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Deep Learning Based Applications in Medical Imaging

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Abstract. Along with the development of medical imaging technology, medical image analysis has become a crucial part of clinical diagnosis. However, traditional image analysis methods rely on manual feature extraction and expert evaluation, triggering problems such as low efficiency and lack of accuracy. Deep learning techniques, especially convolutional neural networks (CNNs), have made significant breakthroughs in medical image analysis in recent years. The aim of this paper is to study the application of deep learning in medical imaging, and explore the advantages and development potential in early disease diagnosis, image segmentation and feature extraction. This paper reviews the basic principles of deep learning and analyses the applicability of deep learning in medical imaging by combining the characteristics of medical imaging. Through systematic analysis of existing literature, this paper summarises the remarkable achievements of deep learning in processing, analysing and applying it to various medical images, such as Optical Coherence Tomography (OCT), Magnetic Resonance Imaging (MRI) and so on. It has been shown that deep learning methods can significantly improve the accuracy and efficiency of medical image processing and demonstrate performance due to traditional methods in tasks such as classification. However, how to improve the interpretability of models and the generalisability of clinical applications are still current research hotspots and challenges.

Keywords: deep learning, medical imaging, convolutional neural network, OCT, MRI

1. Introduction

With the rapid development of artificial intelligence technology, deep learning has been more and more widely used in medical treatment, especially in the field of medical image analysis, which is constantly updated in image diagnosis. Medical imaging is an important tool for diagnosing diseases, including Optical Coherence Tomography (OCT), Magnetic Resonance Imaging (MRI), and many other types. In recent years, deep learning models such as convolutional neural networks have shown significant advantages in medical imaging, which are able to automatically extract image features and improve the efficiency and accuracy of analysis, especially in the areas of tumour detection and lesion identification, which have achieved remarkable results. This paper aims to explore the progress of deep learning application in medical imaging by reviewing and analysing the existing literature, especially the latest achievements in early diagnosis of diseases, image segmentation, feature extraction, and so on. Specifically, this paper focuses on the application of

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deep learning in different medical imaging data, such as OCT, MRI. This paper summarises the specific applications of deep learning on medical imaging and proposes the problems and solutions encountered in the application process, providing reference for the application of deep learning in medical imaging.

2. Theoretical overview

2.1. OCT

OCT (Optical Coherence Tomography), a non-invasive imaging technique, is based on the principle of interferometry, which generates high-resolution images of living structures by detecting the interfering signal between the reflected signal from the reference mirror and the backscattered signal from the biological tissues, so OCT is widely used in the field of medical imaging. OCT enters biological tissues by emitting a low-coherence light beam, and the light is reflected or scattered at the interfaces of different tissue levels. After receiving these reflected light signals, the OCT system performs interference processing through an interferometer to convert the optical signals into electrical signals, and then obtains the intensity and phase information of the reflected light. By performing a Fourier transform on these signals, OCT is able to reconstruct a two- or three-dimensional image of the structure inside the tissue. In the field of medical imaging, because of its non-invasive, micron-level resolution and three-dimensional imaging capability, the importance of optical coherence tomography (OCT) technology is self-evident, and it is gradually becoming a key technology in the field of biomedical imaging. With the increase of application scenarios and detection needs, OCT is developing towards the direction of a new generation of medical imaging equipment with a 3D ultra-large field of view, which has a wide range of application prospects.

2.2. MRI

MRI (Magnetic Resonance Imaging) is a non-invasive medical imaging technology in the field of medicine, which can make use of a strong magnetic field and radio waves to generate a complete image of the internal structure of the body, and because of this advantage, MRI has been widely used in disease diagnosis, treatment planning and so on. MRI technology utilises the physical effects of magnetic resonance of specific nuclei within biological tissues, using a strong magnetic field to align hydrogen atoms, which are mainly found in water and fat, along the direction of the magnetic field. In the strong magnetic field, radio frequency pulses are used to temporarily change the alignment of the hydrogen atoms, and when the RF pulses stop, the hydrogen atoms release their energy and return to their original state. At this point we generate a tomographic image of the inside of the body by detecting the radiofrequency response signal as well as computer reconstruction.The high resolution of MRI provides higher quality soft tissue imaging and is suitable for imaging parts of the brain, spinal cord, joints, muscles, etc. Human tissues are made up of a large number of atoms, and protons in the water molecules are the main target of MRI, so it is different from X-rays and CT, which use ionising radiation, and is safer for human beings. humans is safer.

