Application and Development of AI Imaging Technology in the Biological Clinical Field

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Abstract. In the past five years, relying on the core advantages of multi-modal fusion and special disease modeling, artificial intelligence (AI) imaging technology has achieved leapfrog development from auxiliary diagnosis to accurate prognosis, and promoted the transformation of clinical diagnosis and treatment from "experience-driven" to "data intelligence". This paper systematically reviews the research progress of the two core technology routes in this field. These two routes are the subdivision scenario technology of special disease modeling adaptation and the whole chain diagnosis and treatment technology driven by multi-modal fusion. The purpose of this paper is to analyze the advantages and disadvantages of the characteristics and look forward to the future direction, providing a reference for technology transformation and iterative upgrading.

Keywords: AI imaging, Special disease modeling, Full chain diagnosis.

1 Introduction

The aging of the population and the complexity of the disease spectrum have led to a sharp increase in the number of imaging examinations and an increase in the burden of manual film reading. When the number of images increases, the burden of manual tasks increases, the efficiency of image analysis per unit time will decrease, and the increase in the number of tasks will increase the number of wrong diagnoses, which will also lead to different image analysis. As a result, the diagnostic consistency and efficiency will be insufficient, which also shows the bottleneck of the traditional image analysis mode [1, 2].

Through in-depth learning, the ability of deep integration of artificial intelligence (AI) technology and medical images is gradually strengthened, which promotes image analysis from experience-dependent to data-driven. An AI model can automatically extract the characteristics of lesions and quantify the evaluation indicators through massive labeled data training, and show the discrimination ability close to or even beyond human experts in multi-center verification. This change not only improves the efficiency and consistency of diagnosis, but also gives birth to a new paradigm of standardized, interpretable and traceable intelligent assistant decision-making. Therefore, its feature automatic learning ability is enhanced, which can improve the adaptability of medical imaging tasks, and the performance of segmentation, classification and

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detection is also significantly improved, so AI has become the core technology of image intelligence [3, 4].

Especially in the past five years, with the improvement of computing power and multi-modal clinical data acquisition conditions, the research focus of artificial intelligence imaging technology has gradually changed. Relevant research is no longer limited to the performance optimization of a single imaging task, but begins to focus on the application scenarios closer to the clinical decision-making process, such as disease grading, prognosis assessment and treatment response prediction, to promote the evolution of AI imaging technology from an auxiliary diagnostic tool to a comprehensive diagnosis and treatment support system.

2 Route A: Subdivision Scenario Technology for Special Disease Modeling Adaptation

This route optimizes the model according to the image characteristics of specific diseases and the pain points of diagnosis and treatment, and expands the application boundary of technology.

In the field of neurological diseases, the multimodal brain injury segmentation model integrates multi-sequence MRI information, and the segmentation accuracy is over 90%, providing accurate support for disease assessment [5]; in the field of neonatal disease screening, the ultrasound segmentation SAMUS model adapts to the characteristics of low-contrast images, and the Dice coefficient is above 0.88, improving the accuracy of primary screening [6]. In the aspect of breast disease screening, the AI system combines the characteristics of molybdenum target X-ray and ultrasound images to construct a model for distinguishing benign and malignant breast diseases, and the AUC value exceeds 0.92, especially in dense breast tissue, which shows better sensitivity than traditional film reading [7]. The common feature of these special disease models is that through deep mining and feature engineering optimization of specific disease image data, they achieve a high degree of adaptation to the subdivision scene, and solve the problems of difficult feature extraction and inconsistent diagnostic criteria for specific diseases in traditional image analysis.

This kind of research focuses on specific diseases or clear clinical tasks, focusing on the imaging characteristics and diagnosis and treatment needs of target diseases, and designs the model structure, training strategies and input data forms. Such methods usually rely on single or limited modality image data to achieve fine modeling of key image features in specific application scenarios through customized network structure or loss function optimization, so as to improve the performance of the model in specific clinical tasks.

Its advantages are strong scene adaptability, high clinical practicability, flexible deployment, and easy promotion at the grass-roots level. The limitations lie in the narrow scope of application, the dispersion of R & D resources, and the need to improve the robustness and verification system.

Although the special disease modeling route shows significant advantages in specific scenarios, its limitations have become increasingly prominent. First of all, the narrow scope of application often makes a model only solve one or a few specific problems of specific diseases, and it is difficult to cope with the complex and changeable disease spectrum and diversified needs of diagnosis and treatment in the clinic.

