of the network extracts information from the image's various layers. According to research in computer vision [11], as the layers of neural networks deepen, the extracted information becomes more abundant. In the classification of pathological images, the most commonly used convolutional neural networks include VGG, GoogleNet, and LeNet.

He Xueying et al. improved GoogleNet by using transfer learning and data augmentation to prevent overfitting, which is a result of training restrictions. The precision with which pathology pictures of breast cancer are classified can reach 91%. Zheng Qunhua et al. used AlexNet as the architecture of a convolutional neural network for the four-classification of breast cancer pathological images. By using the image blocking idea, the classification results of each block of images are integrated as the image's classification results using a majority voting algorithm. According to the experimental data, this model has a 99.74% recognition rate.

3.2 Application of Deep Residual Networks in Pathological Image Classification

The solution of deep residual networks is to introduce residual modules into deep convolutional neural networks. The core of residual networks is to directly send data to the output, maintaining the accuracy of the data. The learning objectives and difficulties are simplified, because the entire network just needs to learn the portion that differs between the input and output, and to some extent, improve the model's generalization ability. Wang Heng et al. [12] used a ResNet-50 as the basic network framework and utilized transfer learning to classify pathological images of breast cancer. Through experiments on the pathological dataset BreaKHis, the classification accuracy can reach 97.4%. However, there would still be cases of large parameter quantity, difficulty in training, and poor model generalization performance. Yun Jiang et al. [13] designed a new convolutional neural network, which consists of small SE-ResNet modules, convolutional layers, and fully connected layers. By reducing the number of training parameters in the model and lowering the danger of overfitting, the small SE-ResNet module improves upon the residual module and squeeze-and-excitation operation. Experimental results show that in contrast to the basic SE-ResNet and bottleneck SE-ResNet, the parameters of the small SE-ResNet have decreased by 33.3% and 29.4%, respectively.

3.3 Densely Connected Networks are Used for Pathological Image Classification

Densely connected networks connect the inputs of all layers to the outputs on the basis of the residual network, and the purpose of this is to guarantee that the networks' information flow is optimized, which is also the advantage of DenseNet. With a smaller number of parameters than ResNet, inputs and outputs are directly coupled to every layer, and bypass enhances feature reuse. In addition, the network is easier to train and has a certain regular effect, which not only alleviates the issue of gradient explosion and gradient vanishing, but also alleviates the overfitting of the model. In the last several years, many researchers have also used it for pathological image classification. Ziliang Zhong et al. [14] slightly modified the dataset PatchCamelyon and proposed a DenseNet-based image classification model for metastatic cancer. Experiments have shown that this model can effectively identify metastatic cancer, and after comparison, this model is superior to other classical methods, such as ResNet34, VGG19, etc. Although this method can classify pathological images, the model is too simple, and the extraction of image information is single, and it does not have good generalization ability. Chen CM et al. [15] developed a convolutional neural network computer-aided diagnostic system based on dense connections for delineating malignant targets in histopathological images. By using a ranklet transform-based color normalization procedure to adjust the image's intensity and segment the areas of tissue structure using several tissue identification patterns and spatial probabilities, these multidimensional structures are integrated into a densely connected convolutional neural network to determine benign and malignant prostate regions. The experimental findings demonstrate that compared with the previous similar methods, there is a great improvement, which is of great help in delineating the malignant area and classification.

Table 1. Comparison of Several Traditional Machine Learning Methods with Deep Learning Methods

Traditional machine learning		Deep learning	
Methods	Classification accuracy	Methods	Classification accuracy
Principal Component Analysis (PCA)	99.05%	Convolutional neural networks (GooleNet)	91%
Support vector machines (SVM)	88%	Convolutional neural networks (AlexNet)	99.74%
Random forest (RF)	80-85%	Deep residual network (ResNet)	97.4%

3.4 Auto-encoder is Used for Pathological Image Classification

The key to an auto-encoder is the process of encoding and decoding the raw data. Encoding is a process of dimensionality reduction, in the process of network training, the auto-encoder will only use a few elements in the data, which are considered useful information for the network, and extract them to find patterns between the learned data. Li X et al. [16] used a fully convolutional auto-encoder to understand the main structural motifs found in typical images, used a single-class support vector machine and a first-layer neural network to detect and analyze small blocks that do not have the characteristics of the normal population.

4. Summary and Outlook

From the comparison of several traditional machine learning methods with deep learning methods in Table 1 above, it can be seen that compared with the shortcomings of traditional classification methods of pathological images, the histopathology image classification method of deep learning has obvious advantages. In summary, the application of deep learning for pathological image classification has the following advantages and disadvantages and improvement directions: (1) The convolutional neural network-based approach aims to address the reliance of conventional machine learning classification techniques on synthetic feature extraction, which can automatically extract the detailed features of pathological images and can be represented at each level without manual special annotation. However, as the network depth increases, the transmission of information will gradually weaken, and the gradient will disappear. (2) To address the issue that gradient explosion and gradient vanishing will occur in convolutional neural networks, the model based on deep residual networks introduces a residual structure in convolutional neural networks to strengthen the connection between input and output. (3) The model based on a densely connected network is a more extreme approach based on the deep residual network, which can effectively discover new features in the dataset and enhance the model's accuracy. Owing to the complexity of the model, it could be more difficult to train, and most researchers will use it in conjunction with transfer learning. (4) The auto-encoder-based model solves the problem of difficult data annotation, which can extract the representative features in the dataset without relying on accurate annotation of the data.

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