2.3. Convolutional Neural Networks

Convolutional Neural Networks (CNN) is an architecture in the field of deep learning that is based on multilayer perceptual machines [1]. Convolutional Neural Networks can simulate the working mechanism of the human visual cortex, in addition, it can also fully consider the pixel spatial distribution characteristics of the input values and back propagation with the help of a loss function,

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with its efficient computing power, Convolutional Neural Networks have been used in many fields. Convolutional Neural Networks (CNNs) consist of a convolutional layer, a pooling layer and a fully connected layer. The convolutional layer is the basic module, which uses the convolutional kernel to extract features from the input data, and then extracts different features through weighted summation to produce a feature map. The pooling layer is used to reduce the dimension of the feature map, reduce the amount of computation and prevent overfitting by compressing the feature map to increase the computing speed and reduce the number of parameters. The fully connected layer, in the final part of the CNN, acts as a classifier, integrates the features of the previous layers, performs the regression task, and cooperates with the activation function to perform the classification process and produce the final result. The activation function injects nonlinear properties into the neurons and enhances the network representation, making it suitable for various nonlinear models.

3. Applications of deep learning in medical imaging

3.1. Application in OCT

In computer vision, image segmentation is a very important part, the role is to be able to divide the medical image into multiple regions, so that each region has its own value [2]. OCT images contain multiple tissue layers: retina, optic nerve and blood vessels, etc., there is a demarcation line between these tissue layers, this line is very subtle, in order to make it easier to continue to analyse the image, the precise extraction of the tissue layer is the goal of the image segmentation technique. The goal of the segmentation technique. At the level of OCT image segmentation, Convolutional Neural Networks perform well, and with its encoder-decoder symmetric structure, the U-Net architecture has become the mainstay in this field [2]. Pixel-level segmentation of U-Net not only accurately identifies but also separates the different layers of the retina, because of which diagnosis of ophthalmological diseases is becoming more and more accurate, and image segmentation plays a great role in the field of medicine.

Due to the influence of the environment and genes, the health of the eyes varies among people living in different regions, and eye health has become a health problem that should not be ignored, and in ophthalmology diagnosis and treatment, medical imaging plays an important role, especially OCT, which can accurately and objectively show the structure of the fundus and provide doctors with important detailed information about ophthalmic diseases, thanks to the ability of OCT to provide non-invasive and high-resolution imaging. With OCT, doctors can take a closer look at the structures of the eye and accurately diagnose eye diseases, as well as effectively monitor and evaluate them during treatment. OCT accurately displays a three-dimensional view of the structures and blood vessels of the eye and produces a B-scan image that provides a unique perspective and information, which provides a cross-sectional view of the tissues and is suitable for evaluating the deep structures and blood vessels. deep structures and blood vessels, and is useful for visualising the severity of the disease and its potential progression [3]. For many people with eye diseases, it is important to be able to recognise ophthalmic diseases and accurately quantify retinal layer thickness, but because manual segmentation of retinal layers requires not only a background in relevant medical knowledge, but also manual segmentation, the process is laborious and subjective. With the development of deep learning, a large number of scholars have emerged to study the automatic extraction of retinal layers, due to the lack of a large number of reliable labelled data, so CNN and other mathematical models are combined to make up for the lack of data, and the CNN-GS model is proposed for automatic segmentation of retinal nine-layer boundaries from OCT images of AMD

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patients, and the performance of the automatic segmentation of the retinal boundaries has been significantly improved by deep learning. automatic segmentation performance [4].

The cornea, the outermost transparent refractive medium of the eye, has a unique vault-like anatomical structure and plays a key role in the visual imaging process. Accurate segmentation of the cornea and its diseased areas not only helps to improve clinical diagnosis, but also provides a reliable basis for the development of individualised treatment plans. Early corneal OCT segmentation mainly relied on traditional rule-based algorithms, which achieved automatic segmentation of the anterior and posterior surfaces of the cornea, but required complex pre-processing, and the generalisation ability of pathological corneas was relatively poor. With the increasing application of deep learning in medical imaging, a semi-supervised segmentation network for keratoconus based on label enhancement and pseudo-label optimisation has been proposed, which utilises the original image annotation enhancement module and pseudo-label optimisation module to enhance and optimise both existing image annotations as well as pseudo-labels in training. The local feature extraction advantage of CNN is utilised to process the underlying detail information, and the limitations of a single network architecture in multi-scale feature characterisation are effectively solved in this way through the combination of cross-modal feature fusion and dynamic supervision strategies.

3.2. Applications in MRI

Deep learning is widely used in the field of magnetic resonance imaging, which has largely pushed forward the progress of medical imaging, especially in medical image analysis and image segmentation. As a non-invasive medical imaging technology, MRI does not use ionising radiation, and is able to provide high-quality images of the internal organs and tissues of the human body, which enables doctors to make accurate judgments and make great contributions to the development of medicine.

