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Applications of Deep Learning in Medical Imaging: A Systematic Review

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ABSTRACT
With the increasing number of medical images and the continuous progress of artificial intelligence technology, the traditional medical image analysis methods relying on artificial features and experts' experience have been difficult to meet the dual requirements of efficiency and accuracy in modern clinics. In recent years, deep learning has shown strong application potential in the field of medical imaging, and has gradually become an important tool for improving image processing efficiency and diagnosis level. In this paper, from the three target directions of image segmentation, image registration and image enhancement, we systematically sort out the research progress and application of deep learning in medical image analysis, discuss its practical value in clinical practice with the current research cases, summarise the main challenges faced by the current technology, and look forward to the future development direction of deep learning in medical imaging. By collating and analysing the existing research results, it can provide useful references and ideas for the future development of intelligent analysis of medical images.

KEYWORDS
Deep learning; Medical imaging; Image segmentation; Image registration; Image enhancement

1 Introduction

Medical images are an important basis for clinical diagnosis and treatment decisions. With the continuous progress of medical imaging technology, the number of medical images acquired in the clinic is growing. However, the traditional image analysis methods relying on manual feature extraction and expert experience have gradually shown limitations such as low processing efficiency and difficulty in adapting to large-scale diversified data, which have brought great difficulties to medical image analysis. In recent years, with the development of artificial intelligence technology, deep learning has shown strong potential in the field of medical image processing. By simulating the ability of the human brain to process complex data, deep learning technology can independently identify and extract deep features and complex patterns in medical images [1], which not only improves the efficiency of medical image analysis, but also provides technical support for medical intelligent assisted diagnosis. In this paper, we will take the three directions of image segmentation, image registration, and image enhancement as the starting point, systematically sort out the research progress, advantages, and challenges of the application of deep learning in medical imaging in recent years, and put forward an outlook on the future research direction.

2 Methods

In this paper, we searched the databases of CNKI, WANFANG DATA, CQVIP and Web of Science, and used the keywords of "deep learning", "cancer", and "medical imaging". Using a combination of these keywords , we comprehensively searched more than 90 articles published between 2010 and 2025. Through rigorous screening, we excluded other traditional machine learning methods in medical imaging, and finally selected 19 high-quality papers to analyse the progress of the application of deep learning in medical imaging.

3 Overview of medical imaging types

As shown in Table 1, the common types of medical imaging are magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) [2]. MRI uses magnetic fields and electromagnetic waves to obtain images of the inside of the body and has very high resolution in soft tissues, while CT uses X-rays to penetrate human tissues and receives the attenuated X-ray signals from different tissues through a detector, and then reconstructed by a computer to form a tomographic image, which is suitable for imaging high-density tissues such as bones. PET, on the other hand, uses tracers labelled with radioisotopes to observe the body's function and metabolism.

Table 1 Common types of medical imaging

Literature	Name	Principle	Characteristics
[3]	MRI	Using magnetic fields and electromagnetic waves to obtain images of the inside of the body	High resolution on soft tissue.
[4]	CT	Using X-rays to penetrate body tissues, receiving attenuated X-ray signals from different tissues through a detector, and forming tomographic images through computer reconstruction.	It is suitable for imaging high-density tissues (e.g., bone), and also has some soft tissue resolution.
[5]	PET	Observation of body functions and metabolism using tracers labelled with radioisotopes.	Capable of providing in vivo metabolic function imaging.

4 Overview of deep learning techniques

Deep learning, as an important branch of machine learning, plays a great role in the field of medical image analysis. Common deep learning models in this field include Convolutional Neural Network (CNN), Transformer, U-net and Generative Adversarial Network (GAN), etc., each of which has different advantages, CNN is suitable for local feature processing of medical images [6], U-net is applicable to pixel level image segmentation [7], Transformer is good at capturing the global information of medical images, which is more effective in multimodal image analysis such as CT/MRI [8], and GAN is suitable for medical image enhancement to improve the contrast of medical images [9].

