Medical image diagnosis and auxiliary analysis based on deep learning

Ainikaerjiang·Abulikemu*

Institute of Life Sciences, Guangxi Medical University, Nanning, Guangxi, 530021, China

Abstract: With the development of artificial intelligence technology and Internet medicine, the use of deep learning to realize the location, segmentation and classification of lesions in medical images has become an inevitable trend in the development of new medical models. The application of artificial intelligence technology in medical image diagnosis to improve the efficiency and accuracy of medical image diagnosis has become a hot topic in recent years. Deep learning technology has achieved great success in the field of image processing, and its application in medical image-assisted diagnosis has become more common. This paper introduces the concept and development of deep learning, as well as the development process of deep learning models, convolutional neural networks, and deep belief network models, and reviews the current status of their application research in medical image analysis. First, the current status of deep learning technology in medical image-assisted diagnosis is analyzed, and then the specific application of deep learning in medical images is introduced from the three application areas of classification detection and segmentation. By reading the literature, the application of deep learning models in the field of medical image analysis is sorted out, and on this basis, some key application areas are highlighted, and then the problems existing in the basic deep learning model are discussed, and the problems currently encountered by the deep learning model and the prospects and prospects of deep learning in the medical field are understood.

1. Introduction

Medical imaging is the most effective way to assist clinical diagnosis. It can help doctors quickly analyze the condition and make a diagnosis. Deep learning has emerged as the most prevalent pattern recognition technique at this stage due to its characteristic of having "the entire system trainable." The three basic structural networks of the current deep learning framework are: convolutional neural network, deep belief network, and stacked autoencoder. The common medical images in our lives are mainly: CT (computed tomography), X-rays, B-ultrasound, etc. The acquisition of medical images may involve issues such as patient privacy. The processing of medical images involves image processing technology, pattern recognition technology, machine learning and other aspects [1]Using the deep learning framework to effectively discover this information and find the hidden medical information and laws in it will inevitably provide effective protection for the detection and treatment of early diseases [2]With the continuous development of technology, the accuracy and robustness of deep learning models in medical image processing will continue to improve. In the future, more research will be devoted to the optimization of deep learning models to improve their performance in practical applications. A new model called **E-U-Net++**, which enhances brain tumor segmentation by combining data augmentation techniques with the U-Net++ architecture. Manual tumor identification from medical images can be challenging, and existing segmentation models often struggle due to insufficient data. To address this, the proposed model incorporates data augmentation methods—such as random flipping, cropping, and noise addition—during the training phase. In the testing phase, preprocessed data undergoes center cropping before being input to the trained U-Net++ model. Experimental results show that **E-U-Net++** outperforms both the standard U-Net and U-Net++ models in terms of brain tumor segmentation. This approach demonstrates the potential of improving segmentation performance by using ni data augmentation, especially in scenarios with limited medical data.[3]

*191419anker@gmail.com

2. Main algorithm framework of deep learning in the field of medical imaging

2.1. Convolutional Neural Network (CNN)

The convolutional neural network was designed by LeCun et al. in 1998 and won the 2012 ImageNet image recognition competition. Since then, it has gradually attracted people's attention. The convolutional neural network model consists of an input layer, a convolution layer, a pooling layer, a fully connected layer, and an output layer. At present, classic CNN network models include GoogleNet, LeNet model, and VGG model. Among them, the VGG model is a deep network model with the characteristics of long training time and high recognition accuracy. When using the CNN model for training, the CNN network model is usually improved. For example, the 3D-CNN model can recognize moving objects and can extract features in spatial and temporal dimensions [4]. Modern medical imaging technology uses modern high-performance imaging hardware equipment to scan physiological structure information and pathological information of a certain part of the human body [5]. When the fully connected layer in the CNN network is replaced with a convolutional layer, it becomes a fully convolutional network (FCN), thereby realizing the classification of semantic-level images.

