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Medical Image Classification based on Deep Learning

Xiaolin Ning

School of Shanghai Maritime University, Shanghai 201306, China

*1738951286@qq.com

Abstract

Medical image classification is a medical image that uses a classification algorithm to identify which type of disease the image belongs to, or whether it is a benign disease or a malignant disease. As a hot spot in the field of computer vision research, image classification provides a good and convenient way for medical image recognition and processing and reduces the burden of medical work. Medical image classification is also an important basis for disease detection, disease recognition and human posture estimation. This article introduces the current research status of deep learning in medical image classification and recognition, related deep learning models for classification, data sets and model evaluation standards, current problems and future development trends of medical image classification.

Keywords

Deep Learning, Neural Network, Breast Cancer Image, Lung X-Ray Image, Image Classification.

1. Introduction

According to statistics from the World Health Organization, the number of people dying of cancer in the world may reach 27 million by 2030. [1] The number of medical images that need to be processed is also increasing, The task of classifying and identifying medical images is intensifying. Relying on doctors to recognize X-ray images or CT images to diagnose diseases requires a large number of workers with professional knowledge and relevant experience, the fatigue caused by doctors during long hours of work cannot guarantee the accuracy of the diagnosis results. The occurrence of the new crown epidemic even shows that when a large amount of image data needs to be processed, it is very stressful to rely solely on doctors for diagnosis, it is necessary to use image recognition and classification methods to help doctors assist in diagnosis. Medical image classification methods include traditional medical image classification methods based on artificial features and medical image classification methods based on deep learning. The manually extracted features are classified with support vector machines, random forests and other classifiers. The general steps of medical image classification processing are image preprocessing, feature extraction and classifier design. Image preprocessing includes image data enhancement (rotation, cropping, deformation, scaling, blurring, etc.), median filtering [2], Gaussian filtering [3], normalization and other operations. In the feature extraction stage, the gray-scale features, texture features, etc. of the image are extracted from the medical image and the identification feature area is selected. It transforms the input image according to certain rules to generate another feature representation with certain characteristics. New features have the advantages of low dimensionality, low redundancy, low noise, etc., thereby reducing the requirements on the complexity of the classifier and improving the performance of the model. Finally, the extracted features are classified by training the classifier so as to realize the classification of the image.

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Medical image classification based on deep learning is used to train a neural network to autonomously learn image features and train to obtain appropriate network parameters to classify the input images. The advantage lies in avoiding the area limitation of manual feature selection and the error of feature selection. In addition, deep learning has extensive research and application in image recognition, face recognition, object detection, pose estimation, etc. This provides good technical support for medical image classification. The deep learning network used in the medical image classification method based on deep learning includes convolutional neural network CNN, ResNet, VGG, yolov3, etc.