Normal development of the fetal brain is very important for the health of the foetus, fetal MRI is an important imaging tool, this medical imaging uses ionising radiation, so it is safer for the foetus and the pregnant woman, for this reason MRI has an irreplaceable position in prenatal diagnosis [5]. At the same time, with its high tissue contrast and high spatial resolution images, MRI provides an important basis for fetal brain development monitoring and disease detection. In addition the precise segmentation of brain tissue structure in fetal MRI images can help clinicians assess the development of the fetal brain more comprehensively. Fetal MRI has advantages in monitoring fetal brain development and detecting congenital anomalies, etc. However, the development of the fetal brain is complex and rapidly changing due to a variety of genetic and environmental factors, and fetal MRI is able to provide detailed structural information about the brain that Fetal MRI can provide detailed structural information of the brain to help doctors assess the development of the brain and detect potential abnormalities in a timely manner. Based on the traditional convolutional network and drawing on the example segmentation of natural images, a target mask prediction module is added to the target detection network, targeting the specific structural segmentation of the foetal brain, and automatically segmenting the foetal cortical plate from the MRI image, adopting a staged attentional refinement module, which effectively improves the ability of capturing the image features by progressively focusing on the contextual information at different scales and exhibits a high level of accuracy and robustness.

The construction of a deep learning-based nomogram integrating ultrasound and MRI is an innovative diagnostic approach [6]. Statistics show that breast cancer is one of the most common cancers among women and a leading cause of cancer-related deaths in females. Due to the lack of a

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clear therapeutic target, triple-negative breast cancer is much more difficult to treat, and has a higher rate of recurrence and mortality. To improve the diagnostic accuracy of TNBC, researchers have organized and analyzed patients' clinical pathological and imaging data, utilizing deep learning techniques to extract a large number of image features and break through the limitations of traditional morphological diagnosis. By analyzing conventional ultrasound images, T2-weighted imaging, diffusion-weighted imaging, and dynamic contrast-enhanced MRI images of breast cancer patients, effective features were identified to establish a model distinguishing TNBC from non-triple-negative breast cancer (NTNBC), which was subsequently validated. In this process, ResNet50 was employed as the learning framework for the convolutional neural network, and methods such as intraclass correlation coefficient, least absolute shrinkage and selection operator regression were used for feature dimensionality reduction and selection [7-9]. The diagnostic efficacy of the clinical deep learning histological nomogram of ultrasound combined with MRI in distinguishing TNBC from NTNBC is significantly better than other models, which improves the diagnostic accuracy of TNBC, and better guides the selection of clinical treatment options, and has better clinical application value.

4. Challenges and future

As technology advances, deep learning has shown strong potential in medical imaging for automated analysis, early disease screening, and improving diagnostic accuracy, but still faces multiple challenges.

Firstly, training deep learning models in medicine requires large amounts of high-quality labeled data, which face several constraints. Medical image annotation is specialized and requires expert participation, increasing costs and limiting available data. Additionally, image quality varies across hospitals and equipment, affecting model consistency. The high cost of data acquisition, such as fetal MRI, often results in small public datasets that hinder model performance. Moreover, the significant computational resource demands may restrict use in resource-constrained environments. Increasing open-source datasets could improve data accessibility in the future.

Secondly, as AI continues to mature, a clear and transparent decision-making process in its application remains lacking. Many deep learning models, particularly convolutional neural networks used in medical image analysis, are considered black boxes. Doctors need to understand and explain these models' decision-making processes, as each decision impacts patient safety [10]. While heat maps and feature visualization techniques assist with interpretation, they often fall short of clinical needs. Improving model interpretability and integrating it with clinical decision support systems is crucial for the widespread use of deep learning in medical imaging.

Finally, deep learning models have excelled in laboratory settings but lack large-scale clinical validation. Many OCT-based models are trained and validated on single-center datasets without external testing, primarily due to limited publicly available OCT data and privacy concerns related to cross-institutional data sharing. The involvement of personal privacy data in medical images poses additional challenges. Addressing these issues is essential for ensuring the legal compliance of data acquisition and enhancing the applicability of deep learning in clinical environments.

5. Conclusion

This article provides an in-depth exploration of the application of convolutional neural networks (CNNs) in MRI and OCT, highlighting their transformative potential. As deep learning technologies continue to advance, they are set to revolutionize the analysis of medical images, enhancing

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accuracy and efficiency. This progress extends beyond mere image analysis; it promises to reshape the entire structure and service model of the healthcare industry. By integrating advanced AI-driven techniques, people can anticipate a future where healthcare services are not only more efficient but also significantly more precise, ultimately leading to improved patient outcomes and streamlined medical practices.

However, there are some shortcomings in this paper. Firstly, although this paper details the application of convolutional neural networks on MRI and OCT, the application of other types of medical imaging technologies such as CT and PET is less explored, and future research could be further extended to these areas to provide a more comprehensive perspective. Secondly, the issue of interpretability of deep learning models has not been explored deeply enough in this paper, and future research could focus on developing more interpretable deep learning models to enhance clinicians' trust in the model results.

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