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Several Applications of Convolutional Neural Networks in Medical Imaging

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Abstract. With the development of artificial intelligence, convolutional networks have powerful multi-dimensional data processing capabilities and can extract and process features in various images, which has great potential in the field of medical image processing. The development of convolutional neural networks has greatly promoted the development of computer aided diagnosis technology. This paper reviews the principle of four kinds of convolutional neural networks, including AlexNet, GoogleNet, U-Net, R-CNN, and their specific application research, such as diagnosis and analysis of brain tumors, classification of skin lesions, and detection of breast cancer. Compared with traditional convolutional networks, these new models have their own advantages and disadvantages. This paper also summarizes the advantages and disadvantages of these four neural networks. In the end, this paper also puts forward some current challenges in medical image research based on convolutional neural networks and the future prospects of medical image analysis technology combined with convolutional neural networks.

Keywords: Convolutional neural networks; medical imaging; application.

1. Introduction

Convolutional neural network technology can find the feature relationship between adjacent pixels by means of convolution. Therefore, in the task of processing multi-dimensional image data, compared with ordinary linear networks (which transform images into one-dimensional information processing), convolutional neural networks can reduce the feature loss caused by the transformation of high-dimensional data to low-dimensional data, and have obvious advantages in image processing. Imaging is an important means of disease diagnosis. Many diseases, such as tumors and skin diseases, need medical imaging to assist doctors in diagnosis. The diagnosis of doctors based on medical images is often related to the experience and ability of doctors, and the diagnostic ability of different doctors is different. In some cases, it will even cause misdiagnosis and affect the treatment of patients. The medical image recognition technology based on convolutional neural network is expected to identify diseases accurately and quickly. There are many variants of convolutional neural networks, including but not limited to AlexNet, VGGNet, GoogLeNet, and ResNet, which have different advantages for different medical images. Transfer learning of such models has been widely used in medical image analysis: CaffeNet and DenseNet models are used for arrhythmia detection and cardiac MRI plane recognition, Pre-trained models such as ResNet, VGG and Inception are used to achieve high-precision classification and detection. In the actual study, M. Desai et al used CNN to detect and diagnose breast cancer [1], Z. Tasnim et al. used the CNN model to classify colon cancer cells [2]. In these complex image processing tasks, convolutional neural networks have good performance and great potential in medical image analysis.

2. Convolutional networks and medical imaging

In the medical field, the diagnosis of diseases usually requires a professional doctor to diagnose diseases by combining medical images such as MRI images and CT images. Therefore, it is necessary to develop models that can accurately determine the health status of patients based on medical images. Convolutional neural networks are good at processing and analyzing complex images. The convolutional neural network trains the neural network through the input of two-dimensional or threedimensional data and the operation of convolution, pooling, deconvolution, etc., and finally trains the model that can accurately judge the patient's condition. Medical images are often complex pictures in color or gray, and convolutional neural networks are very good at extracting features from complex images and segmentation images according to certain laws. Therefore, it has good performance in medical image classification, such as identifying various skin diseases based on skin lesion pictures or segmenting tumors from CT images. At present, convolutional neural networks have many variants, which have their own advantages and disadvantages in different medical image processing tasks.

3. Application of different convolutional networks in medical imaging

3.1. AlexNet

Compared with ordinary convolutional neural networks, AlexNet has more filters in each hidden layer, which reduces noise and enhances features; The convolution layer is followed by the pooling layer, which can retain important features; Using the Relu activation function, gradient disappearance can be slowed down; Using Dropout technology to randomly discard some neurons, slow down overfitting, and improve the generalization ability of the model. Therefore, the AlexNet model has a very powerful classification ability. It is often used in medical image classification problems and has excellent performance. In the classification of skin lesions, according to the experiment, AlexNet was used to carry out transfer learning, and the last three layers of AlexNet were replaced with the fully connected layer, Softmax layer and classification layer. Using the improved AlexNet model, skin lesions can be accurately divided into seven types of lesions, including melanoma, melanocytoplasm and basal cell carcinoma. On the same problem, using frameworks such as VGG, GoogleNet, PolyNet and their assemblies, the highest accuracy was only 85.1%. The accuracy of AlexNet model is as high as 98.87%, the sensitivity is 95.60%, the specificity is 99.27%, and the accuracy is 95.06%, which is at least 6% higher in performance than the previous state-of-the-art methods [3]. In addition, AlexNet and its variants have demonstrated excellent classification ability in brain tumor image classification [4] and prostate cancer MRI image classification [5]. However, AlexNet also has corresponding disadvantages: 1, AlexNet often has more parameters and a large model. The AlexNet model used to classify prostate tumors has 60 million parameters [5]. 2, In order to simplify the design and compute efficiency, AlexNet has specific requirements for the convolution kernel size and input layer size, and the image needs to be preprocessed before input. 3, Compared with models such as ResNet, AlexNet architecture is relatively simple and its performance is limited.