With the development of deep learning technology, more and more researchers have begun to study the application of deep learning to the medical field. Spanhol[4] et al. used LeNet [5] and AlexNet[6] models to classify breast cancer tumors into two types, benign and malignant, with accuracy rates of 72% and 80.8%~85.6%, respectively. Li et al. [7] based on the DenseNet model method, proposed a new deep learning network DenseNet for pathological image classification, using stepless convolution of dense blocks to achieve multi-scale feature extraction, and achieved 93.29% four classification accuracy. Campilho et al. [8] combined the Resnet and Inception-v2 models to classify breast cancer pathological images, the accuracy of the four classification tasks was 76%. Rakhlin et al. [9] proposed a calculation method for breast cancer pathological image classification based on deep convolutional neural networks, which combines the advantages of the ResNet50, vgg16 and Inception_v3 models, it achieves an accuracy of 87.2% for the four types of classification tasks. Accuracy of two classification tasks was 93.8%. Suk [10] et al. proposed a SAE-based latent feature representation method, which combines latent features with original features to establish a robust model. [11] proposed a semi-supervised learning model, introduced a deep learning framework to assist in the diagnosis of Alzheimer's disease, used a small amount of labeled information and used a zero-masking strategy to fuse multi-modal neuroimaging features. [12] proposed a CNN-based mammary gland density classifier, which classifies different types of mammary gland density types through a data containing 22,000 mammary gland x-rays. Zhang [13] et al. applied the CNN [6] model to the classification and diagnosis of two-dimensional breast images and used the optimized performance of transfer learning. Examples of early disease diagnosis based on supervised learning include Ciresan, etc., using a special deep artificial neural network as a pixel classifier to segment biological neuron membranes. This is the first time that deep neural networks have been applied to medical images. Literature [14] trained the CheXNet network with the lung image data set of chest-xray14 database and the results of pneumonia detection were outstanding. Dorj[15] et al. used the existing cnn model for feature extraction and used error correction coding support vector machine to classify skin cancer lesions. The average accuracy, sensitivity and specificity have achieved good results. Jiao et al. obtained hierarchical deep learning features through CNN learning, which improved the classification level of breast images. Sheng Kai, Liu Zhong, Zhou Dechao, etc. [16]. A multi-class semi-supervised classification algorithm based on evidence theory is proposed, which improves the classification accuracy of semi-supervised in multi-class classification. Yao et al. [17] proposed the use of long-term and short-term networks to study the correlation of pathological labels of 14 types of lung diseases, and proposed to add long-term and short-term networks to the DenseNet network to learn the correlation between pathological labels of various diseases. HuJ[18] proposed compression and excitation modules (Squeeze-and-Excitation, SE) and compression and excitation networks (Squeeze-and Excitation Networks, SENet) to better extract the space between features and the associated information between channels. The SE module weights features to varying degrees by learning the correlation between features in different channels, increasing the weight of important features and reducing the weight of non-important features. Zehra KARHAN, Fuat AKAL [19] proposed Covid-19 Classification Using Deep Learning in Chest X-Ray Images did a good job of detecting new coronary pneumonia.

This article summarizes the current mainstream medical image classification model based on deep learning. The second part is a brief introduction to medical image classification, the third part is a detailed discussion of the related models of medical image classification based on deep learning, the fourth part introduces related data sets, commonly used model evaluation standards , The future development trend of the medical images classification is summarized in the fifth part. The last part summarizes the article.

2. Medical Images Classification

2.1 Medical Images Classification based on Deep Learning

Image classification methods based on deep learning include supervised classification methods, semi-supervised classification methods, and unsupervised classification methods. The supervised classification method is to train and classify in the case of known labels and guide the output results. The semi-supervised classification method is to train under a small amount of labeled data to recognize and classify a large amount of unlabeled data. The method of unsupervised classification is to use unlabeled data for learning and training and to classify unlabeled data.

Different imaging methods of medical imaging include X-ray, tissue biopsy, computed tomography (CT), magnetic, resonance imaging (MRI), positron emission tomography (PET), ultrasound, etc. Medical image classification tasks mainly use different texture features, geometric features, morphological features and optical density features of benign lesions and malignant lesions to analyze gray-scale features, geometric features, and morphological features between different diseases to select features Parameters, infer different types of features through inversion to achieve classification effects. The main research content of medical image classification includes four parts: image preprocessing, image feature extraction, classification decision and diagnosis results.

The medical image classification method based on deep learning improves the shortcomings of traditional medical image classification method. The manual extraction of features is limited to a certain range, low-level features and high-level features cannot be merged. The one-sidedness of feature extraction makes it difficult to effectively contain changes. The various features above these problems. The medical image classification method based on deep learning can learn more generalized feature representations to adapt to the actual diagnosis and treatment scene. The detection of various medical images can help doctors diagnose and improve the accuracy of image classification.

2.2 Traditional Methods of Medical Image Classification

The traditional medical image classification method is to manually select features and select a classifier for classification. Li Hua, Yang Jianeng [20] introduced in his article that traditional breast pathology image classification methods often use image segmentation techniques, such as nucleus-based segmentation methods and many commonly used image analysis algorithms, such as watershed algorithm, active contour, K-means clustering algorithm and region growing, etc. Through the analysis of cell nucleus related features and internuclear tissue morphology, the image morphology, texture and other related features are extracted, traditional classifiers such as Support Vector Machine (SVM) or classifiers designed based on specific problems are used to perform image processing. In the feature extraction part, general feature descriptors are often used, such as Scale Invariant Feature Transform (SIFT), Gray-Level Co-occurrence Matrix (GLCM) and Gradient Direction Histogram (Histogram of Oriented Gradients, HOG) etc. Generally speaking, traditional medical image classification methods are processed by traditional classifiers such as multi-layer perceptrons and support vector machines, which require highly demanding professional and technical personnel in the feature extraction stage.

