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Application of CNN in Medical Imaging Diagnosis and Clinical Accuracy Analysis

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Abstract. Nowadays, imaging diagnosis plays a crucial role in early disease detection and treatment planning. With the increasing maturity of artificial intelligence technology, convolutional neural networks (CNN) have become the core method for diagnosis. This paper mainly introduces the application of CNN in the imaging diagnosis of lung cancer and cancer, and systematically analyzes its clinical application, optimization and existing limitations. The results indicate that CNN can extract key features from clinical images, accurately identify tumor lesions, distinguish between benign and malignant lesions, and in some representative cases, the diagnostic accuracy can even reach 96% -98%. Optimization includes structural adjustment and transfer learning, effectively improving the stability and generalization ability of the model. However, CNN still faces many limitations, such as data dependency, high computational costs and limited 3D data processing capabilities. This study demonstrates the clinical feasibility of CNN in imaging diagnosis and provides theoretical operations for optimizing design and clinical promotion.

Keywords: Application, imaging diagnosis, optimization, CNN

1. Introduction

Medical imaging serves as the crucial tool of early disease screening, precise staging, and individualized treatment planning, especially for high-incidence cancers and even other infectious diseases. Conventional diagnostic work relies heavily on manual reading by radiologists, which is significantly influenced by variability between people, heavy workloads, and delayed detection of early-stage lesions. However, with the rapid evolution of deep learning, CNNs have emerged as a dominant technique for feature extraction and AI decision-making in medical images [1]. To be more specific, CNN models excel at learning hierarchical visual patterns without handcrafted features, which can enable consistent and efficient analysis of CT and other types of images [2]. These advantages have helped to use CNN-assisted tools in clinical imaging pathways. Globally speaking, CNN-based medical imaging research has expanded rapidly over the past decade. There are mature frameworks for CNN such as GoogleNet, AlexNet and ResNet, which have been widely adopted for lung nodule detection and breast cancer classification. Whose diagnostic accuracy has frequently exceeding 95% [3]. Researchers have systematically explored architecture optimization, transfer learning, and regularization to enhance model generalization and reduce overfitting in

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limited medical datasets. Existing studies have also confirmed that CNN shows great sensitivity and stability for tumor detection which can avoid the subjective influences. Nevertheless, most investigations concentrate on single-disease or single-modal tasks, lacking systematic comparisons across cancer types and give evaluations of clinical practicality, and this is what this essay is going to depict. What is more, problems still remain in data dependency, weak interpretability, 3D volume processing, and demand for devices, which restricts CNN's availability in the real world [4].

In order to improve this situation, this study aims to systematically assess CNN applications in representative clinical parts like lung cancer and breast cancer to clarify performance differences, optimization mechanisms, and inherent constraints. By synthesizing empirical accuracy, optimization strategies, and unresolved limitations, this paper constructs an analytical framework for clinical availability and provides operational insights for model design and translation. The findings are expected to support the standardized promotion of CNN in resource settings and improve the reliability of AI diagnostic systems.

2. Application of CNN in lung cancer diagnosis

Lung cancer has been one of the most common and fatal cancers worldwide. It accounts for11% of new cancer diagnoses and 20% of total deaths caused by cancer [5]. In fact, most lung cancer patients are diagnosed in the middle and late stages, where treatment options are limited, thus leading to high mortality. For instance, in Italy, a high percentage of nodules are curable in the early stage, but 75% of patients are detected only in the advanced stage. AI models such as CNN can help personalize screening programs by collecting and analyzing a large amount of imaging and clinical data, thereby significantly improving diagnostic efficiency. Actually, its detection and classification can even reach a precision of 98% in lung cancer imaging [6].

CNN in lung cancer computed tomography (CT) scan can automatically learn and extract the features it needs from raw imaging without any artificial assistance. Therefore, the workload of radiologists can be significantly reduced and certain subjective errors in traditional diagnosis can be avoided. Then, through the convolutional layer that is introduced above, small filters are able to progressively detect some low-level visual features like edges, textures and local intensity change. Meanwhile, high-level visual patterns including pulmonary nodules, interstitial alterations, infiltrative lesions and abnormal tissue densities that are related to malignant transformation [7]. By automatically learning visual characteristics that have clinical significance, CNN can reduce inter-observer variability and the dependence on professional experience in the reviewing of medical images. Improving the objectivity and repeatability through adding a computer into diagnosis can assist clinicians in identifying early lesions efficiently.

