

Application of Image Processing Technology Based on Deep Learning in Medical Imaging

Yifei Chen

*College of Electronic Information Engineering, Taiyuan University of Technology, Jinzhong, China
2637940943@qq.com*

Abstract: In recent years, with the continuous development of artificial intelligence (AI), its application in medical imaging has expanded significantly, leading to remarkable advancements in the field. This paper focuses on a comprehensive review of deep learning based on image processing technology for medical imaging, emphasizing its critical role in diagnostic and therapeutic processes. By examining the interdependency between medical imaging technology and diagnostic workflows, the application of deep learning image processing in medical imaging of lung, bone and oral organs is discussed. And the significant advantages of this technology in image structure analysis, disease prediction and diagnosis, and treatment plan formulation are demonstrated. Studies have shown that medical imaging currently has problems such as low data standardization and insufficient model generalization. This requires relevant researchers to make unremitting efforts in strengthening data standardization construction and continuous optimization of models in the future, so that medical imaging can provide more powerful support for human health.

Keywords: Artificial intelligence (AI), medical image, deep learning, image processing

1. Introduction

The rapid development of artificial intelligence (AI) has greatly improved the application of image processing in the field of medical imaging, especially at the clinical application level, and has made outstanding contributions to medical imaging diagnosis and treatment. Medical imaging supports the diseases diagnosis through multiple modalities. AI's image recognition and segmentation technology can accurately analyze images, provide significant assistance to doctors in judging diseases and formulate treatment plans. For example, magnetic resonance imaging (MRI) combined with AI can more accurately and efficiently distinguish between different human tissues, helping doctors to judge the condition and improve the quality of diagnosis. At the same time, by analyzing a large number of diagnostic images and data, AI can perform disease prediction, lesion detection and disease classification. For example, for high-density tissue, computed tomography (CT) combined with AI can quickly label the lesion, measure its size and nature, and determine its relationship to surrounding tissue, thus improving the accuracy and efficiency of diagnostic. In addition, AI can also intelligently assist diagnosis and treatment, effectively reducing misdiagnosis and missed diagnosis. Taking lung cancer patients as an example, AI can determine various parameters of the tumor and formulate a detailed treatment plan based on clinical manifestations[1]. From the perspective of technological development trends, medical image AI is developing in the direction of the "Four Transformations"(i.e. standardization, personalization, precision,

globalization). Standardization is committed to making data processing and parameter recommendation more refined and unified, so that AI can play a stable role in different medical institutions. Personalization is based on the characteristics of individual patients to specify scanning protocols, optimize patient examination experience, and promote effective communication between doctors and patients. Precision runs through the whole process of medical diagnosis and treatment, and improves the accuracy of all aspects of the medical process in an all-round way. Globalization integration integrates all aspects of medical treatment, builds a complete medical chain, realizes more unified information circulation, simplifies the process, and improves the efficiency and quality of overall medical treatment[2].

Since AI plays an important role in the development of medical imaging, this paper takes deep learning technology in AI systems as the cornerstone and summarizes some examples of medical image processing in real life, providing important reference value for the future development of medical imaging field.

2. Overview of medical imaging

Medical imaging occupies a key position in the modern medical field and provides great help for accurate and efficient medical diagnosis and treatment. Medical imaging technology includes Roentgen ray (X-ray) imaging, CT imaging, MRI and others. Conventional X-ray imaging has been transformed from analog mode to digital model, with the specific methods mainly computer X-ray photography (CR) and direct digital X-ray photography (DDR), which can improve the image quality and reduce costs. The continuous development of CT image has improved the low image density resolution of traditional imaging methods. Although CT images suffered from image artifacts and other problems in the early application, with the application of computer-aided detection technology (CAD), both of CT images and disease detection rate has been improved. With the help of advanced equipment, MRI technology has greatly improved the image quality, and has become more mature in the diagnosis of cardiovascular, tumor and other diseases, and has been developing in the direction of quantitative image technology, personalized medical results summary evaluation and multi-mode MRI molecular imaging technology[3].

Medical imaging technology is closely related to medical imaging diagnosis. The different characteristics of different medical imaging technology greatly improves the accuracy and efficiency of medical imaging diagnosis, and makes outstanding contributions to the development of medical imaging, and the requirement of high level medical imaging diagnosis also promote the continuous development and improvement of medical imaging technology. Therefore, the two have a strong correlation, complement each other, inseparable[4]. In the future, the development of medical imaging will further improve the level of medical services and provide a more powerful guarantee for people's health.

3. Application of deep learning image processing in medical imaging

This paper mainly analyzes the application of deep learning image processing in the medical fields from the perspectives of lung, bone and oral cavity.