The current problems of medical image classification are as follows: because of patient privacy and the use of a large number of medical devices leads to funding problem have made public medical data sets few and labeled data sets even fewer, however supervised learning requires a large amount of labeled data, which has brought obstacles to the research of deep learning algorithms; medical image features interfere with each other, overlap in different areas and different image brightness caused by different acquisition devices, which leads to the ambiguity and complexity of image features, Medical image signal-to-noise ratio is low, X-ray image acquisition cannot guarantee complete information, X-ray imaging has certain limitations, it is easy to overlap two-dimensional image information of multiple tissue parts, which brings challenges to classification; image labeling requires professional doctor handles the treatment and the pathologist needs highly professional training and rich experience in reading pictures,however these experiences and professions are difficult to inherit and innovate. The doctor's labeling is subjective, and the correctness of the analysis result cannot be guaranteed under the tired state, the diagnosis result of different doctors may be different.

The medical image classification method based on deep learning uses neural networks to perform feature learning autonomously, which solves the limitations of artificial feature extraction and solves the problems of inherent complexity, diversity, and lack of professional physicians to label the medical images. On the other hand, in view of the problem of the small amount of labeled data in medical images, deep learning can be better improved through semi-supervised classification, small sample learning,and transfer learning methods.

3. Deep Learning Model

Many structures in deep neural networks are used in medical image classification, such as convolutional neural networks, generative adversarial networks, deep residual networks, densely connected networks, and yolov3. These models are briefly introduced below.

Convolutional neural networks are inspired by the structure of the human brain, imitating the human brain for information learning and processing. The concept was proposed in the 19th century. The convolutional neural network structure includes input layer, convolutional layer, pooling layer, activation function, fully connected layer and output layer. The structure diagram is shown in Fig. 1. The convolutional layer selects features of different ranges through the convolution kernel. The low-level convolution layer can learn low-level features such as edges and the high-level convolution learns high-level abstract features. The pooling layer is usually connected after the convolutional layer to reduce the dimensionality of the features to ensure the scale invariance of the features, rotation invariance [21] and translation invariance.The specific operation of pooling is shown in Fig. 2. The input is connected to the fully connected layer to obtain global semantic information after the operation of the convolutional layer and the pooling layer. The extracted features are classified in the classification task to obtain the probability distribution based on the input image. Finally, the classifier is connected in the output layer and output the probability value of belonging to a category. Due to the deepening of the network structure, there will be problems such as gradient disappearance and gradient explosion during the training process. The activation function is derivated and multiplied by the weight is greater than 1 and the result of the continuous multiplication continues to increase. The gradient disappears because of the result of multiplying the derivation of the activation function and the weight function is less than 1, the result is getting smaller and smaller after continuous multiplication. The solution is to use Relu, LeakyRelu activation functions, and batch normalization. By standardizing the output of each layer as the mean and variance, it eliminates the effect of zooming in and out of the weight, and then solving the gradient disappearance and explosion.

