Deep Learning Applied to Medical Image Aided Diagnosis Systems

A Li mujiang·Tuersun[1], Weiyang Fang[2], Chaomin Chen[2], Wei Wang[3,*]
[1]*Hospital of Integrated Traditional Chinese and Western Medicine, Southern Medical University, Guangzhou, China*
[2]*School of Biomedical Engineering, Southern Medical University, Guangzhou, China*
[3]*Tumor Hospital affiliated to Guangzhou Medical University, Guangzhou, China*
**Corresponding Author.*

Abstract: At present, in the field of diagnostic medical imaging, only relying on doctors for diagnosis can no longer meet the needs of contemporary clinical development. Traditional computer-aided diagnostic systems are limited by their recognition ability and universality, and can only provide diagnostic decision-making references for doctors. With the in-depth application of artificial intelligence in the field of medical imaging, the application of deep learning technology in medical imaging-aided diagnosis systems, based on deep neural networks, can not only greatly reduce the workload of doctors, but also help to improve the disease screening ability and clinical diagnosis efficiency further. This paper carries out the research on the application of deep learning in the image-aided diagnosis system, and analyzes the application of deep learning in the image-aided diagnosis system. The study shows that deep learning has good research and application results in medical imaging, reflecting the advantages of deep learning to help improve the efficiency and accuracy of clinical diagnosis.

Keywords: Deep Learning; Convolutional Neural Network; Transfer Learning; Computer-Aided Diagnosis; Medical Image

1. Introduction

Due to the rapid development of medical imaging technology and the dramatic increase of clinical medical imaging data, the diagnosis of medical imaging based on traditional doctor reading not only increases the workload of doctors, but also causes visual fatigue due to long-term reading, and there is a certain risk of misjudgment and omission in diagnosis based on subjective experience [1]. Although the computer-aided diagnosis (CAD) system based on the machine learning method has reduced the workload of doctors and reduced the diagnostic risk to a certain extent, because most of the diagnostic contributions of traditional CAD are only for one type of disease, coupled with its inability to distinguish the boundary between the lesion and the surrounding normal tissues and the manual annotation based on experience, its recognition ability and versatility are limited to a certain extent, and it lacks certain objectivity, so it is impossible to accurately diagnose and classify medical images of different diseases quickly and accurately [2].

Artificial intelligence and medical imaging have been used together increasingly often in recent years, and the introduction of deep learning in medical image analysis can greatly improve the feature extraction ability, screening level, and disease diagnosis efficiency of medical images, and can be more efficiently applied to clinical practice. This review provides an overview of deep learning, introduces the research on the application of deep learning in image-assisted diagnostic systems, and finally provides an outlook on the application of deep learning in image-assisted diagnostic systems.

2. Deep Learning

The concept of deep learning, an area of machine learning, comes from the study of artificial neural networks. Using multiple hidden layers of abstraction and raw data as input, it employs backpropagation algorithms to find complex structures in large datasets. From there, it extracts high-level features by mapping the features to a target output and determines how each internal layer's parameters should be changed [3][4].

2.1 Deep Learning Neural Network Model

Neural network models represent the use of deep learning in medical imagery. Common neural network models are convolutional neural network (CNN) [5], fully convolutional network (FCN), deep convolutional neural network (DCNN), and generative adversarial nets (GANs). Considering the various applications of medical image processing, deep learning neural networks are categorized into classification networks and segmentation networks:

Deep learning classification networks originate from the LeNet [6] network, the basic structure of convolutional neural networks, which contains a convolutional layer that performs convolutional operations to obtain low-order and high-order features, a fully-connected layer that merges the local features to create global features, and a pooling layer that reduces the dimensionality of the feature maps, calculates the classification prediction probabilities and gives the predicted classification results. Subsequently, the AlexNet [7] network introduced by Hinton prevents overfitting by deepening the network hierarchy and introducing the dropout method. The VGG network proposed in 2014 decreases the convolutional kernel's parameter count compared to Alexnet, which enhances the nonlinear expression ability while acquiring more features. Inception structure of GoogLeNet Due to its excellent feature extraction ability and good robustness, it is widely used to extract common features to train models, and maintains a high classification accuracy while effectively solving the problem of small amount of data [8]. Residual networks (ResNet) [9] use independent residual blocks to address the gradient vanishing and gradient explosion issues in training neural networks, and at the same time greatly improve the depth of the neural network, which has had a profound impact on the design of subsequent deep neural networks; and the popularity of deep learning segmentation networks is mainly since that they have been widely used to extract common features to train models, and maintain a high classification accuracy while effectively solving the issue of insufficient data.