3.1. Lung

3.1.1. Tuberculosis detection

Due to the complex structure and morphology of tuberculosis, traditional detection methods are prone to misdiagnosis and missed diagnosis. However, deep learning, particularly convolutional neural network (CNNs), can learn a large number of lung image data to accurately identify

tuberculosis lesions. Deep learning networks in the field of object detection are mainly divided into single-stage detector and two-stage detector.

The single-stage detector, represented by YOLO and SSD, can detect all objects in a single inference, offering fast detection speeds. However, especially for small targets, its detection accuracy is relatively lower than that of two-stage detector, making single-stage detector suitable for rapid screening. The two-stage detector based on R-CNN series achieve high detection accuracy by extracting candidate regions and then identifying and classifying regional targets. However, because the network needs to calculate a large number of repeated features, its detection speed is relatively faster than that of the single-stage detector, so the two-stage detector is suitable for fine detection[5].

In integrated detector frameworks, many researchers optimize networks for tuberculosis characteristics. For example, Hooda et al. proposed a tuberculosis detection system based on three standard architectures: AlexNet, GoogleNet and ResNet. This system achieved an accuracy rate of 88.24% across four public databases [6], UI Abideen et al. proposed a pulmonary tuberculosis diagnosis model based on Bayesian CNNs, which achieved an accuracies of 96.42% and 86.46% in two public databases, respectively[7]. These optimized networks have significantly improved the accuracy and efficiency of tuberculosis diagnosis, effectively advancing the progress of tuberculosis detection.

3.1.2. Pneumonia detection

The high incidence of pneumonia requires timely diagnosis and treatment. Traditional detection methods rely on manual feature extraction, resulting in low efficiency and high error rates. Deep learning uses CNNs to automatically learn deep features of lung images, thereby improving efficiency and accuracy. In terms of classification and recognition, pneumonia imaging can be accurately classified by optimizing network parameters using large datasets during the training phase.. For example, Pan et al. proposed that the improved AlexNet network combined with transfer learning technology could distinguish bacterial pneumonia and viral pneumonia in pneumonia chest film with an accuracy of 80.48%[8]. Liang et al. proposed that the ResNet network with the residual idea can effectively solve the problem of gradient explosion or gradient disappearance, achieving a recognition accuracy of 90.50%[9]. Target detection and location recognition of lesions can assist in determining the category of lesion and also mark corresponding region according to the requirements. Taking the Mask-RCNN model proposed by He et al. as an example, pneumonia can be accurately identified through a combination of top-down and bottom-up feature extraction paths, and the boundary of lesions can be clearly defined, helping doctors to quickly locate the lesion area, thus greatly improving the diagnostic efficiency [10]. These optimized models not only strongly promote the development of pneumonia detection, but also provide a strong support for the subsequent development of treatment plans[11].

3.1.3. Lung cancer treatment

In the diagnosis and treatment of lung cancer, deep learning image processing and imaging omics complement each other, providing a foundation for the medical industry. Key features such as shape, size, intensity and texture can be extracted from positron emission tomography (PET) , CT, MRI and other images through processes of acquisition, reconstruction and segmentation, which provide an critical data basis for subsequent analysis. Deep learning leverahes the powerful learning ability of neural network model to deeply analyze and evaluate the data features of imagomics. At the diagnostic level, the CNN prediction model proposed by Sun et al., which incorporates image omics features, can effectively identify benign and malignant isolated pulmonary nodules and masses[12],

Additionally, the texture feature-based ANN prediction model proposed by Chen et al. can quantitatively classify and stage lung tumors according to their heterogeneity[13]. In addition, deep learning can also predict the state of common mutated genes by learning the imaging features of the lungs, indicating the direction of targeted therapy. In terms of treatment and prediction evaluation, WU et al. demonstrated that deep learning combined with CNN technology could predict EGFR mutation status, and providing reasonable guidance for accurately match EGFR-TKIs drugs for patients[14], Luo et al. revealed that through continuously monitoring changes in imaging omics features, deep learning can evaluate medical efficacy in real time, enabling physicians to promptly adjust treatment strategies, and more accurately assess patient prognosis [15]. The combination of deep learning and imaging omics has promoted the transformation of lung cancer diagnosis and treatment from the traditional models to precision medicine, elevating the diagnostic and therapeutic technology of lung cancer to a new height[16].

