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An Overview of Analysis of Medical Images Using Data Visualization and Deep Learning Applications

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Abstract:

Regarding the importance of the right diagnosis in medical applications, various methods have been exploited for processing medical images. Machine Learning (ML) techniques have shown their unique capabilities in the field of medical image processing and segmentation. In recent years, efforts have been made to develop more accurate and efficient ML methodology for segmenting medical and natural images. Various automatic segmentation tools exist, but deep learning (DL)-based methods have proven to be much more accurate in various medical image segmentation tasks in recent years. Recent decades have seen DL achieve unprecedented success across various domains, including images, text, and speech. It also has been successfully implemented in medical image classification using DL methodology. This work focuses on the important role of DL in medical image segmentation, classification, and recognition, which will inspire the further use of DL in the field of medical images analysis and diagnosis.

Keywords*: Deep learning, Medical image recognition, Medical image segmentation, Visualization, Visual analytics.*

I. INTRODUCTION

The Artificial intelligence technology is seeing prosperity since it combines different theory and method, innovatively uses technology and application system, and not only investigates and develops them, but also simulates, extend and expand human intelligence along with it. Nowadays, as a new technology science, Machine learning is widely applied in many fields, which has aroused great interest in industry, academia and popular culture.

Deep learning is a valuable branch of machine learning. It mainly uses multi-level nonlinear information processing and abstraction technology to better deal with supervised or unsupervised feature

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learning, representation, classification and pattern recognition tasks. Deep learning, or representation learning, can be considered a branch or subfield of machine learning methods. It is commonly believed that since the year 2006, modern deep learning methods have appeared in people's vision.

Recently, the application of machine learning technology in the diagnosis of intracerebral haemorrhage has aroused people's interest. When using machine learning methods, including advanced deep learning to deal with some amount of medical images, people find it much more convenient to improve the accuracy of Artificial intelligence technology enables computers to simulate human thinking processes and intelligent activities[1].

II. DEEP LEARNING

2.1 Overview of Deep Learning

The xxxxx As a high-value component of machine learning, deep learning was first proposed by Hinton et al. Published in Science in 2006 by studying artificial neural networks[2]. The purpose is to simulate the data processing characteristics of human brain neurons by using a multi-layer network structure. When compared to the traditional machine learning method, deep learning can be seen as a better representation method of image features. It can be learned and classified in a model structure at the same time. Therefore, we can input the original image directly for training and prediction learning and can achieve a good result. Nowadays, as the leader in machine learning, deep learning has made outstanding achievements in different fields, for example, sequence prediction, speech recognition, computer vision and image processing. The main reasons are: the computer computing capacity has increased greatly; the manufacturers represented by NVIDIA Company launched higher performance array GPU cluster, which is precisely the widespread use of high-performance GPU to provide deep learning with the extensive use of high-performance GPU. With the continuous improvement of the artificial intelligence theory knowledge system and the improvement of the data acquisition method, deep learning can be realized by using the hierarchical method through more efficient computing units to complete the fast and effective feature learning and prediction regression. In in-depth learning, the model of an automatic learning network with multiple hidden layers is built by training large-scale data sets. Through automatic learning, each layer can get useful features, then extract layer by layer data features, and obtain low-dimensional, sparse and higher-level features, which have obvious advantages in medical image processing. The structure of the deep learning model is divided into three types: generative depth structure, differentiated depth structure and hybrid structure[3]. The commonly used model structures are autoencoder (AE), deep Boltzmann machine (DBM), restricted Boltzmann machine (RBM), deep belief networks(DBN),recurrent neural network (RNN), convolutional neural networks (CNN) etc.

2.2 Introduction of Deep Learning Framework

With the continuous breakthrough of deep learning technology, in addition to the contribution of many academic experts, in theory, the industry has also made great contributions. Many open-source deep

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learning frameworks can be used to quickly build neural network models and directly apply them to the actual system. Next, the design ideas and advantages of several popular open-source frameworks are introduced.

- Caffe Framework

Convolution architecture for feature extraction (Caffe) is a convolution neural network framework based on C++/CUDA/Python, which was developed by Berkeley vision and learning centre (BVLC), created by DR. Jia Yangqing. The biggest feature is the ability to do feature extraction, and it can be switched fast in CPU and GPU.