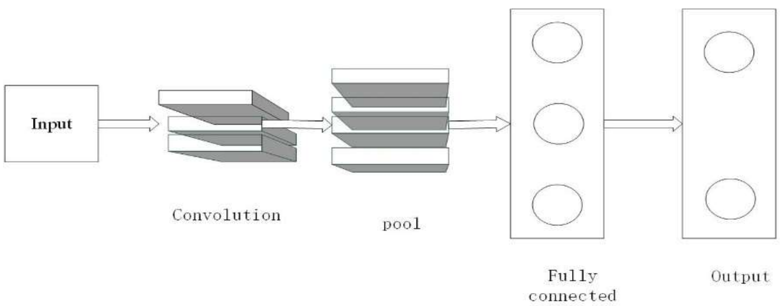

Fig. 1. The structure of CNN

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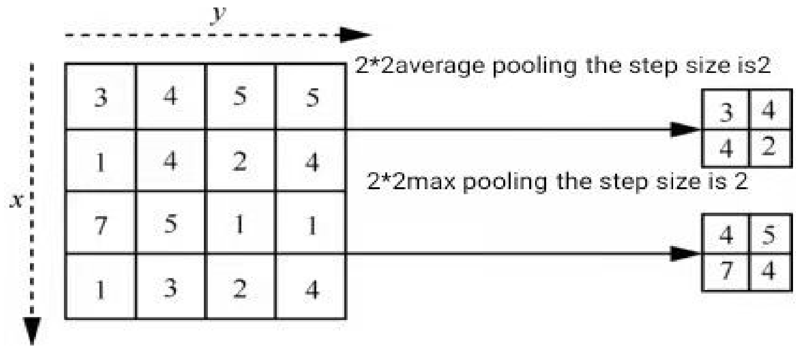

Fig. 2. Schematic diagram of pooling process

3.1 Generative Adversarial Network

In 2014, Google proposed the original generative confrontation network(GAN) [22]. Its idea is derived from the zero-sum game theory. The network structure is composed of generators and discriminators. During the training process, the generators and discriminators continuously optimize their own parameters. The generated image is expected to be considered by the discriminator to be a real image,the discriminator requires that it can correctly identify the generated image. In this process of confrontation training, the Nash equilibrium is finally reached, so that the model achieves the optimal effect. In view of the adversarial training idea of GAN, it stands out among many training models, so it widely used in image recognition and classification, as well as in medical image classification and recognition. With the research of scholars, GAN is continuously optimized and new models appear. Zhang H, Xu T, Li HS and others proposed StackGAN [23] in 2017, which is the first network to generate images with a resolution of 256×256 based on text descriptions. Model. InfoGAN[24] was proposed by Chen X, Duan Y, Houthooft R and others in 2016. It divides the input noise z into two parts, one part is the noise signal z and the other part is the interpretable implicit signal c. The problem of unclear correspondence between input noise and data semantic features. Brock A, Donahue J, Simonyan K proposed BigGAN[25] in 2018. Under ImageNet (128×128 resolution) training, IS (inception score) is as high as 166.3. BigGAN gains performance improvement by expanding the model. It is in training. large Batch (2 048) is used and a larger number of channels is used in the design of the convolutional layer. In the field of biomedicine, Schlegl et al. [26] proposed WGAN [11] (wasserstein GAN) to detect diseased retinal optical coherence tomography imaging data to achieve good detection results; Wolterink et al. [27] used WGAN to synthesize the geometry of blood vessels, It is used to supplement the CT angiography of the coronary heart, which is convenient for the follow-up study of this type of image.

The training process of GAN is:

1) Randomly sample and generate a random vector Z in a specific distribution, input the random vector into the generator network G to obtain a simulation image G(Z);

2) Input the sample image X and the simulated image G(Z) into the discriminator network D in batches and output the normalized probability values D(X) and D[G(Z)] through softmax;

3) Fix the parameters of the generator network G and train the discriminator;

4) Fix the parameters of the discriminator network D and train the generator;

5) Repeat steps 1) to 4) until the number of iterations is reached;

6) Input the test sample image into the discriminator Dmand output the image category.

The training of generative adversarial network is simply to minimize generator loss and discriminator loss, expressed in mathematical formula as:

$$\min_G \max_D E_{x-pdata(x)}[\log D(x)] + E_{z-pz(z)}[\log(1-D(G(z)))] \tag{1}$$

The essence is to minimize the KLD of ps and pdata, that is, the difference between the two distributions (1) is also the state of generating the Nash equilibrium of the adversarial network. Pdata represents the real data distribution, ps represents the data distribution generated by the generator through a specific distribution variable Z.