3.2. Bone

3.2.1. Bone and joint system diagnosis

In the diagnosis of bone and joint diseases, deep learning technology significantly enhances image quality through application in image reconstruction, synthesis, registration and segmentation. For image reconstruction, the medical imaging method combined with deep learning effectively suppress noise and enhance image quality. For example, the RED-CNN network proposed by Chen et al. restores details while eliminating noise in low-dose chest CT images [17]. Additionally, the LEARN network subsequently proposed by Chen et al. autonomously learn regularization terms and parameters to make the reconstructed image clearer and facilitate doctors to find small lesions[18]. In image synthesis, the problem of scarce image data can be solved by extending the dataset and simulating imaging, which increases the diagnostic accuracy. For example, the extended CycleGAN network proposed by Hiasa et al. utilizes MRI to synthesize CT images, thus improving the accuracy of bone segmentation[19]. Image registration combined with deep learning can be used to optimize network parameters through training data to quickly find spatial relationships between multiple images. van Eijnatten et al. proposed to use VoxelMorph model to register longitudinal abdominal and pelvic CT images, which greatly improved the registration performance and the registration speed by 300 times [20]. Image segmentation combined with deep learning is crucial for quickly determining the location and morphology of lesions, and the model represented by U-Net network has been widely used in the medical image segmentation. Liu et al. used the automatic segmentation algorithm based on image block and full CNN to achieve automatic segmentation of shoulder joint MRI images, and the segmentation effect was good [21]. In addition, the automatic proximal femur segmentation method based on U-Net network proposed by Bjornsson et al. can achieve sub-millimeter segmentation accuracy, and the prediction time of each segmentation is only 12 to 15s, which greatly improves the accuracy and efficiency of diagnostic [22]. Therefore, the application of deep learning in bone and joint system imaging have substantially improved diagnostic outcomes and established a robust foundation for the field [23].

3.2.2. Musculoskeletal system diagnosis

Deep learning also plays an important role in the diagnosis of musculoskeletal system diseases, providing accurate and effective solutions in a number of key links.

For the diagnosis of fractures, deep learning combined with multiple imaging techniques enhance diagnostic accuracy and efficiency. By integrating YOLO and U-Net, Son et al. achieved accuracy and recall rate of 0.95 and 0.87 respectively, in locating fracture on mandibular panoramic X-ray [24]. In addition, Simukayi et al. used GAN networks and digital reconstruction X-rays to

analyze hip X-rays, which improved the accuracy rate of diagnosis and classification of femoral neck fractures to 0.923[25]. At the same time, the DRF-Net model proposed by Yang et al. can quickly classify distal radius fractures with an accuracy rate of 84.2%, providing effective technical support for clinically assisted fracture diagnosis[26].

In bone tumors diagnosis, deep learning technology through autonomous learning has a promising prospect for improving diagnostic efficiency and accuracy. Zhao et al. an accuracy of 0.935 and a time of only 11. 3s in the network-assisted diagnosis of bone metastases based on a deep neural network model combined with ImageNet pre-training [27]. The CNN model proposed by He et al. can predict the recurrence of giant cell tumor of bone, especially when combined with clinical characteristics, the prediction accuracy and sensitivity are improved to 78.6% and 87.5%, respectively[28]. At the same time, the multistage Seg-Unet model proposed by Do et al. achieved an accuracy of 99. 05% in segmentation and classification of knee bone tumors, which can help reduce the misdiagnosis rate of bone tumors[29].

In osteoporosis, the combination of deep learning techniques can extract effective features from different image data for auxiliary judgment. For example, VGG16 and non-local neural network models can predict osteoporosis, transfer learning based CNN classification of knee X-ray images can assist in early diagnosis of osteoporosis, and ANN classifier models can provide high accuracy in bone mass measurement[30-31].

When deep learning is combined with musculoskeletal system imaging for diagnosis, the diagnostic effect shows a more significant trend, making deep learning show great potential and vitality in the field of musculoskeletal system imaging.

3.3. Oral cavity

3.3.1. Oral structure diagnosis and treatment

The application of deep learning in the diagnosis and treatment of oral structures is currently focused on identification, positioning and segmentation, treatment plan formulation and preoperative evaluation. In terms of tooth recognition, positioning and segmentation, Xu et al. used the two-level hierarchical CNN structure and related optimization methods to effectively improve the accuracy of tooth segmentation, and exceeded the accuracy of traditional geometric methods[32]. Chen et al. utilized the faster regional detection mode of CNN features in the TensorFlow library, achieving 90% accuracy and recall in identifying teeth in the apical slices[33]. In addition, Kheraif et al. combined the hybrid image segmentation method with CNN networks to detect problems such as abnormal number of teeth and structure, and the detection accuracy rate reached 97.07%[34]. In the positioning and segmentation of oral anatomical structure, Arik et al. achieved higher detection accuracy of anatomical landmarks and classification accuracy of anatomical types by referring to CNN in the automatic quantitative cephalometry, which is conducive to a clear understanding of oral anatomical structure[35]. In addition, Kwak et al. used two-dimensional and three-dimensional deep learning networks to detect and segment mandibular canals in CBCT images, achieving global accuracy values of 96.0% and 99.0%, respectively[36]. The automatic method based on U-net deep learning proposed by Vinayahalingam et al. can be perfectly adapted to detect and segment the root and inferior alveolar nerve of the mandibular third molar on the panoramic film[37].