- MxNet Framework

MxNet is developed by distributing a machine learning community (DMLC), which is a deep learning framework that is oriented toward efficiency and flexible design.

- TensorFlow Framework

TensorFlow is an open-source deep-learning library using Python as its basis, it was developed by Google Brain and based on the first generation learning framework Disbelief. Users can design neural network models simply and conveniently by using them. TensorFlow integrated the most popular units in deep learning by using a dataflow atlas. TensorFlow not only supports CNN, RNN and LSTM algorithm in image recognition, voice recognition, and natural language field but also supports deep reinforcement learning, such as solving high dimensional partial differential equations and updating constantly and fast.

- Keras Framework

Keras is a simple and highly modular open-source neural network library developed in pure language. It can be run on TensorFlow\Theano\CNTK and MxNet. It provides the most convenient API interface at the present level.

III. THE APPLICATION OF DEEP LEARNING IN MEDICAL IMAGES

Brain parenchyma refers to brain tissues such as grey matter, white matter and meninges covered outside the cerebral hemisphere, which is collectively referred to as all brain tissues. To realize the automatic recognition of cerebral haemorrhage, the brain parenchyma in the skull must be segmented, and other irrelevant brain structures must be eliminated while the bleeding area is extracted. Many researchers have explored this area. Yang Bin et al. used fuzzy C-means (FCM) extension algorithm to extract the boundary contour of the skull and ventricle region but did not make further recognition of brain essence. Sun Tao proposed a brain parenchymal segmentation algorithm based on feature vectors, which can segment the intracranial white matter, gravy matter and cerebrospinal fluid regions. However, this

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algorithm is only applicable to healthy brain structures without considering the image features when lesions occur. Zhou Ping established the texture chromatography vector map of CT images of the brain and realized the recognition of brain lesions, but this algorithm could not classify the identified lesions and could not distinguish cerebral haemorrhage, calcification, density abnormalities and other lesions. Wang Haibo realized the segmentation function of cerebral haemorrhage lesions based on the FCM clustering algorithm, but the experimental data he used to be all from patients with suspected cerebral haemorrhage, and he did not consider the possible false-positive recognition of his algorithm in healthy brain tissue, so he had certain limitations. Yu Jiefu used a machine-learning algorithm to analyze the image features of intracranial haemorrhage and was able to identify intracranial hematoma and intracerebral haemorrhage, but the recognition accuracy remained to be improved.

3.1 Medical Image Classification

Medical images can be summarized into three aspects: classification, target detection and pixel-level segmentation. Image filtering has been used in the process of medical image analysis for a long time, and the main principle can be understood in this way. Firstly, input certain images to be observed, then use a trained model to do the predicting work, at last, disease or severity grading diagnostic variability is formed. Image screening belongs to an image-level classification. In the early days, the deep learning model focused on tasks such as SAE, DBN and DBM networks, as well as unsupervised pre-training methods. At present, researchers mainly analyse the neuroimaging diagnosis of Alzheimer's disease (AD) and mild cognitive impairment (MCI). These algorithms usually use multimodal images as important input elements to extract MRI, pet and other modes. Complementary feature information on CNN has become a standard technology for image screening and classification and has been widely used.

MOLLE p v proposed an attribute method to realize the application of interpretable CNN in medical image diagnosis[4]. CNN is trained and binary classified in the skin injury database, and the feature map is visualized to test the characteristics of CNN learning. The contribution of input features to the final CNN target neurons is determined by visual comparison and analysis of different feature maps.

This paper analyzes the characteristics of dermatological medical images learned from CNN, which is trained for skin injury classification. Through the information come from the feature map of CNN, it can be seen that the advanced convolution layer with a relatively high layer has a high activation in similar concepts used by dermatologists, such as lesion boundary, and dark area in the lesion, surrounding skin, etc. In addition, the authors also found that some feature maps had higher activation in various pseudo imaging regions, such as specular reflection, gel smear application and yardstick.