2.2. Deep Belief Networks

A deep belief network (DBN) is composed of multiple layers of neurons, which are divided into explicit neurons and implicit neurons (hereinafter referred to as explicit neurons and implicit neurons). Explicit neurons are used to receive inputs, and implicit neurons are used to extract features. Therefore, implicit neurons are also known as feature detectors. The connection between the top two layers is undirected, forming a joint memory. The other lower layers have directed connections up and down [6]. The lowest layer represents the data vector, with each neuron corresponding to a dimension of the data vector. The key component of the DBN is the restricted Boltzmann machine [7]. The process of training DBN is carried out layer by layer. In each layer, the data vector is used to infer the hidden layer, and then this hidden layer is used as the data vector of the next layer (higher layer). Once the pre-training is finished, the network will acquire an improved initial state, although it is not yet optimal. Then, labeled data is used to train the network, and the error is propagated from top to bottom. Typically, the gradient descent method is employed to refine the network [8]. At present, deep belief networks are mainly used in image processing.

2.3. Transformer

Transformers have a variety of applications in medical research, mainly including natural language processing, image analysis, multimodal learning, and generative models .

2.3.1 Natural language processing

Transformers can be used to analyze medical literature, medical records, and other medical texts to extract key information and knowledge. For example, it can automatically classify clinical trial reports, extract topics from medical literature, or automatically extract key information such as symptoms, drugs, and treatment plans from medical records .

2.3.2 Image analysis

In image analysis, Transformers can be used for medical image processing and analysis. For example, image segmentation is performed to extract different structures and organs in medical images, or image classification is performed to diagnose and predict diseases.

2.3.3 Multimodal learning

Medical research often requires the integration of data from multiple modalities, such as images, text, physiological signals, etc. The Transformer model can process multimodal data through a multi-head attention mechanism to learn the association and fusion information between different modalities. This approach can be applied to tasks such as multimodal disease prediction, generative models, and medical image analysis[9].

2.3.4 Generative models

Transformer can also be used to generate medical data, such as medical images, medical records, and medical questions and answers. For example, medical images can be generated to help doctors diagnose diseases and plan treatments, or medical questions and answers can be generated to support medical education and knowledge reasoning .

2.3.5 Specific application cases

In the field of neuroscience, Transformer has been used to analyze changes in human brain structure and functional connectivity, identify genetic variants behind neural phenotypes, and decode emotional patterns . In the fields of neurology and psychiatry, it is also widely used in the study of various neurological and psychiatric diseases, such as Alzheimer's disease and Parkinson's disease [10].

3. Characteristics of medical images

The common medical images in our daily life mainly include: CT image features, magnetic resonance image features, B-ultrasound features , etc. Using the confirmed case information, the current doctor's clinical diagnosis experience and the current patient's case information can quickly help doctors diagnose the disease [11]. Modern medical images have the following characteristics due to the addition of new technologies [12]: (1)The quality of medical images is poor [13]. In CT, MRI and ultrasound images, there are serious noise, low resolution, insufficient grayscale contrast, etc. (2)The amount of medical image data is small [14]. In clinical research, since there is only one set of corresponding image data for each case, there is less training data when training deep learning models. In the collation of daily medical images, it is found that the different shooting angles and methods of different hospitals, departments and equipment also affect the effect of the final training model. (3)Most medical images have multiple modalities [15]. Compared with the traditional network structure of natural images, the existence of multi-modality requires us to fully consider the extraction method of each modality image feature and the fusion method of feature information between different modalities when designing the network. Therefore, the medical image segmentation task is much more difficult than the natural image segmentation task.

3.1. Characteristics of CT images

3.1.1 Section image

CT images are section images that can display the tissue density distribution map of a certain section of the human body. This imaging method overcomes the disadvantage of overlapping tissue structure images in ordinary X-ray examinations, allowing each organ tissue structure to be clearly displayed, and improving the detection rate of lesions .

3.1.2 High density resolution

CT images have a high density resolution, equivalent to 10-20 times that of conventional X-ray images. This enables CT to clearly display organs composed of soft tissues, such as the brain, mediastinum, liver, pancreas, spleen, kidneys and pelvic organs, and can accurately display lesion images on a good image background.