In terms of oral treatment decision making, represented by U-Net network and YOLO-v3 model, the image processing accuracy and picture clarity of molar and inferior alveolar neural tube have been improved qualitatively, which assists doctors to formulate a better treatment plans[37-38]. For preoperative evaluation, U-NET-based deep learning models can clearly diagnose metastatic or non-metastatic lymph nodes, thereby reducing unnecessary biopsies[39-40]. In the aspect of

assisting orthodontic preoperative evaluation, a two-stage, coarse-to-fine deep learning method was adopted and a multi-task convolutional network deep learning model was developed to improve the accuracy of labeling and the practicality of the model[41-43]. In the preoperative assessment of auxiliary implantation, the prediction accuracy of implantation surgical plan can reach 93.8% with the model based on LeNet-5 architecture proposed by Sakai et al. [44]. For auxiliary tooth defect repair, Tian et al. used a two-stage deep convolutional generation adversarial network to reconstruct the crown surface, showing excellent performance and high clinical practicability[45]. The field of oral structure diagnosis and treatment combined with deep learning technology is full of strong vitality, and the development of oral structure diagnosis and treatment in the future is very impressive[46-47].

3.3.2. Oral disease diagnosis

Deep learning has significantly impacted the diagnosis of dental diseases. For example, Cantu et al. achieved more accurate, sensitive, and specific results in diagnosing proximal caries using CNN network compared with clinical dentists to a certain extent[48]. Ekert et al. used CNN network to detect periapical inflammation, and the results showed high sensitivity and specificity[49]. In addition, Fukuda et al. used CNN network to diagnose the diastatic root crack, reaching a 93% accuracy rate [50]. Deep learning also holds substantial value in the diagnosis of periodontology. Krois et al. applied CNN to the intelligent diagnosis of periodontal bone resorption caused by periodontal diseases, and the average accuracy of the results could reach 81%[51]. Chang et al. used CNN to automatically detect alveolar bone resorption of each tooth and automatically stage periodontitis, and the results showed high accuracy and excellent stability[52]. In addition, Lee et al. used CNN to diagnose and predict periodontitis, showing high accuracy of the results and giving constructive suggestions on the formulation of later adjuvant treatment plans[53]. Therefore, deep learning plays a pivotal role in oral disease diagnosis, with future advancements heavily reliant on its technical support [54-55].

4. Challenges and prospects of medical imaging

Deep learning image processing technology has made great achievements in the application of medical image, but several challenges remain. In the standardization of medical image data, there is a general lack of high-quality training data, significant variability in existing datasets, and insufficiently consistent and clear standardized of data description. Additionally, model generalization tends to exhibit instability, with most AI models performing well on the training data, but exhibiting poor reproducibility and portability during internal and external verification [56].

In the future, medical imaging will develop in a more accurate, more intelligent and more humane direction. In terms of technological development, the construction of data management standards helps to achieve the standardization of medical data, while the combination of privacy protection technologies such as federated learning also helps to establish sound data sets and promote the application of deep learning in the medical field. In model development, it is committed to building models with stronger universality and robustness. By expanding the data sample size and training models with different types of image data, the purpose of improving practical application efficiency can be achieved. In the practical application landscape, combined with technologies such as biosensors and deep learning on wearable devices, medicine may be transformed into a new model of predictability, preventability, personalization and participation. This shows that the future potential of medical imaging is unlimited[57].

5. Conclusion

In the evolution of modern medicine, the deep integration of AI with medical imaging has greatly propelled advancements in the medical field. This paper focuses on the application of image processing technology based on deep learning in medical images, and elaborates on its specific application in medical images of lungs, bone, mouth and other organs. It highlights the significant advantages of deep learning in disease diagnosis and treatment plan formulation.

As a core technologies in AI, deep learning models based on neural network can automatically learn the deep features of medical images, overcoming the limitations of traditional methods that rely on manual feature extraction. Learning from a large amount of image data can realize high-precision lesion detection and disease classification, as well as reconstruction, segmentation and recognition of medical images, thus improving the accuracy and efficiency of diagnosis. Moreover, it can also provide strong technical support for the related work of follow-up treatment plans and reduce unnecessary workload of doctors. However, there are still some challenges in this field, such as low standardization of image data and insufficient generalization of models. The future needs to strengthen the standardization construction of medical image data, improve the consistency and normalization of data, and constantly optimize the deep learning model to enhance the adaptability of the model in different data and scenarios.

At the same time, the article itself also has some shortcomings, including the narrow scope of discussion on medical imaging and the lack of experimental verification. In the future, the extensive application of the research results of medical image processing using neural network model in the medical field will make the scope of discussion become broader, the experimental content become more substantial, and the development of medical image will be full of vitality.

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