3.2. U-net

U-net neural network has excellent performance in image segmentation, so U-net is widely used in various medical image segmentation tasks. The U-net neural network consists of two main components: the contracting path and the expensive path. Similar to a normal CNN architecture, the Contracting path consists of multiple convolutional neural networks followed by a ReLU activation function and a maximum pooling layer after each convolutional network. The innovation of U-net lies in expensive path. It uses the method of convolution to up-sample the feature map, and then cuts the feature map from the contracting path to the feature map obtained from the up-sample, and then convolution and activation function are used again. In the final output layer of U-net, a 1*1 feature map is used to map the feature map to the desired number of categories. Thanks to the symmetrical structure of U-net and its jump connection, U-net can perform pixel-level image segmentation while ensuring accuracy. There are many variants of the U-net structure, including but not limited to 3D U-Net, Attention U-net, and Edge U-net [6]. The Edge U-net model has a good performance in MRI image segmentation of brain tumors. Edge U-net model adds edge information fusion on top of ordinary U-net model to enhance the accuracy of the restored high-resolution image boundary. And a new loss function is used, which combines the boundary information and makes additional optimization for the accuracy of the boundary information. The Edge U-net model was trained using MRI images of brain tumors. Compared with other models, the highest Dice of this model was 88.8%, 91.76% and 87.28% for meningioma, glioma and pituitary brain tumor, respectively. This model has better segmentation ability on tumor images with complex edges, surpassing the most advanced models [7].

3.3. GoogLeNet

GoogLeNet has a higher efficiency, reducing the size of the input image while ensuring the important information of the image. GoogLeNet has 22 layers that can be learned. Like common convolutional neural networks, Googlenet has convolution layers and pooling layers, which can initially extract features and downsample. Unlike ordinary convolutional neural networks, the Inception module is incorporated. Inception module is composed of 1*1, 3*3 and 5*5 patches or filters. The 1*1 convolution filter can effectively reduce the parameters of GoogLeNet, thus reducing the computation and improving the efficiency. Convolution operations of 3*3 and 5*5 capture spatial features at different scales, while maximum pooling of 3*3 helps downsample and capture key features. Following the Inception module, GoogLeNet uses global average pooling instead of the traditional fully connected layer, further reducing the number of parameters in the model. Finally, the softmax layer is used for classification. Due to its excellent image classification ability, it has important applications in the diagnosis of melanoma [8], the classification of MRI features of brain tumor images [9], and the detection of lung cancer CT images [10]. For the diagnosis of melanoma by GoogLeNet, G. Hirano et al. used data enhancement and GoogLeNet model for learning and prediction, and the accuracy rate reached 77.2%, which was close to the diagnosis level of dermatologists. This model still has a lot of room for improvement and has a good development prospect [8]. T. V. S. S. S. Sekhar et al. used GoogLeNet to carry out transfer learning on the classification images of brain tumor MRI, used SVM and K-NN classifiers to improve the classification accuracy, and trained their model using the publicly available Figshare dataset. The model achieved 94.9% accuracy using Softmax classifier, 97.6% accuracy using SVM and 98.3% accuracy using K-NN classifier [9]. In addition, M. S. AL-Huseiny et al. applied the GoogLeNet model to lung cancer detection, and the overall accuracy of the GoogLeNet model after transfer learning in detecting malignant nodules in lung CT images was 94.38%[10].

3.4. R-CNN

R-CNN's object detection system consists of three modules:1) Region suggestions generation: Use selective search algorithm to generate region suggestions. 2) Feature extraction: Use convolutional networks such as AlexNet or VGG to extract fixed-length feature vectors from each region proposal. 3)Classifier: Use SVM to classify each region. After that, there is boundary box regression, which uses linear regression to adjust the boundary box position in the candidate region and minimize the gap between the predicted boundary box and the real boundary box, so that R-CNN can locate the target object more accurately [11]. The basic R-CNN has the problem of low computational efficiency and long training time. Many researchers have proposed improved versions such as Fast R-CNN, Faster R-CNN, Mask R-CNN. R-CNN has the characteristics of high detection accuracy, modular design, strong applicability, etc., and has a good performance in medical image analysis. Y.Su et al. used convolutional neural network and Faster R-CNN to detect CT images of patients. Compared with traditional algorithms, the detection accuracy was increased by more than 20%, the average accuracy reached 91.2%, and the detection sensitivity of small targets was also improved, and the accuracy reached 88.2%[12]. J. Y. Chiao et al. used Mask R-CNN to detect and classify ultrasound images of breast cancer, which could automatically detect, segment and classify breast lesions. The method achieved an average accuracy of 0.75 on the validation set and an accuracy of 85% on the classification of benign and malignant tumors[13].