3.1.3 Grayscale

CT images are displayed on the fluorescent screen by different grayscale levels of black and white. These grayscales reflect the X-ray absorption coefficients of the corresponding voxels, and grayscales reflect the degree of absorption of X-rays by organs and tissues. For example, air-containing lung tissue absorbs less X-rays and appears as a black image on the CT image; soft tissues such as muscles or organs absorb medium doses of X-rays and appear as gray images; bone tissue has a high calcium content and absorbs more rays, appearing as a white image.

3.1.4 Multi-planar reconstruction

The cross-sectional images acquired through CT scanning can be processed and reconstructed using computer software to generate multi-plane cross-sectional images needed for diagnosis, such as sagittal and coronal views. This post-processing technology makes CT images more flexible and diverse, and can meet different diagnostic needs .

3.1.5 Quantitative analysis

CT can measure specific CT values for quantitative analysis based on the X-ray attenuation coefficient of the tissue. This makes CT examination not only limited to qualitative diagnosis, but also allows for more accurate quantitative evaluation [16].

3.2. Characteristics of MRI

The most prominent advantage of MRI is its good soft tissue resolution and high contrast resolution. It can clearly distinguish soft tissue structures such as muscles, tendons, fascia, fat, and can accurately distinguish gray matter and white matter. MRI has the ability to slice in multiple directions (including cross-sectional, coronal, sagittal and any oblique positions, without changing the position of the person being examined), and there is no blind spot for observation. MRI uses multi-plane, multi-sequence, and multi-parameter imaging technology, so it can clearly show the location and range of the lesion and its relationship with the surrounding tissues and organs, so as to accurately locate the lesion.

MRI has unique advantages in the qualitative, localization and quantitative diagnosis of many lesions. MRI has no X-ray radiation damage, which truly avoids the damage to the human body caused by radiation from other imaging examinations such as X-ray, CT, and radionuclide scanning. 3. MRI can clearly show the heart and blood vessels without contrast agents. At the same time, as a non-invasive examination, it saves patients from the extra pain and risks of intubation and intravenous contrast agent injection.[17]

3.3. Ultrasound imaging characteristics

3.3.1 B-ultrasound (ultrasound examination) mainly include the following aspects

(1)Non-invasiveness and safety: B-ultrasound examination will not cause trauma to the body, is highly safe, has no radiation, and has little impact on the human body.

(2)Convenience and economy: The B-ultrasound examination process is relatively simple, does not require complicated preparation, has a short examination time, and is low in cost .

(3)Repeatability: B-ultrasound examination can be performed multiple times, which is convenient for observing changes in the condition .

(4)Real-time imaging: B-ultrasound can display changes in the internal structure of the human body in real time and is suitable for dynamic observation .

(5)Wide application: B-ultrasound is applicable to many fields, such as abdomen, cardiovascular, obstetrics and gynecology, etc. It can be used to examine the liver, gallbladder, pancreas, heart, blood vessels, fetal development, uterus and appendages , etc.

3.3.2 Disadvantages

(1)Interference by gas: It is not effective for examining gas-containing organs such as the gastrointestinal tract.

(2)Limited resolution: It may not show small lesions clearly. **(3)Operator dependence :** The examination results depend on the operator's experience and skills to a certain extent.

(4)Weak penetration of bones: It is difficult to clearly show the internal structure of bones.

(5)Cannot make a qualitative diagnosis: It can only find lesions, but it is difficult to determine their nature.

Working principle of B-ultrasound: B-ultrasound transmits ultrasonic waves to the human body through a probe. When the sound waves encounter different tissues, they will produce different reflected waves. The instrument receives and processes these reflected waves to form an image. [18]

4. Application of deep learning algorithms in medical image diagnosis

The application of deep learning algorithms in medical image diagnosis mainly includes the following aspects:

(1)Medical image recognition: Deep learning can help doctors more accurately identify abnormal areas in images by automatically extracting features from images and using deep neural networks for classification. This method has higher accuracy and efficiency than traditional image classification methods . In addition, deep learning can also achieve image segmentation. By combining technologies such as convolutional neural networks (CNN) and recurrent neural networks (RNN), each pixel or object in a medical image can be accurately classified, which helps doctors better understand the image content and improve the accuracy of diagnosis.