The popularity of deep learning segmentation networks mainly originates from the theory of a full convolutional neural network (FCN). FCN [10] realizes the transformation from image pixel to pixel category and semantic segmentation by transposing the convolutional layer to transform the height and width of the intermediate-layer feature map back to the dimensions of the input image so that the prediction result corresponds to the input image in spatial dimensions. U-Net [11] proposed in 2015 is a semantic segmentation network based on the FCN semantic segmentation network, which adopts the typical structure of downsampling plus sampling, realizing that it can be trained with very few images and can be used for larger or multi-scale medical image segmentation. With the addition of a mechanism for attention, SegNet [12] was proposed to map the values of the feature maps to new feature maps by maximally pooling the coordinates, which effectively preserves the integrity of the high-frequency details in the segmentation, and then there are also excellent segmentation network models such as DeepLab V1 network, RefineNet.

2.2 Similarities and Differences between Deep Learning and Machine Learning

The common point between traditional machine learning and deep learning methods is that the task of both in medical image analysis is image segmentation and classification, and its goal is to effectively extract the abstract features contained in a specific region of the input image and convert them into the corresponding category labels, which is also the key to achieve the segmentation or classification task [13]. Compared to traditional machine learning, which is unable to convert complex disease patterns into a limited number of feature representations and thus requires additional steps such as manual annotation and manual correction of the region of interest (ROI), combining and filtering to adjust the feature parameters when analyzing medical images, deep learning can skip these manual processes, and learn to obtain richer and more Higher-dimensional features can be learned directly from the training data, even without using labeled data for training, which simplifies the feature selection process and efficiently increases the speed and precision of medical image detection and classification while adjusting to different data tasks [14].

3. Application of Deep Learning in Medical Imaging Aided Diagnostic System

Most of the image-assisted diagnostic systems on the market today are still computer-assisted diagnostic systems based on traditional machine learning, whose recognition ability and versatility must be improved, and the application of deep learning technology with higher learning and training capabilities to image-assisted diagnostic systems is becoming a popular research topic in today's AI medical image diagnostic industry.

3.1 Interpretability of Deep Learning in Medical Imaging

Compared with traditional machine learning methods, deep learning has the problem of interpretability due to the "black-box" characteristic of providing only direct results without a specific diagnostic basis or pathological etiology in medical image analysis [15]. Nonetheless, some studies on attention mechanisms validate the interpretability of deep learning to a certain extent: Chen Chaoyi [16] and others found that the application of deep learning on AI-assisted diagnostic systems focuses on the visual attention model that focuses on the lesion region that contains key information, which is interpretable to a certain extent; Chen Yuanqiong [17] achieved the visualization, multimodal imaging, and multimodal image analysis of the lesion region through the introduction of the heat map combined with the attention mechanism. visualization, multimodal images paired with semantic segmentation network to achieve the semanticization of medical records, etc. analyzed the interpretability of deep learning in medical imaging applications; Jing Jie [18] et al. analyzed the feasibility of the attention process to develop into a secure foundation for deep learning applied to AI-assisted clinical diagnosis through the visualization of the model judgment. From this, it can be seen that deep learning applied to medical imaging diagnosis has a certain feasibility and broad prospects for development.