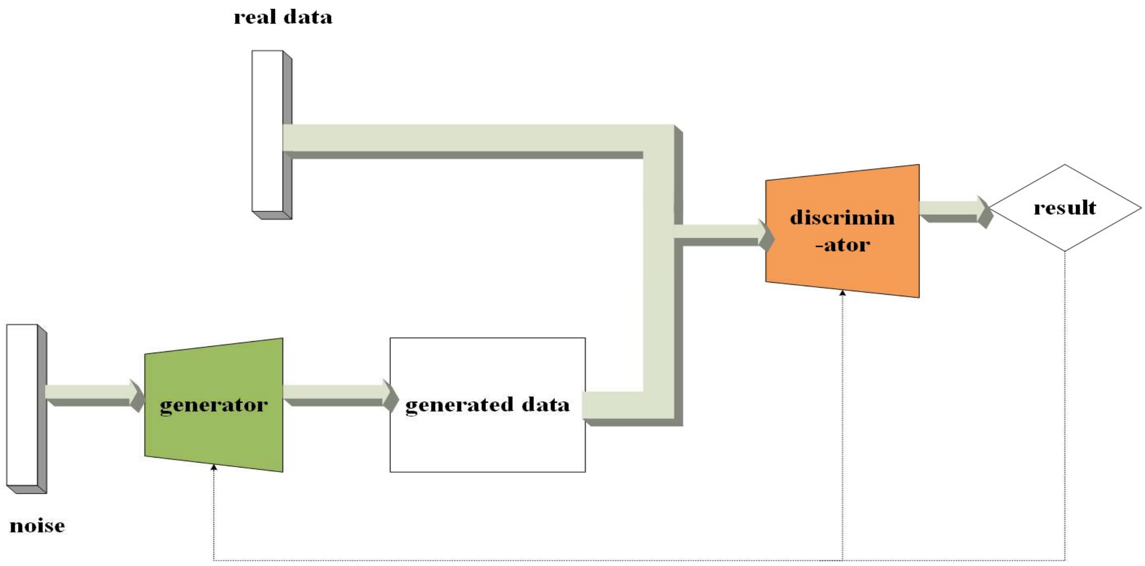

Fig. 3. The structure of GAN

The generator is a differentiable network that accepts random variables Z to generate fake samples. The generator learns the probability distribution to approximate the generated image as much as possible to the real sample. The discriminator is also a differentiable network, which discriminates whether the input data is real data and feeds the result back to the generator to guide the generator training. When the output result of the discriminator is 0.5, it indicates that the generator and the discriminator training reach a balanced state.

The feature of GAN is that compared with traditional neural network CNN, GAN can learn loss function and adjust self parameters. The generator can generate some samples, which can solve the problem of Insufficient sample. Compared with intensive learning and transfer learning, the strategy of adversarial learning is more in line with human thinking habits and the network structure is optimized to be more robust.

3.2 Yolov3 Network

The Yolov3 network structure diagram is shown in Fig.4. The network structure is widely used in the field of target detection and object recognition. The characteristics of the network are as follows:

Use the DarkNet-53 network and integrate ResNet to prevent the loss of effective information and prevent the gradient from disappearing during deep network training; without the Pooling layer, use Conv for downsampling to further prevent the loss of effective information.

Multi-Scale strategy, here includes Multi-Scale Train and Multi-Scale Predict. Multi-Scale Train uses images of different sizes as input during training, so that the model can adapt to images of different sizes; Multi-Scale Predict takes different sizes of down-sampling during prediction. That is FPN (Feature Pyramid Networks) architecture .YOLOV3 performs target detection at sub-sample is 32, 16 and 8 respectively, so that targets of multiple sizes can be predicted.

Category prediction is mainly to improve the original single-label classification to multi-label classification, so the network structure replaces the original softmax layer for single-label classification with a logistic regression layer for multi-label classification.

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We use this network to perform experiments on lung X-ray image data, using six types of data in chest-xray data, using 0.7 of 6000 image as the labeled training set and 30% of the data set as the test set. The algorithm design is as follows.

Algorithm.

Input: training set.

Output: Probability value of which category it belongs to.

Begin:

1). Dataset production, the dataset is divided into training set and test set according to 7:3.

2). Design cross entropy loss function in $-\sum_{1}^{N} y^{i} \log y\wedge^{i} + (1-y^{i})\log(1-y\wedge^{i})$ formula y^{i} represents the real label $y\wedge^{i}$ represent network predictions labels.

3). Send the training set to the training network.

4). When a certain number of iterations is reached, the network training is completed and the test set is sent to the trained network for network testing.

End.

The final experimental results are shown in Fig. 5. Experimental results show that the network has achieved a classification accuracy of 90% and even more than 90% on the dataset.