3. Application of CNN in breast cancer diagnosis

CNN has become a core technique in diagnosis for breast cancer detection and classification using mammography as a computer-aided tool. By automatically extracting hierarchical features from mammographic images, CNN models improve the limitations of traditional methods that need help manually. Also, there are advanced assistance such as GoogleNet and AlexNet that can support efficient identification of tissues as normal, benign or malignant by learning subtle textural and structural differences in lesions [8].

The clinical importance of CNN lies in improving early detection accuracy by reducing radiologists' work burden, and minimizing subjective misdiagnosis, just like that in lung cancer. By training with optimizers, deep CNN models can achieve high classification efficiency with low loss.

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It can also be combined with preprocessing techniques including Wiener filtering, contrast-limited adaptive histogram equalisation (CLAHE), and Wavelet Packet Decomposition (WPD) for better generalization; therefore, CNN can enhance image quality and further boost diagnostic performance. Compared with other AI methods that could be used for breast cancer, CNN delivers higher accuracy and better stability under the same experimental conditions [9]. The automatic, quantitative, and objective analysis of CNN effectively improves the reliability of breast cancer screening, especially for small lesions and early-stage tumors. Its high practical applicability makes CNN an indispensable tool for clinical diagnosis and personalized treatment planning; therefore, CNN can ultimately contribute to reduced mortality and improved patient outcomes [9].

4. Differences in CNN application between lung cancer and breast cancer

Although the techniques and main functions of CNN in lung cancer and breast cancer are quite similar, they still differ significantly in feature types, lesion characteristics, and clinical requirements. Breast cancer images focus on masses and calcifications, which require CNN to capture fine textures and subtle morphological changes. Therefore, CNNs use small convolutional kernels and shallow networks to detect in mammograms [10]. In contrast, lung cancer images rely on nodules, such as whether it is ground-glass and the boundary features in CT scans. This means CNNs require larger receptive fields and a deeper network to locate small nodules and distinguish benign from malignant nodules in minutes.

For a summary, breast imaging demands high sensitivity for early lesions, so CNNs emphasize detail preservation and texture analysis. However, lung imaging requires strong anti-interference ability and multi-scale detection capabilities due to the complexity. In clinical application, breast CNNs prioritize stability and repeatability, while lung CNNs focus on positioning accuracy. These differences lead to distinct network structures, differences in preprocessing strategies and CNN training design.

5. Application of CNN in tuberculosis diagnosis

The high practical applicability of CNN can also be reflected by the following study. A study presents a self-trained CNN for tuberculosis (TB) diagnosis using chest X-ray (CXR) images, aiming to verify the high availability and practicality of CNN in medical imaging diagnosis. About 7,000 labeled CXR images were used for the input data, which is evenly mixed with normal and TB-positive cases. Several different processing techniques are adopted, for example, wavelet transformation, CLAHE and gamma correction to improve the image quality. Also, to ensure the variation of the data set, some images are processed through methods such as random flipping, rotation, scaling, and brightness adjustment. Therefore, they can improve the generalization of the model by making it adjust and overcome the inexplicable and rare cases, and the accuracy of the model will be improved in the end.

The constructed CNN model consists of common convolutional layers, max-pooling layers, flatten layers, and dense layers. They also use rectified linear unit (ReLU) activation in hidden layers and sigmoid activation for binary classification. The Adam optimizer and binary loss function were adopted for model training, which is a typical configuration with some unique techniques leading to better quality. In the end, experimental results show that the self-trained CNN achieves 96.57% test accuracy, with a precision of 97%, a recall of 96%, an F1-score of approximately 96%, and AUC close to 0.99 [3]. All of the above strongly support that CNN is able to correctly identify tuberculosis or normal cases with ultra-high precision and a low rate of missed diagnosis. The high

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F1 score provides a balanced evaluation, showing its strong clinical detection capability. Compared with transfer learning methods that have not been trained, this model demonstrates higher diagnostic accuracy with lower computational operations [11].

The results indicate that CNN can automatically extract decisive features from chest X-rays without any manual engineering or complex training, which can support reliable and efficient TB detection. CNN demonstrates strong practical applicability in limited resource settings, providing a high-performance, aided diagnostic tool at a low cost. This study can also further support the high availability of CNN structure in pulmonary disease imaging diagnosis, which has also been introduced in the beginning, with good clinical application value.

6. Optimization strategies of CNN in medical imaging analysis

A study improves the performance and clinical availability of CNNs in medical image analysis, and three main optimization strategies have been proposed that can overcome the inherent limitations of traditional CNN structures. These approaches can effectively enhance model stability, accuracy, and practicality in real clinical cases.