3.2 Specific Application of Deep Learning in Image-Assisted Diagnosis System

The term "computer-aided diagnosis" describes the use of imaging and medical image processing technologies in conjunction with computer analysis and computation to help identify foci and increase diagnosis accuracy, which at present mainly refers to the CAD based on medical images, and is widely used in the identification of lung foci and the lung diseases diagnosis in CT images, ultrasound images for the diagnosis of breast, thyroid and other cancers, and even MRI images for brain diseases diagnosis such as Alzheimer's disease, and other diseases. The diagnosis of these brain diseases by MRI images enhances the specificity and sensitivity of doctors' diagnoses. The main process of CAD for medical imaging is divided into four parts: data preprocessing, image segmentation, feature extraction and selection, and prediction and classification.

3.2.1 Data preprocessing

The purpose of data preprocessing is to extract lesions from normal structures so that the computer can recognize lesions and suspicious structures from a complex anatomical background. Basic digital image processing such as local contrast enhancement and histogram equalization for improving image contrast, automatic enhancement techniques and Fourier transform for removing image noise, as well as methods such as wavelet transforms, region growing, and morphological methods [19] are used in traditional CAD to process the raw image to provide higher quality input for the subsequent processes and to facilitate the machine to recognize lesions or suspicious structures.

When deep learning is used for medical image analysis, a significant amount of labeled data is typically needed for the training of the fully supervised neural network model, which is a tedious and time-consuming procedure that can lead to overfitting issues. Reasonable preprocessing of medical image data can solve the problem of limited actual training datasets effectively for deep learning and improve the ability of neural network models to select features of regions of interest for classification. Ciompi [20] et al. utilized the concept of data augmentation for deep learning to solve the problem of insufficient clinical training data and the lack of clinical training data, and the problem of overfitting can be solved by rotating and augmenting the three peripheral planes of the vertical of a lung CT image to obtain nodule images with different sections. the problem of insufficient clinical training data and easier access to the desired lung nodule features; Roth [21] et al. expanded the dataset by scaling, panning, and rotating in a randomized over-training sample and similarly added test samples for the detection of lymph nodes and colonic polyps. In addition to this, the same type of problem can be solved by transfer learning (transfer learning) with generative adversarial neural networks [22]. Transfer learning refers to the fine-tuning of pre-trained models on other relevant datasets to the actual dataset that needs to be trained, to avoid the problem of the limited dataset and reduce the time of training, as categorization accuracy increases [23]. Shao-De Yu [24] increased the number of samples by rotating and mirroring the data samples to reduce the overfitting problem during model training while using pre-trained AlexNet and GoogLeNet to migrate to the subsequent deep convolutional neural network model to improve the effectiveness of breast tumor diagnosis. GAN, on the other hand, uses a generator to process the input noise to output the simulated samples and the judger to screen the distinction between the actual samples and the judgmental ones. Actual samples and simulated samples are used for denoising the image data and reducing the overfitting problem of the data.

3.2.2 Image Segmentation

Image segmentation aims to obtain a standardized region to be analyzed, i.e., the acquisition of the region of interest. Traditional CAD is generally based on the clinician's experience of manually labeling the lesion region, and then segmenting the ROI and other regions by image segmentation techniques such as pixel gray value segmentation and edge detection segmentation. Although this process can be easily evaluated without complex post-processing or software, it also requires a lot of time and manpower for outlining and labeling and parameter screening trial and error, and due to the existence of human subjectivity, it is prone to large deviations within the observer and the observed, which affects the accuracy of the subsequent prediction and classification, and there are still certain application limitations in clinical practice [25].