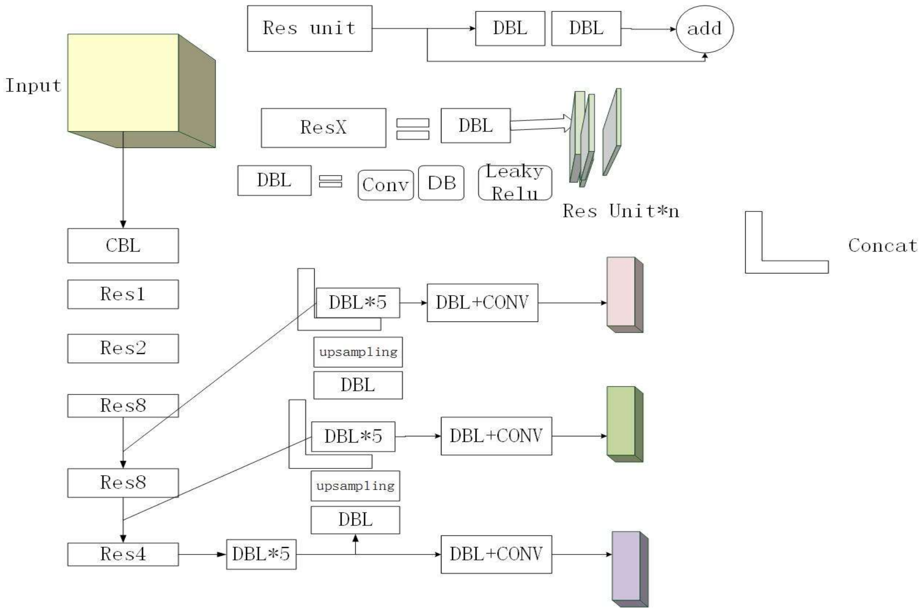
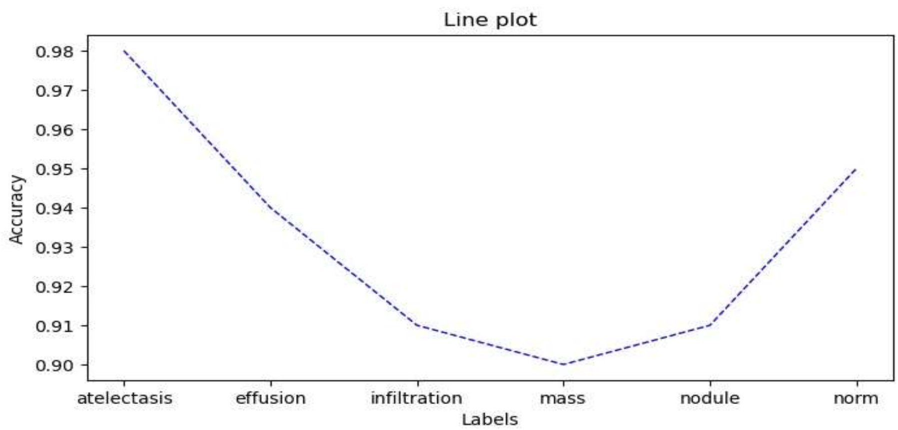
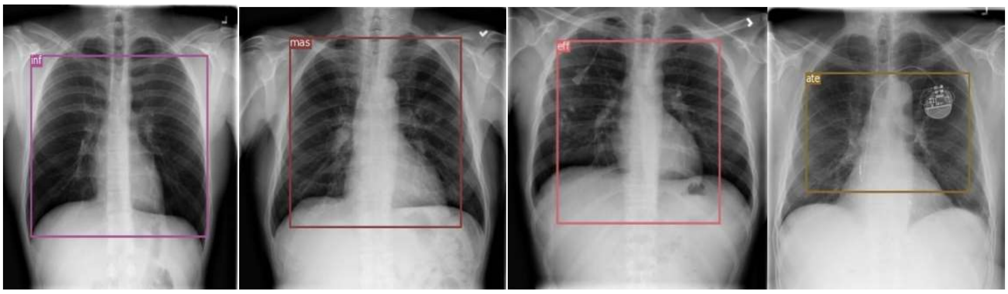


Fig. 4. The structure of yolov3



(a)



(b)

Fig. 5. Experimental results

4. Introduction and Evaluation Criteria of Medical Image Dataset

4.1 Medical Image Dataset

Due to industry regulations in the medical industry, patients' privacy issues, medical equipment's cost of capturing images and the need for professional doctors to label images, the number and work intensity of professional doctors are limited. These reasons lead to a small number of medical data sets. Currently commonly used public data sets include lung X-ray image dataset (Chest-Xray14 dataset) and breast cancer disease (BreakHis) dataset.

