Research Status and Prospects of Deep Learning in Medical Images

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***Abstract*—With the continuous innovation and development of artificial intelligence, the theoretical research on and application of deep learning, one of its branches, has also reached a certain height, and has become a research hotspot in all walks of life. In the medical field, traditional manual image reading and other medical image analysis methods have been unable to adapt to the sharp increase in the amount of impact data. Based on this, the combination of deep learning and medical imaging has eased this pressure. This article first briefly analyzes the relevant theories of deep learning, and focuses on its applications in medical image classification and recognition, medical image segmentation, and computer-aided diagnosis. Finally, the application of deep learning in medical images is prospected.**

Keywords-artificial intelligence; deep learning; medical image

I. INTRODUCTION

Artificial intelligence (AI) is a discipline based on computers to simulate human thinking processes and intelligent behavior. With the development of AI technology, it has become a multi-discipline involving computer science, psychology, philosophy and linguistics. An emerging frontier discipline that intersects. In recent years, with the emergence of deep learning algorithms, the exponential growth of computing power, rich big data resources and training-based autonomous learning methods, the new generation of AI technology has ushered in explosive development and application [1].

The continuous innovation and development in the field of artificial intelligence has made the theory and application of deep learning (DL) methods a hot research topic. In the medical field, with the improvement of medical imaging equipment, there are X-ray, ultrasound imaging (US), computed tomography (CT), magnetic resonance imaging (MRI) and positron emission A large number of medical images such as positron emission computed tomography (PET) are generated. In the era of medical image big data, massive and complex image data brings two new problems: for one thing, the medical image data to be processed has a higher dimensionality, requiring a model with stronger learning and adaptability; for another, medical images Big data is more fragmented and the data structure is more complicated. It is often necessary to integrate different information. Traditional manual reading has been unable to fully meet the diagnostic needs [2]. Therefore, the application of the DL method in medical images has attracted much attention, mainly including image recognition, image segmentation, image classification and so on.

II. DEEP LEARNING'S OVERVIEW

DL is a type of machine learning. It is a class of multi-layer neural network learning algorithms. It can learn features through deep nonlinear network structures, and combine lower-level features to form higher-level and more abstract deep representations to achieve complex function approximation. Characterize the distributed representation of the input data so that the essential characteristics of the data set can be learned [3]. The DL method starts from the original features, automatically learns advanced feature combinations, and extracts abstract features from a series of images. The entire process is end-to-end. The input layer inputs information, enters the hidden layer, and outputs information to the output layer to ensure the final output. Excellent solution.

DL is divided into supervised learning and unsupervised learning. The common models of supervised learning in medical image processing are recurrent neural network (RNN) and convolutional neural network (CNN). Unsupervised learning is to process unlabeled data and train to generate models. Common models in medical image applications are Deep Confidence Network (DBN) and Auto Encoder (AE) [4]. Using deep learning methods, abstract features can be automatically extracted from massive medical image data, which not only eliminates the influence of subjective factors, but also extracts more advanced abstract features, which helps doctors make accurate diagnosis of diseases.

A. RNN and CNN

The hierarchical structure of RNN is composed of input layer, hidden layer and output layer. The biggest feature is that the neurons between the hidden layers are connected, that is, the output of the neuron at a certain time can be input to the neuron again as input. This tandem network structure is very suitable for time series data, which can maintain the dependency relationship in the data, so it has memory ability. However, this model is difficult to train, and often has the problem of gradient disappearance or gradient explosion, and it cannot achieve the goal of long-term dependence. To this end, long-short-term memory networks and gated loop units are proposed to solve the long-term dependence problem.

CNN is a classic deep learning network and the biggest advantage is that its multi-layer structure has the ability of automatic learning [5]. The basic structure of CNN includes convolutional layer, pooling layer and fully connected layer. The convolutional layer extracts different features of the input

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data, and reduces the complexity of the model through weight sharing, making the network easier to train; the pooling layer obtains features with spatial invariance by reducing the resolution of the input features, which plays a second role of extracting features; a fully connected layer or classifier that integrates local information with class distinction in the convolutional layer and pooling layer. Therefore, CNN is usually the first choice for medical image classification.

B. *AE and DBN*

AE includes coding layer, hidden layer and decoding layer. The coding layer compresses the image data and the decoding layer expands it. The hidden layer in the middle is used to learn the complex relationship of pixels in the image, and plays the role of extracting the target feature and reducing the dimension. In order to achieve classification, a classifier is added to the top coding layer of AE. AE variants include sparse autoencoders and noise reduction autoencoders [6].

DBN was proposed by Hinton et al. It is a generative model. Through the weights between the neurons of the trainer, the entire neural network can generate training data according to the maximum probability. DBN can be used to identify features, categorize data, or generate data [4]. DBN consists of multiple layers of neurons, which are divided into dominant neurons and recessive neurons. Dominant neurons are used to receive input, and recessive neurons are used to extract features, also known as feature detectors. There is a connection between neurons, but there is no connection between neurons in the layer.

III. APPLICATION OF DL IN MEDICAL IMAGES

A. *Medical image classification and recognition*

With the DL method's development, computer vision is used instead of human vision to quantitatively analyse the image. In recent years, many researchers have applied deep learning to medical image recognition and further extended it to clinical applications, and have achieved certain results. The research results are shown in Table 1.

