Application Research of Image Processing Based on Artificial Intelligence in Medical Field

Xuanchen Dong[1,*][a], Liyuan Xiong[2][b] and Churui Zhang[3][c]
[1]Houston International Institute· Dalian Maritime University, Linghai Road, Ganjingzi District, China
[2]Electronic Engineering, Chengdu University of Information Technology, Xuefu Road, Shuangliu District, China
[3]Electronic Information School· Wuhan University, Ba Yi Road, Wuchang District, China

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Abstract: This paper discusses in depth the contribution of image processing based on artificial intelligence to medicine. Medical images include ultrasound images, X-rays and magnetic resonance images. However, interpreting these images often relies on subjective judgment and professional experience, which is not only time-consuming, but also prone to human error. Therefore, image processing plays a very important role in the medical field. This paper summarizes the optimal AI solutions for ultrasonic, X-ray, and CT image processing through a large literature review. In ultrasonic image processing, deep learning technology reduces the reliance on subjective judgment and improves the accuracy of diagnosis by automatically learning image features. In X-ray image analysis, models such as u-net+Attention have been developed to detect the high risk factors for postoperative recurrence of lumbar disc herniation and improve the accuracy of image interpretation. For CT images, deep learning models are applied to improve the accuracy of diagnostic results. The paper also demonstrates the effectiveness of these AI techniques in different medical imaging applications through experimental results. The application of this technology not only improves the accuracy and efficiency of diagnosis, but also provides strong support for clinical treatment, which has important research value and broad application prospects.

1 INTRODUCTION

With the popularity of the internet and mobile devices, image data has exploded, which provides rich materials for the training of deep learning. At the same time, with the continuous progress of hardware such as GPU, large-scale neural can be processed efficiently. Lay the foundation for the application of deep learning in the image recognition field. The theory of deep learning continues to achieve breakthroughs, especially the proposal and development of convolutional neural Networks (CNN), providing a powerful method for automatic feature learning for image recognition. CNN can automatically learn hierarchical feature representations in images through multiple layers of convolution and pooling operations, thereby better capturing both local and global information in images, significantly improving the accuracy of image recognition.

Deep learning image recognition technology has been applied in many industries, among which, it can be used for the analysis and diagnosis of medical images in the medical industry, such as the automatic identification of X-ray, CT, MRI, and other images and lesion detection. It can detect lesions quickly and accurately, assist doctors in diagnosing diseases, and improve the efficiency and accuracy of diagnosis, which has great significance for the early detection and treatment of diseases. This research focuses on the three aspects of ultrasound, CT and X-ray imaging. First of all, artificial intelligence plays a big

[a] https://orcid.org/0009-0003-4886-4932
[b] https://orcid.org/0009-0002-5472-7769
[c] https://orcid.org/0009-0009-5234-8889
*Correspongding author

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role in processing ultrasound images.However there is a problem that ultrasonic images require more subjective judgment, which need to be solved.CADe , CADx, Machine Learning (ML) and Deep Learning(DL) are used for making the ultrasonic image processing more accurate. Secondly, artificial intelligence is used in X-ray images. In order to explore the high risk factors of PETD surgery recurrence, improve the clinical treatment effect of lumbar disc herniation, through a large sample of related risk factors after PETD operation long time-course follow-up analysis, initially established the model of the probability of PETD surgery recurrence prediction and the full convolutional neural network based on u-net + Attention. Finally, CT images, previous studies used residual network (ResNet) for image classification, and recurrent neural network (LSTM) for the results correction. For the segmentation task, a V-type network (VB-Net) is used for model training to calculate the hematoma volume.

Focusing on the above problems and challenges, this paper analyzes and summarizes the research progress and current situation of the utilization of image recognition based on deep learning in the medical field. This paper introduces the role of deep learning in different medical images in detail, and prospects that more medical images can be processed by AI in the future.