First, architecture and hyperparameter optimization are performed [1]. Key elements like convolution kernel size, pooling mode, activation functions, batch size and network depth are reasonably adjusted to balance the feature extraction ability and computational complexity. To be more specific, appropriate activation functions like ReLU can improve convergence and avoid gradient disappearance. Also, improved kernel and pooling patterns provide pathological details with fewer calculations. Such structural optimization enables CNNs to capture lesion features more accurately and efficiently [2].

Second, regularization and generalization enhancement for the model are adopted to suppress overfitting. Techniques like dropout, L1/L2 regularization, batch normalization, and early stopping are widely used. To be more specific, dropout randomly disables neurons during training to prevent them from relying too much on specific features [12]. Regularization constrains weight updates and improves model stability. What is more, early stopping can avoid overtraining by monitoring and evaluating performance. These methods together will significantly improve the generalization ability of CNN, especially when there are only small medical datasets.

Third, the training process is also optimized, including data augmentation and transfer learning. Data augmentation, such as flipping and rotation, used in the above experiment, can enrich sample diversity without increasing collection costs. Also, transfer learning uses pre-trained models to reduce dependence on large-scale data and lower computational costs by adopting mature characteristics. These strategies can not only speed up training but also make a high-performance CNN available even in resource-limited environments [13, 1].

Through the comprehensive improvements shown above, CNNs achieve higher diagnostic accuracy, stronger generalization, lower computational demands, and better stability. These advantages can directly improve the practical availability of CNNs in clinical imaging applications, making them reliable.

7. Existing limitations of CNN in medical imaging analysis

Despite the widespread application of CNNs in medical imaging analysis, it still suffers from inherent limitations that restrict clinical reliability, interpretability and deployment flexibility. First, for clinical availability, it strongly depends on a large amount of high-quality images for training. Specifically, CNNs require well-labeled imaging data to learn generalized features, but medical

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datasets are often small and imbalanced. Images are limited by privacy and collection costs, and the annotation process is time-consuming. Therefore, insufficient datasets will easily lead to overfitting, which can further result in unstable performance on clinical samples. Although it is undeniable that the optimization methods that vary data through image processing mentioned above can partially solve this problem, the most fundamental issue still exists, which is the scarce source of data.

Second, weak interpretability and poor transparency hinder clinical use. CNNs operate as black-box models, which means that clinicians cannot clearly capture how the network extracts features or makes decisions. Although Gradient-weighted Class Activation Mapping (Grad-CAM) can provide visual heatmaps, it only focuses on local parts rather than the complete reasoning process, which is insufficient for disease diagnosis requiring high precision.

Third, structural limitations in processing 3D volumetric data restrict its performance in CT, Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET). As 2D CNNs fail to capture spatial continuity and depth information in volumetric scans, the sensitivity in lesion localization and staging will be dramatically reduced. While 3D CNNs can resolve this issue, higher computational complexity and memory consumption will be needed [4].

Fourth, high computational resource demands limit real-world use. Actually, almost all CNN training and inference rely on high-performance GPU or TPU, which are unavailable in primary hospitals and regions with limited resources. Lightweight models such as MobileNet may reduce computation but lead to a loss of accuracy [11].

Fifth, poor cross-device and cross-center generalization still exists. CNNs are sensitive to differences in elements like imaging equipment, scanning parameters, contrast agents, and even patient positioning [4]. This is because models are trained on single-center data, so it is common for performance to degrade significantly on multi-center data, as they lack domain adaptability.

Sixth, objectively speaking, CNN still has difficulty in handling small lesions and subtle features, which reduces its clinical value. Early-stage lesions or tiny nodules are easily overlooked because CNNs focus on overall structures rather than small local changes.

Finally, the fixed structure and poor task adaptability require manual redesign. Most CNNs are tailored for specific tasks and cannot flexibly adapt to different classification or complex pathological patterns without retraining, which is extremely time-consuming and complex.

8. Conclusion

CNN, as a core technology in the field of artificial intelligence, has shown broad application prospects in the diagnosis of lung cancer, breast cancer, tuberculosis and other diseases. It can effectively improve the efficiency and accuracy of medical imaging diagnosis, reduce the workload burden of radiologists, and assist in early lesion screening. Through reasonable optimization strategies, the performance and practical applicability of CNN can be further enhanced. However, CNN still has inherent limitations such as insufficient data, weak interpretability, and high computational resource requirements. With the in-depth research on optimization strategies and the continuous improvement of related technologies, CNN is expected to be further promoted and applied in clinical practice, providing more reliable support for medical imaging diagnosis and improving patient prognosis.

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