Although this paper makes some analysis and comments on the features learned from CNN, the specific causal relationship between it and the output of the CNN analyzing process cannot be derived from this process. In addition, through the feature map, no other structures, such as spherical, point and vascular structures can accurately highlight the key points of dermatologists in the scanning process. To further utilize the tool of CNN in assisting dermatologists in decision-making work, more research is

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needed in this field.

C Biffi and O Oktay[5] put forwards their view of new cardiac remodeling and indicated that the deep-seated model will help automatic classification of heart diseases effectively. In this paper, a three-dimensional convolutional variation automatic encoder (VAE) model for medical image classification of patients with heart disease is proposed. The model utilizes interpretable anatomical patterns learned from three-dimensional segmentation and allows visualization and quantification of pathological specific reconstruction patterns in the original input space of the image. The model can fully utilize interpretable task-specific anatomical features obtained directly from three-dimensional segmentation. The model architecture proposed in this paper is specially used to visualize and quantify the characteristics of learning in the original segmentation space, as a result, the classification process to make a decision can be explained, and it is possible to realize the quantitative analysis of disease severity. In addition, a simple method is proposed to navigate the lower-dimensional manifold of network learning. The experimental results show that potential representativeness can be used to monitor the potential clinical utility of patients.

This method can explain the effective application of the deep learning classification method in medical image diagnosis. It can help clinicians improve diagnosis and provide a reference for the grading of patients. The method can be applied to heart research, actually, and it can also be used to finish other image analysis tasks related to pathological changes.

Arevalo et al. Adopted a new feature learning method that used CNN to automatically learn the features and classify breast X lesions, this could be used in breast cancer diagnosis[6]. Koori et al. compared different feature learning methods. Through training in a large dataset of about 45000 mammograms, the study found that automatic CNN feature extraction methods showed superior characteristics to manually design in terms of data processing, with relatively low sensitivity and it is more effectiveness. The two methods are equivalent at high sensitivity [7].

The classification of targets or lesions can help doctors diagnose diseases, such as benign and malignant breast lesions. The processing process is to identify or mark specific areas through preprocessing methods, and then classify targets or lesions in specific areas. Accurate classification focus on both the location of lesion appearance and its global context information on location. CNN is widely used in the classification of lesions. Kawahara et al. Classify skin lesions through multi-processing CNN, and the image resolution of each CNN is different. Each of them processes images with different resolutions [8]. Jiao et al. Applied CNN to different levels of depth feature extraction to improve the accuracy of breast cancer classification. Tajbakhsh et al. compared the performance of two end-to-end training large-scale training artificial neural networks means (large-scale training artificial neural network) and CNN to detect pulmonary nodules in CT images and identify benign and malignant pulmonary nodules. Through the experiment in the study, it could be inferred that when only less training data is used, MTANN shows significantly higher performance than CNN [9].

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3.2 Medical Image Positioning and Detection

In clinical practice, how to accurately locate specific biological symbols as well as actual anatomical structures when using the medical images is of vital importance that should be paid more intention. The location of medical images usually needs to analyze the information of three-dimensional elements. The deep learning algorithm can treat the three-dimensional space as a combination of two-dimensional orthogonal surfaces, in this case, people only do some classification tasks instead of positioning ones, which could be finished by settling with the advanced learning module, and also used three different methods to get the standard tag data: pseudo-random generation, affine registration generation and statistical appearance model (SAM) generation transformation, and then use the synthetic deformation field to the brain 2D MR images of the body and the heart are registered.

The article by Uzunova et al. shows that among the three methods, the learning and training effect of CNN based on the standard label data generated by SAM is the best[10]. Similarly, Sniker et al. also used the method of generating standard label data for registration[11]. Some scholars use traditional registration methods to register image pairs, and then generate standard labels. For example, Snitker et al. use Deformable Vector Field (DVF) generated by DIR as standard labels to compare the predicted value with the standard label. The mean square error between the two is used as a loss function to register the 3D CT images of the lungs. Aiming at the registration problem of the lungs, Eppenhhof et al. also proposed a CNN-based method to estimate the registration error in the nonlinear registration of 3D images[12]. In addition, Eppenhhof et al. modified the U-Net architecture and used the synthetic geometric transformation of training images to train the network to register the variable images of the 3D CT of the lungs.