2 METHOD

2.1 Ultrasonic Image

Artificial intelligence, especially machine learning and deep learning technologies, plays an important role in ultrasonic image processing These technologies are able to automatically analyze and interpret ultrasonic images, reducing the reliance on manual interpretation. Computer aided detection（CADe）and computer aided diagnosis（CADx）are two key technologies in ultrasonic image processing. CADe is used to automatically detect abnormal areas in the image, helping doctors to find potential problems in the image, especially in the initial screening, can reduce the workload of manual examination and improve the efficiency of diagnosis. However, CADe is prone to false positives or false negatives, leading to misdiagnosis or missed diagnoses, and model performance is strongly dependent on the quality and quantity of training data. CADx is used for further analysis and diagnosis of these abnormal areas. CADx not only provides test results, but also can be used for diagnostic inference, such as judging the benign and malignant nature of the tumor, and the output is more granular, providing information about the type and stage of illness. CADx involves more reasoning and decision-making processes, is computationally expensive, and the black box nature of the model may lead to a lack of trust among physicians when using it. By training a large amount of ultrasonic image data, machine learning and deep learning models are able to learn the feature patterns in the image, thereby improving the accuracy of image processing. These techniques can be applied to image filtering, segmentation, enhancement, etc., to improve image quality and extract useful diagnostic information.

2.2 X-ray Image

VGG16 performs well in X-ray image classification, mainly due to its deep network structure and 3×3 small convolutional kernel design, which can effectively extract complex features from low to high level, and is suitable for capturing subtle lesions such as pneumonia and fractures in X-ray. Its transfer learning ability is remarkable, and it can quickly adapt to medical imaging tasks on small datasets through pre-training weights and fine-tuning. In addition, VGG16 has a simple structure, strong interpretability, and supports feature visualization, which is convenient for doctors to verify model decisions. Despite the large number of parameters and the high computational cost, these issues can be mitigated through data augmentation, regularization, and GPU acceleration. The maturity and stability of VGG16 make it of great value in medical image analysis, especially for the research and clinical pilot of small and medium-scale datasets.

The u-net+Attention fully convolutional neural network is used for automatic analysis and interpretation of X-ray images. By introducing an attention mechanism, the model is able to locate and analyze key areas in the image more accurately, thereby improving the accuracy of diagnosis. U-Net combined with the Attention mechanism excels in medical image segmentation, enabling accurate segmentation of complex structures, such as tumors or organs. With the introduction of the Attention mechanism, U-Net can better focus on important areas and improve the segmentation accuracy, especially in complex or blurry image areas. However, the U-Net structure requires large computing resources, especially after the introduction of Attention, and the training time is longer, especially when training on large-scale datasets, it may take a long time to converge.

Convolutional neural network (CNN) can automatically learn the features in medical images, especially the local structures in the images, such as tumors and blood vessels, which are suitable for classification, detection and segmentation tasks, and have become the basic methods in medical image analysis. However, CNNs require a large amount of labeled data for training, and when the data is insufficient, the performance of the model may be unstable, and it is difficult to model the global structure.

2.3 CT Image

Residual Network (ResNet) is a deep learning model with powerful image classification capabilities. It is capable of accurately classifying different types of images by learning feature representations within the images. In CT image processing, ResNet can be used for identifying and analyzing lesions, organs, and other structures. ResNet solves the gradient vanishing problem in deep network training through residual connections, allowing the network to be deeper and more complex, making it very suitable for complex medical image analysis, such as tumor detection and lesion classification. However, the complexity of the ResNet model is relatively high, increasing the complexity of computation and training difficulty, and it requires a larger and more diverse dataset.

Long Short-Term Memory (LSTM) is a special type of recurrent neural network with the ability to learn long-term dependencies. In CT image processing, LSTM can be used to correct and optimize preliminary classification results, improving the accuracy of diagnosis. LSTM is particularly suitable for processing time-series data and is applicable for dynamic image analysis, such as sequences in medical imaging, including dynamic scan data from CT and MRI. LSTM can capture relevant information over long periods, which helps to capture the evolution of lesions over time. However, the structure of LSTM is relatively complex, the training process is more time-consuming. The structure of LSTM is not adept at processing spatial features of images, often combined with CNNs, which increases computational complexity.