TABLE I. RESEARCH ACHIEVEMENTS OF DEEP LEARNING IN MEDICAL IMAGE RECOGNITION

Time	Model	Clinical Application
2016	CNN	Malignant tumor detection
2014	CNN	Interstitial lung disease classification
2016	CNN	Pulmonary nodule classification
2013	DBN	Huntington's disease
2013	DBN	Low-lint intraepithelial lesion
2014	DBN	Multiple sclerosis
2015	3S-CNN	Esophageal cancer
2016	CNN	Breast lesions

Based on the DBN method, Wu classifies the ultrasound contrast images of benign and malignant liver focal lesions, demonstrating the superiority of the DL algorithm [7]. CNN can directly identify a given image data set through the feature extraction mechanism, and learn and extract relevant features from it. Reference [8] uses a large number of CT images of different pneumonia types to autonomously learn and classify the features of corresponding pneumonia. Compared with support vector machine algorithms, the accuracy of CNN method classification ranks first, reaching 87.1%; Aubreville's research shows that the average accuracy of CNN's confocal laser endoscopic image recognition for oral squamous cell carcinoma is 88.3% [9]; Kang combines image features and DCNN by constructing an image color data field that matches human visual characteristics and uses Wavelet transform describes the multi-scale features of the image, and finally realizes color image recognition through unsupervised DBN [10].

In the field of multi-modal and three-dimensional images, DL also plays an unparalleled role. While using convolutional DBN, Brosch considers the minimization of the number of spatial transformations in the frequency domain [11], which opens up a new direction in the field of DL analysis of three-dimensional images; an automatic and accurate method of complete CNN can realize multimodality of MRI images of intervertebral discs Three-dimensional positioning of data; DL models based on multimodal data sets may improve the performance of images. Li proposed a three-dimensional convolutional DL architecture for deep MRI brain image extraction, which can handle any number of modalities [12].

B. *Medical image segmentation*

Medical image segmentation is to identify the pixels of organs or lesions from the background image, and the accurate segmentation of organs or lesions is conducive to quantitative analysis of clinical indicators such as target volume and shape on the image. In medical image segmentation, the most famous architecture is U-net, which is characterized by the combination of equal amount of up-sampling layer and down-sampling layer. The basis of U-net is a fully convolutional neural network [13], but it is different from a fully convolutional neural network. Among them, the shallower high-resolution layer of U-net is used to solve the problem of pixel positioning, and the deeper layer is used to solve the problem of pixel classification. The shallow feature map and the deep feature map are combined for image segmentation and edge detection. However, U-net often ignores the influence of feature maps of different scales. The feature pyramid network proposed later is used to detect objects of different scales.

Budak proposed the use of a cascaded deep convolutional encoder-decoder neural network for segmentation of liver and liver tumor [14]. The results show that the DICE score of the method for liver segmentation is 95.22%, which is in good agreement with manual liver segmentation Sex; the DICE score for liver tumor segmentation is 63.4%. Although this value is very low, it is still 3.3% higher than the performance level of other methods on average. It can be seen that in medical image segmentation, many deep learning-based architectures have a high degree of consistency with the automatic segmentation of organs or lesions with manual segmentation.

C. *Computer aided diagnosis (CAD)*

CAD was first proposed by Ledley in 1966. It refers to the use of imaging, medical image processing technology and other methods, combined with computer analysis and calculation, to assist in the discovery of lesions and improve the accuracy of diagnosis. Existing research shows that the CAD technology based on the DL method can be applied to the early diagnosis, detection and evaluation of clinical diseases, and has excellent reference and guidance significance for clinical diagnosis.

Lesion recognition is one of the important applications of DL methods in CAD. Traditional lesion recognition, such as wavelet transform method, is not accurate for lesion recognition. Applying deep learning to lesion recognition has unique advantages: DL model can be faster Processing data and predicting abnormal lesions through the DL model can reduce the probability of lesions, while improving the accuracy and efficiency of doctor diagnosis [15]. Compared with ordinary image recognition, the medical image recognition problem is more complicated. For some complicated medical image recognition problems, it can be solved by constructing a deeper and more complex deep learning model.

D. *Minimally invasive surgical guidance (MIS)*

Compared with traditional surgery, MIS have many advantages, such as: less trauma, less pain, and shorter postoperative recovery time. Now it has become a general surgical option. However, MIS needs to obtain additional information to monitor surgical tools moving in the body, and minimally invasive surgical tool detection and deep learning algorithms can provide such important information for operational navigation in MIS [16].

To date, a variety of detection and tracking algorithms for minimally invasive surgical tools based on deep learning have been applied to MIS.

IV. Conclusions

With the advent of artificial intelligence research boom, it has become the norm to use deepening and mature deep learning models to segment, extract features and classify medical images. The mining and development of medical image information is no longer limited to the traditional single algorithm. Research on medical images based on DL is booming, greatly improving the accuracy of clinical diagnosis of certain diseases.

The application of DL to the field of medical image analysis has great practical significance and social value in the high-precision intelligent identification, analysis and diagnosis of diseases, and has become a research hotspot in recent years. And this process reduces manual intervention. Segmentation, classification and recognition of images through relevant algorithms and models, etc., to achieve accurate analysis of specific areas of the image, and finally combined with computer technology, provide reference and reference for clinical disease diagnosis.

V. Prospects

Although DL has achieved some empirical research results in medical image recognition, on the whole, the application of DL in medical image recognition is still in its infancy, and there are still many problems that need to be studied in the future.

In medical images, the acquisition of large-scale medical image data is extremely difficult due to data collection and rare diseases. You can effectively solve this problem by using transfer learning and fine-tuning in image processing, but the best solution should still be Establish more publicly available medical image data sets, and extract more abstract features from public data sets to achieve breakthrough research progress in medical image recognition [17].

At present, the research of deep learning methods on medical imaging is mainly focused on diseases with a relatively high incidence rate, and there are few studies on some rare diseases. The different images collected will affect the extraction of features and play a decisive role in the final result. For this purpose, a more advanced Algorithms to effectively overcome the impact of differences in images acquired by different devices, which is also an important research direction in the future.

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