For example, Yang et al. can identify the mark at the end of the femur by combining the information of CNN in three orthogonal directions, and defining the three-dimensional position of the mark as the intersection point of three 2D tiles[13]. Vos et al. parsed the 3D CT volume into a 2D form to identify the 3D rectangular bounding box of the target, and then locate the anatomical regions of interest such as the heart, aortic arch, and descending aorta [14].

The key point to the detection of objects of interest or lesions in medical images is to classify each pixel. At present, most deep learning-based target detection systems use CNN to perform pixel classification tasks and then use some form of post-processing to obtain the target. Chen et al. from The Chinese University of Hong Kong used a series of 2D deep features to better approximate the features of 3D medical images in an innovative way, combined with SVM classifiers to realize SWI (Susceptibility weighted imaging) automatic detection of CMBs (Cerebral microbeads)[15].

3.3 Medical Image Segmentation

The task of medical image segmentation is usually defined as recognizing the contour or internal voxel set that composes the object that arouses our interest. In general, medical image segmentation aims to fulfil the task of recognizing the contour or internal voxel set that composes the object that arouses our interest.

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Many researchers focus on how to use deep learning methods when they deal with medical image analysis issues. Indeed, different organs with their unique substructures could be seen in medical images, and the segmentation of images helps people to carry on some quantitative analysis when using data of volume and shape of certain organs or substructures, such as the ventricular volume and the contractile ejection rate of the heart. In addition, when using radiotherapy technology to treat tumor patients, organ delineation is also one of the very important steps. The main applications of deep learning in this area are histopathology image and microscope image segmentation; brain tissue structure segmentation and heart ventricle segmentation. By using segmentation skills of image features that are taken from surgical and biopsy tissue specimens in the computer, it could be seen clearly about the development of the disease, this is conducive to further diagnosis and prediction. In practice, many kinds of useful methods dealing with histopathological images and microscope image segmentation are based on CNN. Kumar et al. used block-based CNN to segment the nucleus of H&E stained pathological images[16].

In medical image segmentation, the mainstream network frameworks used are CNN, full convolutional network (FCN), U-Net, recurrent neural network (RNN) and GAN model. Currently, commonly used medical image segmentation models include 2.5D CNN, which uses 2D convolution for segmentation on the cross-sectional, anamorphic, and coronal planes. Under the premise of saving computational costs, it adopts useful neighborhood information out of three-dimensional space to improve the segmentation process.

- FCN

FCN is the initial model in deep learning semantic segmentation. Through the fully convolutional neural network and up-sampling operation, the semantic segmentation results can be roughly obtained. In practice, jump connections are widely used in improving the fineness of medical image segmentation, this is achieved by combining the low-level spatial information with the high-level semantic information. FCN and its variants (such as parallel FCN, focus FCN, multi-branch FCN, cyclic FCN, etc.)[17-20] play an important role in medical image segmentation development, and they act out good performance.

- U-Net

U-Net is a special encoding and decoding structure that includes both convolutions and deconvolutions tasks. During the process, high-level semantic features and low-level spatial information can be combined by using jump connection technology, thereby ensuring the accuracy of segmentation. U-Net and its variants (such as Nested U-Net, V-Net[21-22], cyclic residual U-Net) have achieved good segmentation results in medical image segmentation, which is the basic model applied in current medical image segmentation.

- RNN

RNN segmentation model mainly considers the contextual relationship between slices and slices in

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medical image segmentation and then inputs the slices as sequence information into the RNN and its variants to achieve accurate segmentation. Typical models include CW-RNN (clockwork RNN) and context LSTM model[23-24], which sharpen the segmentation edge by capturing the relationship between adjacent slices. On this basis, Chen JX, et al. proposed a two-way context LSTM model-BD C-LSTM, that is to learn the context relationship in the cross-sectional bidirectional, sagittal bidirectional and coronal bidirectional, and the result is better than using multi-scale segmentation. The pyramid LSTM model is better[25-29].

- GAN

The work of GAN-based segmentation usually consist of two parts, the generator aims to generate the initial segmentation result, while the discriminator could help refine the segmentation result of usage. Generally, in the segmentation network, the generator often uses the FCN or U-Net network framework, and the discriminator is a common classification network structure, such as ResNet, VGG, and so on. Medical image segmentation based on GAN has been widely used in medical image segmentation work of different organs and tissues [26]. TABLE shows the data sets used by common medical image segmentation models and their segmentation performance comparison [34-38].