(2)Disease prediction and risk assessment: Deep learning can predict patients' health status and disease risks by analyzing large amounts of medical data. This method can automatically learn features in the data and make predictions through deep neural networks, which has higher accuracy and reliability than traditional statistical methods . For example, deep learning models can assess patients' disease risks, predict patients' future risks of illness by analyzing medical data such as medical history and examination results, and provide a basis for doctors to develop personalized prevention and treatment plans .

(3)Personalized treatment: Deep learning also plays an important role in personalized treatment. By analyzing individual differences and medical data of patients, deep learning can help doctors develop more accurate treatment plans. For example, deep learning can predict a patient's response to a certain drug, thereby helping doctors choose the drug and dosage that is most suitable for the patient .

(4)Telemedicine: Deep learning technology makes telemedicine possible. Doctors can remotely access patients' medical imaging data and make diagnoses and recommendations, which is of great significance for medical care in remote areas .

(5)Multimodal data integration: Deep learning is not limited to image data, but can also integrate other medical data types such as text, sound, and physiological data. This integration of multimodal data helps doctors assess the patient's condition more comprehensively and improve the accuracy and efficiency of diagnosis .

(6)Other applications: The application of deep learning in medical imaging diagnosis also includes image reconstruction, post-processing, annotation, regression, registration, and image super-resolution. For example, deep learning can be used for magnetic resonance imaging (MRI) reconstruction, and the accuracy and speed of reconstruction can be improved through technologies such as generative adversarial networks (GAN) [19].

4.1. The spiking neural networks (SNNs)

Spiking neural networks (SNNs), inspired by the brain, have gained significant attention due to their benefits such as low power consumption, high parallelism, and robust fault tolerance. While SNNs have shown promising results in single-modal data tasks, their application in multi-modal audiovisual classification remains limited, and the ability to capture correlations between the visual and auditory modalities in SNNs requires further enhancement. To address these challenges, we introduce a new model called the Spiking Multi-Modal Transformer (SMMT), which combines SNNs and Transformers for multi-modal audiovisual classification. The SMMT model integrates single-modal sub-networks for both visual and auditory inputs, along with an innovative Spiking Cross-Attention module for modality fusion, thereby improving the relationship between the visual and auditory signals. This approach achieves competitive performance in multi-modal classification tasks while maintaining low energy consumption, making it an efficient and effective solution. Extensive evaluations on a public event-based dataset (N-TIDIGIT&MNIST-DVS) and two self-created audiovisual datasets of real-world objects (CIFAR10-AV and UrbanSound8K-AV) highlight the effectiveness and energy efficiency of the proposed SMMT model in multi-modal audiovisual classification tasks. [20]

5. Application of deep learning in liver disease diagnosis

5.1. Liver imaging analysis

Liver CT/MRI image analysis: Deep learning can help automatically identify and segment the liver and its lesion areas from CT or MRI images, especially for the early detection of lesions such as liver cancer and cirrhosis. CNN can effectively identify features such as liver tumors, vascular lesions, and fatty liver, reducing the workload of radiologists and improving the accuracy and efficiency of diagnosis.

Detection and classification of liver cancer: Early diagnosis and classification of liver cancer can be achieved by training deep learning models to identify tumors and non-tumor tissues in liver images. For example, using deep learning models to analyze liver CT images can distinguish between benign and malignant liver nodules and evaluate their size, shape, and other characteristics.

5.2. Assessment of liver function

(1)Blood biomarker analysis: Deep learning can also be used to analyze biomarkers related to liver function in the blood, such as liver enzymes (ALT, AST), bilirubin, albumin, etc., to help assess the health of the liver. By analyzing a large number of patients' clinical data, deep learning models can predict the risk of abnormal liver function and assist doctors in early intervention.

(2)Image analysis: Deep learning technology can be used to analyze CT or MRI images of the liver to automatically identify and segment the liver and its lesion areas. This is particularly important for the early detection of lesions such as liver cancer and cirrhosis. Through models such as convolutional neural networks (CNN), deep learning can effectively identify characteristics such as liver tumors, vascular lesions, and fatty liver, improving the accuracy and efficiency of diagnosis . Deep learning can combine patients' historical medical records, imaging data, and other clinical information to assist doctors in developing personalized treatment plans. For example, deep learning can predict the effects of different treatment options (such as drugs, surgery, or interventional therapy) to optimize treatment options.