5 Research and application of deep learning in medical imaging

5.1 Deep learning in medical image segmentation

In the application of radiotherapy, doctors need to accurately outline the tumour target area as well as the organs at risk (OAR) layer by layer after obtaining the patient's CT scan image. However, the traditional method mainly relies on doctors to manually complete the CT image outlining work before radiotherapy, which has obvious limitations, not only consumes a lot of time and energy of doctors, which affects the efficiency of diagnosis and treatment, but also the results of the organ at risk (OAR) outlining results may vary from doctor to doctor. All these factors may cause patients to miss the best time for treatment, thus exacerbating the contradiction between doctors and patients, which is not conducive to the healthy development of the medical industry [10]. And the continuous development of deep learning technology makes up for this defect. It shows great advantages in the field of medical image segmentation and outlining, which can automatically, quickly and accurately outline tumours and critical organs, significantly improving the efficiency of radiotherapy, reducing manual errors, and striving for faster treatment timing for patients.

In 2020, WANG Zhi and others [11] developed DeepViewer, a deep learning-based software system for automatic outlining of tumours and critical organs in radiotherapy, which adopts improved U-Net and DenseNet full convolutional neural networks for 22 types of critical organs in tumour radiotherapy (e.g., left lung, right lung, bladder, brainstem, etc.) for automatic outlining. In this study, CT images of 173 tumour patients were selected to evaluate the accuracy of DeepViewer by Dice similarity coefficient, and the average value of Dice coefficient of more than 10 organs exceeded 0.9. The DeepViewer system runs automatically in the background, which significantly improves the efficiency of the outline of organs of concern, especially for large organs with clear boundaries, and reduces the need for doctors to automatically outline the organs of concern. It is especially suitable for the automatic outlining of large volume organs with clear boundaries, which reduces the workload of doctors and provides a more efficient and accurate auxiliary tool for lung cancer radiotherapy. In 2021, ZHANG Fuli and others [12] combined DenseNet with Fully Convolutional Networks (FCN), and proposed an image segmentation method based on FC_DenseNet deep learning network. The core structure of the model is divided into an analysis path and a synthesis path, and the analysis path consists of multiple Dense Block modules and Transition down modules connected in series, which are connected layer by layer using Short cut, and are used to extract image features layer by layer. The synthesis path is up-sampled by the Transition up module to gradually recover the image size. The feature maps of the same size in the analysis path are connected to each other as the Dense Block input of the next layer to improve the accuracy of the reconstructed image. Finally, the feature maps are fed into the Softmax function, through which the FC_DenseNet model outputs the probability that each pixel belongs to a different organ, generates a segmentation mask, and optimises the segmentation results using morphological denoising. The design of the model significantly improves the feature utilisation rate and still achieves high-precision segmentation with small sample data, demonstrating the superior performance of the method in medical image segmentation.

5.2 Application of deep learning in medical image registration

In the process of clinical diagnosis and treatment, the integration of multimodal image data through medical image registration technology can achieve the comprehensive collection and comprehensive analysis of patient information. However, the diversity and complexity of medical images make medical images face many challenges in the alignment process. However, the continuous development of deep learning technology has brought new breakthroughs in the field of medical image alignment, which reduces the manual intervention of medical image registration, improves the accuracy and automation level of medical image registration, and promotes the progress of medical image registration technology [13]. In 2021, Li Shanshan and others [14] proposed the VV-Net model, which is an end-to-end 3D medical image registration method based on V-Net, and improves the accuracy through progressive registration and feature supplementation mechanism. The model contains three V-Nets: the first V-Net performs coarse registration of moving images, the second V-Net further fine aligns them, and the third V-Net extracts features from the deeper layers of the first V-Net and fuses them into the second V-Net to supplement the complex deformation information. This progressive alignment approach performs well on multiple brain MRI datasets, and the registration accuracy is greatly improved compared with the traditional method, which can effectively achieve 3D registration of brain images.

In 2023, CHENG Tianqi and others [15] proposed a (large kernel multi-scale deformable medical image registration network based on cross-attention.) LK-CAUNet, which can effectively represent the spatial correspondence between fixed and moving images.LK-CAUNet, based on U-net, accurately captures the final cross-image correspondence by introducing a cross-attention module, thus achieving high-precision medical image registration.