The Chest-Xray14 data set was released by Wang [30] and others. It contains 14 types of lung diseases: atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, pneumothorax, consolidation, edema, emphysema, fibrosis, pleuralthickening, hernia The database contains 11,120 X-ray images of 30,805 patients.

The BreakHis[31] data set includes 7909 images of benign and malignant breast cancers, tissue images collected from 82 patients with different magnifications, the magnifications are 40×, 100×, 200×, and 400×respectively. There are 2480 benign images divided into 4 categories (adenosis (A), fibroadenoma (F), phyllodes tumor (PT), and tubular adenoma (TA),malignant images contain 5429 images divided into 4 categories (ductal carcinoma (DC)), lobular carcinoma (LC), mucinous carcinoma (MC), and papillary carcinoma (PC). The detailed dataset introduction is shown in Table 1 and Table 2.

Table 1. Four types of benign breast cancer data sets

Magnification	A	F	TA	PT	total
40×	114	253	109	149	598
100×	113	260	121	150	614
200×	111	264	108	140	594
400×	106	237	115	130	562
total	444	1014	453	569	2368

Table 2. Four kinds of malignant breast cancer data sets

Magnification	DC	LC	MC	PC	total
40×	864	156	205	145	1370
100×	903	170	222	142	1437
200×	896	163	196	135	1390
400×	788	137	169	138	1232
total	3451	626	792	560	5429

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4.2 Evaluation Criteria for Medical Image Classification

Commonly used evaluation indicators are accuracy, misclassification value, F1, F5, recall rate, precision rate, confusion matrix, ROC curve, AUC, PR curve, AP, mAP.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + TN} \tag{4}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

Among them, True Positive (TP) represents the number of cases that have been correctly identified as having disease, False Positive (FP) represents the number of cases that have been incorrectly identified as having disease, True Nagative (TN) represents the number of cases that have been correctly identified as not having disease. False Nagative (FN) means the number of cases that were incorrectly identified as not having disease.

5. Prospects for Medical Image Classification based on Deep Learning

With the development of deep learning technology in the field of computer vision, with its independent learning of image features to update network parameters, good feature representation, feature learning and feature fusion capabilities. The above reasons promotes the application of deep learning in medical image processing. Deep learning has gained the attention of medical researchers. Combining with the problem that there are many types of medical images, the differences between the classes of features are not obvious, the problem of small amount of labeled data, the development of deep learning in medical image classification can optimize the semi-supervised learning method to solve the problem of small amount of label data or try to use unsupervised classification combined with semi-supervised classification alleviates the problem of low number of tags and improves the usability of medical image data sets.

Reduce the subjectivity of the label. At present, the labels of medical images are marked by professional doctors, which have strong subjectivity and personal experience differences. If possible, they are marked by multiple doctors.

Introduce the global effective information of the image and carry out the contextual information fusion. Conventional CNN is used in medical image classification. ResNet network can not extract the context information of the image well, which has an impact on the accuracy of image classification. Try to combine traditional image classification methods to improve feature fusion and image classification accuracy.

Improve the generalization ability of the network and the algorithm, so that the network not only has a good classification effect on one type of data set, but also has a good processing effect on the processing of multiple or even all medical datasets. Improve the interpretability of the deep learning model, understand the classification system while also knowing how to process the data, which is helpful for subsequent improvement and optimization.

6. Conclusion

About the current medical image classification method based on deep learning, this article introduces the development of deep learning medical image classification, focusing on the relevant medical image classification model, the dataset of medical classification and the evaluation criteria of classification results. The future development trend of medical images based on deep learning. The development of deep learning technology has reduced the burden of image annotation and recognition for doctors to a certain extent, it helped doctors perform auxiliary diagnosis to improve classification and recognition accuracy. The development of deep learning technology and neural network provides new solutions for medical image processing.

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