(3)Disease prediction and risk assessment: By analyzing patients' historical data and genetic information, deep learning models can help predict the risk of liver disease . For example, some models can assess an individual's likelihood of developing liver cancer based on information such as gene mutations, lifestyle factors, and blood biochemical indicators, and enable early detection and intervention.

(4)Telemedicine: Deep learning technology makes telemedicine possible. Doctors can remotely access patients' medical imaging data and make diagnoses and recommendations, which is of great significance for medical care in remote areas.

(5)Hepatitis detection and monitoring: Deep learning can also be used for the diagnosis of hepatitis, especially by analyzing patients' clinical data, imaging data, etc., to help identify high-risk groups among chronic hepatitis patients who may develop cirrhosis or liver cancer. [21]

5.3. Personalized treatment recommendations

1. Clinical decision support system: Deep learning can also combine patients' medical history, imaging data and other clinical information to assist doctors in developing personalized treatment plans. For example, deep learning can predict the effects of different treatment options (such as drugs, surgery or interventional therapy) to optimize treatment plans. 2. Liver disease prediction and risk assessment : Early disease screening: By analyzing patients' historical data and genetic information, deep learning models can help predict the risk of liver disease. For example, some models can assess the likelihood of an individual developing liver cancer based on information such as gene mutations, lifestyle factors, and blood biochemical indicators, and detect and intervene early.

5.4. Great potential of deep learning in liver disease diagnosis

(1)Data quality and diversity: Medical data are often limited by issues such as privacy protection, data inconsistency, and insufficient annotation. In order to improve the universality of the model, more diverse, high-quality clinical data are needed for training.

(2) Explanation issues: Deep learning models often lack explainability when making decisions, and it is difficult for doctors to understand how the model draws conclusions. Therefore, future research needs to focus on how to improve the explainability and transparency of the model.

(3)Clinical validation and promotion: Although deep learning models perform well in research, in actual clinical practice, the performance of the model still needs to be rigorously verified and compared with existing diagnostic standards to ensure its safety and effectiveness. [22]

6. Application of deep learning in lung diagnosis

6.1. Pneumonia

Pneumonia detection: Deep learning models such as YOLOv8 are widely used in pneumonia detection. By analyzing X- ray lung images, these models can quickly identify pneumonia symptoms, improve the speed and accuracy of diagnosis, and reduce the burden on medical staff .

Pneumonia Detection System: Based on the YOLOv8 deep learning framework, the intelligent pneumonia diagnosis system can quickly identify pneumonia symptoms by analyzing X-ray lung images. The system supports image, batch image, video and camera recognition and detection, and is suitable for scenarios such as hospital emergency departments, rural and remote medical centers .

6.2. Pulmonary nodules

Lung nodule detection : Computed tomography (CT) is a commonly used imaging method for diagnosing lung nodules and lung cancer. Deep learning technology can effectively improve the detection rate of lung nodules and lung cancer, helping doctors diagnose lung diseases more accurately .

Lung nodule detection system : Using deep learning technology, an end-to-end probabilistic diagnosis system can be built for the detection and diagnosis of lung cancer. This system can significantly reduce the number of lung cancer-related deaths and reduce the burden on radiologists through low-dose CT scans .

6.3. Advantages and Challenges of Deep Learning in Pulmonary Diagnosis

Advantages: Improve diagnostic accuracy: The deep learning model can automatically identify features in images and learn to distinguish different lung diseases through a large number of sample training, reducing misdiagnosis and missed diagnosis. Improve diagnostic efficiency : The automated diagnostic system can quickly process large amounts of imaging data and shorten diagnosis time, which is especially important in resource-limited areas and emergency situations. Reduce the burden on doctors : Through automated and intelligent diagnostic tools, doctors can focus more on handling complex cases and improve the efficiency and quality of overall medical services.