5.3 Application of deep learning in medical image enhancement

The quality of medical images directly affects the accuracy of clinical diagnosis, but lesion images acquired by traditional imaging techniques often have many limitations. Factors such as uneven illumination conditions and complex imaging environments can lead to a decrease in the quality of medical images, thus affecting the accurate identification of the lesion area by doctors, which in turn increases the complexity of clinical diagnosis [16]. Therefore, in order to improve the quality of medical images, the development of medical image enhancement technology is particularly important. Advances in deep learning technology have brought great support to the field of image enhancement, enabling doctors to perform clinical diagnosis more efficiently. In 2021, LI Zi-ou and others [17] investigated the application of Wasserstein distance-based GAN-like model in brain MRI enhancement techniques. Aiming at the problems of training instability and pattern collapse of traditional GAN models, this research team proposed an improved WassersteinGAN model, which significantly improves the stability of training and the quality and diversity of generated samples by introducing the K-Lipschitz conditional constraints. In addition, this research team designed a novel FID metric that integrates the quality and diversity of generated images. This research provides an effective solution for medical image data enhancement, which has important theoretical and practical significance. In 2022, LIAO Shi-min and others [18] proposed an improved CycleGAN network for low-dose CT image enhancement. The method introduces a shallow feature pre-extraction module in the front-end of the generator, which enhances the extraction ability of CT image features, and adopts a depth-separable convolution to replace part of the ordinary convolution, which effectively reduces the complexity of the network. Experimental results show that the improved network significantly outperforms the traditional method and the original CycleGAN network in terms of image quality, and is able to better maintain the details of tissue structure while effectively suppressing noise and artefacts, which is of higher clinical application value.

6 Future prospects

The continuous progress of artificial intelligence technology has made deep learning show great potential in the field of medical image processing, especially in the areas of image segmentation, image registration and image enhancement, which have achieved significant results, as shown in Table 2, but there are still many problems in the actual clinical applications. From the current point of view, although many models perform well on specific datasets, their stability and adaptability in different hospitals, imaging devices and patient groups are still insufficient, and the generalisation ability needs to be urgently improved. Meanwhile, deep learning models mostly rely on large-scale data for training and lack understanding of medical expertise, making it difficult to cope with diverse and dynamic diagnostic demands in complex clinical environments. Therefore, the effective integration of doctors' professional experience with deep learning methods can help improve the accuracy and clinical applicability of the models. At the practical application level, due to the differences in hardware conditions and operating environments, the computing efficiency and flexible deployment of models also become important factors affecting their use. Constructing models that are lightweight in structure, efficient in computation, and applicable to common medical devices will help promote the use of this technology in primary care organisations. In addition, medical image data is highly sensitive, how to achieve efficient data sharing and collaborative model training while protecting patient privacy is also an urgent issue at present. Of course, new privacy-preserving mechanisms such as federated learning [19] provide a feasible path to this challenge. Overall, deep learning plays an increasingly important role in promoting the development of medical image analysis in the direction of intelligence, precision and practicality.

Table 2 Application of deep learning in medical image field

Application Fields	Research Team	Model/System	Features
Image segmentation	WANG Zhi Research Team	DeepViewer System	Suitable for automatic outlining of large volume organs with clear boundaries.
Image segmentation	ZHANG Fuli Research Team	FC_DenseNet model	This model is designed to significantly improve feature utilisation and achieve high segmentation accuracy even with small sample data.
Image registration	Li Shanshan research team	VV-Net Model	It effectively realises 3D alignment of brain images.
Image registration	CHENG Tianqi research team	LK-CAUNet model	It can effectively represent the spatial correspondence between fixed and moving images to achieve high-precision medical image registration.
Image enhancement	LI Zi-ou research team	WassersteinGAN model	It improves the stability of training and the quality and diversity of generated samples.
Image enhancement	LIAO Shi-min Research Team	Improved CycleGAN network	It can better maintain the details of tissue structure while effectively suppressing noise and artefacts, which has higher clinical application value.

7 Summary

With the increasing number of medical images, traditional manual analysis can hardly meet the clinical demand for efficiency and accuracy. Deep learning technology, with its powerful feature extraction and learning ability, has gradually become an important driving force for the intelligent development of medical images. This paper focuses on three aspects of image segmentation, image registration and image enhancement, combing the research results and practical applications of deep learning in this field in recent years, and demonstrating its obvious advantages in improving the quality of medical images and improving the diagnostic efficiency of doctors.

At the same time, deep learning technology still faces problems such as insufficient model generalisation ability, lack of understanding of medical knowledge, and high demand for computational resources in the process of clinical practice . In the future, we should further promote the lightweight design of models, enhance their cross-platform adaptability, and explore the deep integration with doctors' professional experience to achieve a higher level of intelligent assisted diagnosis. In conclusion, deep learning technology will play an increasingly important role in medical image analysis, providing more efficient and intelligent technical support for medical diagnosis.

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