Comparatively, deep learning methods can automatically learn deep, distinguishing features from data, and through its high-precision segmentation network can realize automatic outlining of ROIs, with a significant improvement in performance compared to traditional image segmentation methods. First of all, for the fully supervised deep learning models, although this type of model still needs to use specific datasets with annotations and labels to construct neural networks, the segmentation accuracy can be effectively improved by the above-introduced neural network models such as FCN, U-net, etc. Brosch [26] et al. achieved a good DSC value by applying the FCN network to segmentation of MRI images of multiple sclerosis foci, and Cui et al. achieved a good DSC value; Cui et al. achieved a good DSC value by using the FCN network in segmentation of MRI images of MS foci. good DSC values; Cui [27] et al. used Cascade CNN-based cascade network to segment MRI images of gliomas, firstly using FCN network combined with migration learning to screen tumor regions in glioma images, and then accurately segmenting the screened tumor regions by DCNN; Roth [28] et al. used two holistically-nested convolutional networks (HNN) for labeling the region where the pancreas is located and outlining the pancreas contour, respectively, to achieve accurate pancreas segmentation based on the fusion of pancreas edge information and internal information, and Holger [29] proposed a 3D U-net model based on them, using two 3D-FCNs for coarse screening and specific analysis of regions of interest, respectively, to achieve segmentation of fine regions. In addition to fully supervised models, the complex labeling segmentation work can be reduced by introducing unsupervised or weakly supervised learning methods without introducing errors caused by subjective factors [30]. Common approaches include segmentation models based on the ideas of incremental learning or self-training, co-training, and the introduction of class-activation mapping and attention mechanisms [31]. Hwang [32] et al. used a self-learning method in combination with the training of classification and localization networks to achieve accurate ROI localization for X-ray datasets with only image-level labeling; Wu [33] et al. for a weakly supervised approach with only image-level labeling, the introduced an attention mechanism in class-activation mapping to achieve segmentation of brain tumors in MRI images; a weakly-supervised CNN-based segmentation network for lung nodules is proposed by Feng et al. [34] , which accomplished automatic segmentation of lung nodules with only image-level labeled datasets for training; and Bai et al.[35] achieved accurate segmentation of MRI hearts with unlabeled data through a self-training-based approach. image with accurate segmentation.

3.2.3 Feature Extraction, Selection and Predictive Classification

As feature extraction, selection, and subsequent prediction and classification are often coherently designed and optimized in deep learning neural network frameworks, it is often easier and more effective to tune the performance of the entire classification network model through a systematic approach in contrast to traditional machine learning methods.

The feature extraction and selection method refers to transforming the extracted ROI regions into representative figures that provide effective information through computational methods, and then form a subset space of features by suspending representative features from the obtained high-dimensional features. For building models to predict and classify diseases, traditional machine learning mostly uses support vector machine (SVM) models, decision tree methods, random forest methods, plain Bayesian classification, and multilayer perceptron (MLP), etc., to use extracted and screened features as inputs to the model to train the prediction results. In contrast, using deep learning techniques, a neural network model designed based on the coherence of the target task can determine those image features indicating the presence of a lesion that is automatically acquired by the model itself during training instead of manually filtering the input features and automatically extract the required optimal subset of features as inputs to the prediction and classification stage after training, and adjusting the parameters to give the diagnostic and classification results through continuous training iterations.

Fully supervised deep learning models based on CNNs and their improved versions are the main methods currently used for the process from feature extraction to predictive classification in image-assisted diagnosis but they require the annotation of the training samples to train the network by labeling information. Since the sample dataset for training is often limited, the labeled dataset is even more time-consuming and difficult to collect in large quantities, which limits the training effect and stability of the CNN model to a certain level. Facing this problem, the migration learning method mentioned in the data preprocessing stage is undoubtedly an effective solution, which can significantly enhance the effectiveness of the CNN model by fine-tuning the migration of the pre-trained CNN network in other related image domains to the labeled specific medical images.

In terms of feature extraction and selection, DCNN can learn to adjust the weights iteratively through backpropagation to automatically extract relevant features from the training samples of a given task and can discover the feature representations through training without the need to manually design the features as inputs. Zheng et al. showed through the study and analysis of ultrasound renal data that feature extraction combined with migration learning based on a deep CNN model can improve the pattern classification model based on conventional imaging features including texture features and geometric features. Hosseini-As et al. proposed a deep supervised adaptive 3D-CNN network, which can achieve automatic extraction and identification of brain features for Alzheimer's disease, and utilize these features for predictive classification of brain MRI images. In addition to this, network models such as deep typical correlation analysis and multimodal Boltzmann machines can be used to fuse information at the feature expression level of the multimodal images from which the features were extracted. Li et al. used a multimodal deep neural network (DNN) for feature-level migration learning to realize the migration of PET signals to MRI for Alzheimer's disease diagnosis. For predictive classification, Hoo-Chang et al.[36] retrained medical images using pre-trained Alex and Goog Le Net fine-tuned migration to a new DCNN, which effectively improved the classification; Shen et al. proposed a Multi-Crop CNN model with a special pooling layer structure, which extracts the central features of the output of the convolutional layer and then converts multiple features into a convolutional operation to improve the classification of lungs. The convolutional operation was performed to improve the recognition and classification of lung nodules; Zhang and others developed a diagnostic system applicable to clinical COVID-19 that used the Deeplab V3 network model to segment the lung lesion region and 3D ResNet-18 model to extract features and classify them, respectively, and achieved good prediction and classification results.