V-Net (VB-Net) is a deep learning model specifically designed for medical image segmentation tasks. It can automatically identify and segment bleeding areas in CT images and automatically calculate hematoma volume. This method can provide doctors with more accurate and intuitive diagnostic information. VB-Net uses variational Bayesian methods for inference, which can provide uncertainty estimates for medical image diagnosis, helping to handle complex and ambiguous medical images. VB-Net is robust to noise and missing data, but Bayesian inference methods usually involve complex probabilistic calculations, and the training and inference processes are relatively slow, and implementation and debugging are more complex.

3 APPLICATION RESEARCH

Artificial intelligence plays a big role in processing ultrasound images. Ultrasound image processing is more difficult than MRI because ultrasound images require more subjective judgment. In order to solve this problem, CADe and CADx have become the main solutions, but CADe and CADx still have a large degree of limitations in the collection and processing of data. Machine learning (ML) and deep learning (DL) can make ultrasonic image processing more accurate. Machine learning can only identify basic cases from the data set, so relying solely on machine learning to analyze disease categories based on ultrasound images becomes more difficult because many diseases vary too much for the data set to cover all cases. Lee YH and Shin Y of Yonsei University found that DL was much more accurate than ML in classifying skeletal muscle diseases (Shin, Yang, Lee, 2021). This is because deep learning can imitate the neural network of human brain and use a large number of labeled data for learning training (LeCun, 2015). In order to identify Duchenne muscular dystrophy (DMD), echo intensity and muscle thickness were quantified to distinguish echo-enhanced myopathy muscles, and subsequently ML and DL were used to compare ultrasound images of patients with normal muscle images and automatically partition the parts containing body myositis, polymyositis, dermatomyositis, and normal manifestations. In this process DL is more accurate than ML regardless of the type of skeletal muscle disease. It can be seen that DL technology has become the core technology of ultrasonic image processing.

Cal Shaohui, Lin Qiaojuan et al. introduced AI into the diagnosis of pulmonary nodules. The thickness of 64 row spiral CT and 64 row CT layer of Somatom Definition AS model was set to 1 mm, followed by interval-free reconstruction, the window width was set to 1 450 HU and the window position was set to-831.1HU to ensure accurate identification of lesions.Related data (such as communication data, medical digital imaging, etc.) after import relevant imaging examination, AI pulmonary nodule diagnosis system, will identify and check two stages, then use computer-aided quantitative parameter system data preprocessing, single box detector simulation training, nodule measurement operation, automatically check the nodule edge, this series of operation do the three-dimensional state of nodule long diameter, short diameter, volume, maximum cross-sectional area and other parameters. However, the study of Li Juan, Tang Xiangyu et al. used AI analysis for intracranial hematoma, using two datasets (Li, Tang, 2021). Data set 1 contained 9594 plain scan images of craniocerebral CT, of which 223 patients with positive intracranial hemorrhage were used as the test set, and the rest were used as the training set. Dataset 2 contains 819 CT images of bleeding foci that have been manually delineated, of which 74 were used as a test set to verify the consistency between algorithm segmentation and manual segmentation. Data input of the CT images was first performed, and all of the CT images were performed in a standard DICOM format. Data preprocessing included image correction, skull removal, and grayscale normalization. In the cross-axis data, the position of the two endpoints in the midline brain is detected based on deep learning, and the CT image of the cross-axis is rotated, which automatically positions the brain position. Then, the brain tissue area was automatically segmented based on deep learning, and the interference information including the skull and other images in the image, was automatically removed. After the gray scale normalization to [-1,1], the calling residual network (ResNet) of the image was classified according to five bleeding types and a total of six labels. For each layer of classification results, call circulating neural network (long short-term memory network, LSTM) results correction.For bleeding focus segmentation task, after image pretreatment, call V network (VB-Net) model training, which through the voxel statistics and spacing conversion, the introduction of the algorithm and the model can automatically get each bleeding statistics to calculate the hematoma volume, is a big improvement.

Jinxiu Cai et al. studied a deep learning-based chest X-ray (CXR) image classification model(Cai, 2022), using the Vgg16 network to classify different types of chest X-rays, and successfully distinguished between adult anteroposterior chest x-rays, lateral x-rays, bedside x-rays, and infant x-rays. The model showed high accuracy (94%~100%) in the test set and external validation, and was able to automatically screen out qualified images for subsequent disease diagnosis. The characteristics of this research are that the automation level of image classification is improved through deep learning models, the errors of manual operation are reduced, and the work efficiency of the imaging department is improved. In the future, the model is expected to be further optimized and extended to more image quality evaluation scenarios.