TABLE I. Typical deep learning medical image segmentation method

Parts	Datasets	Target	Top1 Method	TOP1 Result
Brain	Brats	Detection of segmented brain tumors	DL CNN+U-Net+Original CT+CNN	CT=0.87 Core=0.81 Enhance=0.72
Eyes	diabetic retinopathy detection competition	Detection of diabetic retinopathy	fractional max-pooling	Score=0.84958
Chest	Luna16	Detect nodules in chest radiograph	ZNET	CPM=0.811
Pathology and Microscopic Images	Camelyon16	Determine whether the pathology section is a tumour	patch normalize+Inceptionv3 network+tumor heatmap +RF classification	AUC=0.9935
Mammogram processing	Dream challenge	Determine whether breast cancer	modified VGG+DATA Augment+random crop	AUC=0.8735
Heart image processing	Second Annual Data Science Bowl	Calculate heart volume	U-Net+Deep learning	Score=0.003959
Liver segmentation	sliver07	Get liver location	Semi-automatic segmentation algorithm from blood vessels	Score=85.7
Prostate segmentation	Promise12	Get Prostate location	CNN+U-Net+ResBlock	Score=86.85

Some changes in volume, shape of the brain tissue structure may lead to neurological diseases of the brain, such as depression, schizophrenia and bipolar disorder. Therefore, using advanced technology to

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analyses the anatomical structure of brain tissue could benefit the diagnosis and treatment of neurological diseases of the brain [39-40]. For example, Zhang et al. used three modal images of T1, T2 and FA (Fractional anisotropy) as input, and used deep CNN networks to solve the challenging task of infant GM, WM and CSF segmentation, thereby assessing the pros and cons of infant brain development.

IV.CONCLUSION

The latest development of DL provides a reference for automatic segmentation and analysis of medical images. It provides a new way of thinking so that people can find the image from the data Morphology or texture pattern has been achieved in different medical fields' great progress. However, due to the black box feature of the DL model, it is intuitive. It is still a problem to be solved to understand and explain the learned model Problems. DL method is used for intelligent segmentation of the medical image. It has broad application space and prospects.

Research of deep learning technology used in medical fields is still going on. There are surely great challenges to face up, but medical data analysis in a more advanced way is still of great value, which should be given enough thought. This paper expounds on the application status of deep learning models in the field of medical image analysis from the aspects of deep learning framework, medical image data, medical image preprocessing, medical image classification, and medical image segmentation. Although deep learning models (such as CNN, LSTM, GAN, attention mechanism, graph models, transfer learning, etc.) have made many breakthroughs in medical image analysis, deep learning is applied to the clinic to assist clinical accurate diagnosis and personalized treatment Still subject to the following restrictions.

First of all, the existing deep learning models have high requirements for the number and quality of images, and clinically labelled medical image data is difficult to obtain, and the current method of clinical diagnosis prediction is often supervised learning, and the data is insufficient. It will inevitably affect the accuracy and stability of the forecast. Therefore, how to improve the accuracy of classification prediction using weak supervision, transfer learning, and multi-task learning when there is the number of labelled data is limited will be a continuing research hotspot.

Second, clinical applications require high interpretability, and current deep learning outcomes especially some of the features are not explained enough. Although at this stage, researchers have proposed to use visualization and some parameter analysis to interpret the model and results, there is still a certain distance from the formation of interpretable imaging markers required by clinical needs. Therefore, research related to the interpretation of deep learning models in medical imaging and how to make them more easily to use is a hotspot in future research.

Finally, how to further improve the robustness of model prediction is a difficult point to be solved. Most of the existing deep learning models are only effective for a single data set, and cannot predict other data sets well without training. However, due to different factors such as acquisition parameters, acquisition equipment, acquisition time and other factors in medical imaging, the image performance of

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the same disease may be quite different, which leads to the poor robustness and generalization of the existing models. How to combine brain cognition thinking to improve the model structure and training methods, as well as improve the generalization ability of deep learning models, is also a key issue to be studied in the field of medical image application.

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