The above is the introduction and application of four kinds of convolutional neural networks. Table 1 summarizes their advantages and disadvantages and applications.

Table 1. Four CNN's advantages, disadvantages and their applications.

Types	Advantages	Limitations	Applications
AlexNet	1)Deep structure, deep network structure can extract more complex features, improve the accuracy of classification. 2)ReLU activation function effectively solves the problem of gradient disappearance and accelerates training 3)Strong generalization ability and improved model generalization ability through a variety of data enhancement techniques and the use of Dropout technology at the full connection layer to reduce overfitting	1)It has a large number of parameters, a large model and a high demand for computing resources. 2)Convolution kernel size is fixed, and a fixed convolution kernel size may not be the best choice for some tasks. 3)The architecture is simple, and performance may be poor compared to other models	Classification of skin lesions, detection and classification of MRI images of brain tumors, etc.
U-Net	1)Excellent segmentation performance, thanks to the symmetric structure of deconvolution operations and skip joins, can extract important features while maintaining resolution 2)Suitable for small sample data set, because the sample data in the medical field is usually small, which is very suitable for medical image segmentation. 3)Flexible framework with multiple variants 4)Good generalization ability, thanks to its jump connection, can combine features of different dimensions well.	1)With a large number of parameters, the training process requires a lot of computational resources. 2)Poor processing of complex boundary details. The improved model of Edge-U-Net[7] can improve U-Net's ability to handle boundary details 3) There is a high risk of overfitting because of the parameter Angle. 4)The network mechanism is complex, involving a large number of convolutional operations and deconvolution operations.	Tumor MRI image segmentation, organ and tissue segmentation, multimodal image fusion, cell tissue section analysis, etc
GoogLeNet	1) Fewer parameters, high calculation efficiency 2) Efficient feature extraction thanks to the Inception	1) The training is complicated, and the workload of debugging and optimization is large.	Classification of CT images for lung cancer, diagnosis of melanoma,

	module. 3) Flexible framework for transfer learning	2) Sensitive to data processing, improper data processing may lead to degraded model performance	classification of MRI images for brain tumors, etc.
R-CNN	1) High detection accuracy, thanks to its convolutional neural network combined with selective search. 2) Modular design, R-CNN is divided into three parts: regional suggestion generation, feature extraction and classification, and each module can be optimized independently. 3) Strong applicability R-CNN can not only be used for target detection, but also for instance segmentation.	1)Low computational efficiency, such as Faster R-CNN and other models have improved computational efficiency 2)The training is complex. The training of R-CNN includes region suggestion generation, feature extraction, SVM classifier, etc 3)The detection effect of small targets is not good, and boundary box regression can improve this deficiency	Lung nodules, prostate cancer, breast cancer detection.

4. Conclusion

Convolutional neural networks, as an important branch of deep learning neural networks, are very good at processing computer vision tasks. Convolutional neural networks play an important role in medical image analysis. This paper summarizes four kinds of convolutional neural networks (AlexNet, U-Net, GoogLeNet, R-CNN) mainly used in medical image analysis, briefly points out the characteristics and working principles of each neural network, and points out its advantages and disadvantages. The application of each convolutional neural network in the field of medical imaging is explained, and its advantages compared with other models are given. Finally, a table is drawn to give readers a clear and intuitive understanding of the advantages and disadvantages of each convolutional network model. In terms of model algorithms, most high-performance models currently have problems such as large consumption of computing resources, large number of model parameters, complex network architecture, or difficulties in debugging and optimization in the debugging stage during training. In terms of data collection, the training of convolutional neural network model is faced with the problem of scarcity of high-quality medical image data sets. The papers cited in this paper, such as Transfer learning with GoogLeNet for detection of lung cancer[10], all mentioned the impact of insufficient data scale and diversity on model performance. Also due to data privacy and security concerns, the sharing and use of medical data has been severely restricted, making it more difficult for model developers to obtain large-scale and diverse data. At the same time, the medical image analysis system based on deep learning, due to the lack of interpretability of its decision-making process, leads to the lack of social trust in it, and is temporarily difficult to clinical application. In the future, convolutional neural network models of deep learning still have a lot of room for improvement:1) Improve model performance, simplify model and improve model calculation efficiency. 2) Appropriate government organizations help model developers obtain more high-quality medical image datasets. 3) Study the theory of deep learning neural network, strengthen its explainability, and lay a foundation for its clinical application. It is believed that in the future, AI can replace clinicians in the diagnosis of diseases, and can have a better performance than clinicians in the diagnosis of diseases, helping patients to detect diseases at an early stage, so that each patient can get timely treatment.

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