Ramadhan Hardani Putra et al. reviewed the application of artificial intelligence in digital dental radiology, covering multiple aspects such as caries diagnosis, periodontal bone loss analysis, cyst and tumor classification, etc (Ramadhan, 2022). The study has shown that deep learning (DL) and convolutional neural networks (CNNs) excel in dental image analysis, automatically identifying complex image patterns and providing quantitative analysis. The research is characterized by the fact that it demonstrates the potential of deep learning for a wide range of applications in dental imaging, especially in terms of automated diagnosis and image quality enhancement. In the future, with the expansion of datasets and the improvement of algorithms, deep learning is expected to play a greater role in dental clinical practice.

Finally, Xian Chang et al studied the identification of key parameters of lumbar X-ray based on deep learning model, and constructed a fully convolutional neural network based on U-net+Attention, which was used to automatically measure the intervertebral space height index, lumbar spine motion angle and segmental mobility (Xian, 2024) . The average IOU of the model on the test set reached 0.940 and the Dice coefficient was 0.980, showing high segmentation accuracy. The characteristics of this study are that the automatic measurement of lumbar spine imaging parameters is realized through deep learning technology, which reduces the error and workload of manual measurement, and improves the accuracy of clinical decision-making. In the future, the model is expected to be further optimized and applied to more spine image analysis scenarios. In summary, the contribution of deep learning in the field of X-ray is mainly reflected in automation, high precision and high efficiency. Through different deep learning models, researchers have successfully solved the problems of medical image classification, segmentation, and parameter measurement, and significantly improved the efficiency and accuracy of image analysis. In the future, with the continuous advancement of technology and the expansion of data sets, the application of deep learning in the field of medical imaging will be more extensive and deeper, which is expected to provide stronger support for clinical diagnosis and treatment.

4 CONCLUSION

This paper discusses the application and effect of artificial intelligence in ultrasonic image, CT image and X-ray image processing. The results show that artificial intelligence technology, especially deep learning methods, has shown significant advantages and great potential in the field of medical imaging diagnosis.

In ultrasonic image processing, deep learning overcomes the limitations of traditional CAD systems by imitating the human brain's neural network and using lots of labeled data for training. This greatly improves the accuracy of skeletal muscle disease classification. This technological advance not only improves the reliability of diagnosis, but also provides stronger support for the early detection and treatment of related diseases.

In CT imaging diagnosis, the application of AI technology has realized the automatic detection and accurate parameter determination of lung nodules and the efficient analysis of intracranial hematoma. The deep learning algorithm lets the system automatically identify and classify bleeding types, calculate hematoma volume, and provide quick, accurate diagnosis for clinicians. This helps improve patient outcomes by enabling timely treatment.

For X-ray images, the deep learning-based model performed well in the identification of key parameters in the lumbar spine and the analysis of chest X-rays. The model of automatic measurement of lumbar parameters provides a powerful tool for predicting the risk of surgical recurrence, reducing human error and improving work efficiency. At the same time, the binary diagnosis AI model of chest X-ray film has reached a high accuracy in the diagnosis of "abnormal finding" and "no abnormal finding", which effectively improves the daily work efficiency of the medical imaging department.

To sum up, the application of artificial intelligence technology in medical image diagnosis not only improves the accuracy and efficiency of diagnosis, but also provides more powerful support for clinical treatment. With the continuous progress of technology and the accumulation of data, the application of artificial intelligence in the field of medical imaging will be more extensive and in-depth, which is expected to further promote the development of medical imaging diagnostic technology and improve the treatment effect and quality of life of patients. Future research should continue to explore more efficient and accurate algorithms, optimize model performance, and strengthen multi-center cooperation to promote the widespread application and standardization of AI technology in medical image diagnosis.

AUTHORS CONTRIBUTION

All the authors contributed equally and their names were listed in alphabetical order.

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