In addition to the use of transfer learning methods to solve the problem of the limited amount of labeled image data and mostly small samples, the use of semi-supervised learning and weakly supervised learning represented by incompletely supervised deep learning models can also effectively solve this type of problem. Chen et al. used an unsupervised learning approach to correctly identify lung tumors on CT scans and breast malignancies on ultrasound pictures using stacked denoising auto-encoders (SDAE) combined with an ALL strategy that uses axial maps for training and testing, with a classification accuracy of 94.4%; Kun Liu et al. extended a semi-supervised GAN based on the traditional unsupervised GAN, and utilized small amounts of labeled and unlabeled data to achieve semi-supervised classification and diagnosis of lung diseases in X-rays; Cao et al.[37] proposed a weakly supervised classification method that introduces a noise filtering network, which solves the problem of noisy labels when the model for classifying breast tumors is being trained and improves the diagnostic performance of breast tumor benign and malignant.

4. Summary

After the rapid development in the last few years, the application of deep learning in the field of medical image diagnosis has become more and more obvious. The medical imaging diagnostic system based on deep learning technology can analyze multiple types of medical images, decrease the workload of clinicians, avoid errors caused by human factors, screen diseases more quickly and accurately, assist doctors in the diagnosis of diseases, and further improve the accuracy of clinical diagnosis and work efficiency.

While deep learning's use in medical imaging diagnosis has more significant advantages than other methods, there are still some problems to be solved in the present application of deep learning in this field. For example, the high training accuracy of deep learning neural network models is often based on the use of many labeled sample datasets, however, in reality, the collection and manual labeling of medical imaging data requires vast amounts of effort and time, and the training of most of the models can only be limited to the use of small sample data. To deal with this type of problem, furthermore to the use of data augmentation, migration learning, and other methods to solve the overfitting problem, the introduction of semi-supervised learning or weakly supervised learning methods, only small amounts of labeled data or even without the use of labeled data can be used for training the neural network model, which reduces the complexity of the manual labeling, and to a certain extent, improves the model recognition efficiency and classification ability. From this point of view, semi-supervised or weakly supervised deep learning models will have a lot of development space in the future medical imaging diagnosis field, and how to improve the semi-supervised learning method will be an important direction for future research in the field of medical imaging. Additionally, due to the low contrast of medical imaging data, the classical deep learning methods are difficult to perfectly differentiate between fine structures and fuzzy boundaries, and upcoming studies still need to continue to optimize the structure of the deep learning network for different types of medical images and to increase the deep learning model's capacity for generalization. Moreover, the application of deep learning also faces the fundamental problem of interpretability, although some studies are committed to enhancing the interpretability of deep neural networks in medical imaging, it still requires a certain amount of time to establish the maximum degree of interpersonal understanding and trust to realize a medical imaging assisted diagnosis system with high interpretability and strong generalization ability, which provides patients with the rapid diagnosis while giving interpretable diagnostic bases. a certain amount of time.

In conclusion, the use of deep learning in image-aided diagnosis systems is a more effective way to combine artificial intelligence with medical imaging, and it is highly in line with the clinical needs of medical imaging diagnosis in the modern day. The effectiveness and precision of neural network models for medical image analysis will be further enhanced, and the use of deep learning in image-aided diagnosis systems will have a wider development space and application prospects, as a result of the ongoing advancements in artificial intelligence and medical imaging technologies.

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