Challenges: Dataset acquisition : High-quality lung image datasets are key to training deep learning models. Obtaining sufficient and high-quality datasets is a challenge. Model interpretability: The "black box" nature of deep learning models makes it difficult to explain their decision-making process, which to some extent limits their application in medical decision-making . Technology popularization: Applying deep learning technology to actual clinical practice requires professional technical support and training, and popularization and promotion are somewhat difficult. [23]

Chest diseases are among the most prevalent health conditions. Chest X-rays serve as a crucial tool for examining and diagnosing these diseases. The integration of artificial intelligence with X-ray images can help address the shortage of medical resources and ease the heavy workload of healthcare professionals. In this study, we introduce the real-time detection model YOLOv4 for chest disease diagnosis. Chest X-rays are typically grayscale images with only 256 shades, which lack sufficient information for high-precision diagnosis. To overcome this, we propose a pseudo-color conversion technique for grayscale X-ray images. This conversion enhances the images by transforming grayscale X-rays, which contain limited information, into colored X-rays with more detailed features. Subsequently, we apply YOLOv4 to train and detect the colored chest X-ray images. We assess our approach using public datasets, and the experimental results demonstrate that our method effectively identifies and locates chest X-ray abnormalities. [24]

7. Discussion

Improve diagnostic accuracy and efficiency: With the continuous optimization of deep learning algorithms and the improvement of hardware performance, the accuracy and efficiency of medical image diagnosis will be further improved. This will help doctors diagnose diseases faster and more accurately, reducing the possibility of misdiagnosis and missed diagnosis. Personalized medicine : Deep learning can analyze large amounts of patient data to help doctors develop personalized treatment plans. For example, by analyzing a patient's genetic data, medical history, and imaging data, a deep learning model can predict a patient's response to different treatment options, thereby selecting the most suitable treatment.

Telemedicine and medical resource optimization: Deep learning technology makes telemedicine possible, especially in remote areas and places with scarce medical resources. Doctors can remotely access patients' medical image data to make diagnoses and treatment recommendations, thereby optimizing the allocation of medical resources. Multimodal data fusion : In the future, deep learning will play a greater role in integrating data from multiple modalities (such as images, text, physiological signals, etc.). This will help doctors comprehensively assess patients' health status and improve the accuracy and comprehensiveness of diagnosis.

Automated and intelligent medical equipment: Deep learning will promote the automation and intelligence of medical equipment. For example, intelligent image analysis systems can automatically identify and annotate lesions in medical images, reducing doctors' workload and improving work efficiency. Continuous technological innovation and application expansion : With the continuous development of deep learning technology, new algorithms and models will continue to emerge, further expanding its application scope in medical image diagnosis. For example, generative adversarial networks (GANs) have broad application prospects in medical image reconstruction and super-resolution imaging.

In short, the application prospects of deep learning in medical image diagnosis are very broad, and it will play an important role in improving diagnostic accuracy , personalized medicine, telemedicine, multimodal data fusion, and intelligent medical equipment. With the continuous advancement of technology, deep learning will bring more innovations and breakthroughs in the medical field.

8. Conclusion

Recent advancements in artificial intelligence have greatly improved the segmentation, feature extraction, and classification of medical images using deep learning models. By training large datasets with convolutional neural networks (CNNs) or stacked autoencoders, recognition accuracy for pathological slices has surpassed 90%. CNN-based automatic segmentation of liver tumors has shown better accuracy compared to traditional methods, improving diagnostic systems' sensitivity, specificity, and accuracy. Medical image segmentation typically focuses on lesions or whole organs to assist clinical diagnosis and treatment.

However, deep learning models still face challenges: (1) Model structure: Despite many innovations, most models remain based on simple architectures, necessitating more effective models. (2) Training methods: Most models still rely on unsupervised learning, which is far from fully realized. (3) Training time: Increasing model complexity leads to longer training times, highlighting the need for improved algorithms and faster training. (4) Labeling: The growing volume of unlabeled data requires more efficient automatic labeling methods. (5) Adversarial samples: Small changes to input data can mislead classifiers, and current regularization methods fail to adequately address this issue.

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