Secondly, the decentralization of R & D resources is another prominent problem. Due to the different imaging characteristics and diagnosis and treatment needs of different diseases, the development of each disease-specific model requires independent data collection, annotation, model design, training and verification process. This makes the limited scientific research strength and funds dispersed to many subdivisions, which makes it difficult to form a scale effect, and is not conducive to the accumulation and breakthrough of general technology. Many research teams may be repeating similar basic work, resulting in a waste of R & D resources.

Moreover, the robustness of the special disease model still needs to be strengthened. Although it performs well in specific training data sets and experimental environments, the performance of the model often degrades significantly when the data distribution changes, such as patient data from different devices, different scanning parameters, different populations and even different regions. This phenomenon of "overfitting" to specific data sets limits the application of the model in a wider range of clinical scenarios.

Finally, the lack of perfection of the verification system is also an important factor restricting the development of the special disease model. At present, the validation of many disease-specific models is often limited to single-center and small-sample data, and there is a lack of multi-center and large-scale clinical prospective studies to fully prove their long-term effectiveness and safety. This makes the clinical transformation and regulatory approval of the model face many challenges, and also affects the trust and acceptance of clinicians. Some models may have achieved remarkable results in the laboratory environment, but in real and complex clinical practice, their performance may fall short of expectations, and may even raise concerns about the reliability of their decision-making because of their "black box" characteristics. Therefore, how to establish a scientific, standardized and comprehensive model verification system for special diseases is a key problem to be solved in the future development of this route.

3 Route B: Full Chain Diagnosis and Treatment Technology Driven by Multimodal Fusion

Multi-modal fusion-driven full-chain diagnosis and treatment technology achieves precise support for the whole chain of diseases by integrating multi-source data such as images, pathology and genes, and its core achievements are concentrated in the field of cancer diagnosis and treatment. The prostate cancer "imaging-pathology" model constructed by Shao Lizhi's team of Anhui University has an AUC of 0.983 for benign and malignant diagnosis, with a grading accuracy of 89.1%, achieving non-invasive and precise diagnosis and treatment [8]; the DeepGEM model jointly developed by Guangzhou Medical University and Tencent can complete the prediction of lung cancer gene mutation in one minute, with a core target accuracy of up to 99% [9]; The MUSK model of Stanford University integrates massive pathological maps and text data to accurately predict the prognosis and immunotherapy response of various cancers [10].

The technical core of this route is to construct a multi-modal data association analysis framework, and to realize the deep coupling of image and non-image data through a cross-modal feature fusion algorithm. Its typical technical path includes three levels: first, data layer integration, using federated learning, privacy computing and other technologies to break the multi-source data island, to achieve standardized correlation of images (CT, MRI, pathological sections), clinical indicators (blood routine, tumor markers), molecular data (gene mutation, proteomics); The second is feature level fusion, which mines the complementary information between modalities through attention mechanism, graph neural network and other methods. The last is application layer collaboration, which constructs a full-cycle decision support system covering disease early screening, typing diagnosis, efficacy evaluation and recurrence monitoring. Compared with the scenario specificity of Route A, this route has the following significant advantages: First, it breaks through the bottleneck of single modality information and improves the reliability of diagnosis through multi-dimensional data cross-validation; The second is to realize the full chain coverage from "disease diagnosis" to "prognosis prediction-treatment planning", and the third is to provide data support for individualized medical treatment, and to achieve precise hierarchical management through multi-modal characteristic portraits of patients. However, its development still faces challenges, such as the high cost of multi-modal data annotation, the limited generalization ability of the model due to the difference in data distribution across centers, and the possible introduction of spurious associations due to noise interference between modalities. In the future, people need to focus on breaking through multi-modal data quality control, dynamic fusion algorithm optimization and cross-agency collaborative verification system construction to promote the large-scale application of technology in the diagnosis and treatment of complex diseases.

Compared with the modeling method of special disease, the research of multi-modal fusion-driven focuses more on the multi-source information collaboration in the process of disease diagnosis and treatment. By jointly modeling medical images, pathological sections, molecular detection results and clinical text data, this kind of method constructs cross-modality feature representation to make up for the lack of information in disease classification, prognosis assessment and treatment response prediction in a single imaging modality, aiming at achieving full-chain clinical decision support covering diagnosis, grading and prognosis.

Its advantage lies in the comprehensive information dimension, which can realize the cross-scale correlation analysis from macro-image to micro-molecular mechanism, and provide data support for the formulation of an individualized treatment plan. The limitations are reflected in the difficulty of data standardization, the imperfection of the multi-center data sharing mechanism, the high complexity of the model, and the more stringent requirements for computing resources and clinical validation system. Especially, the whole chain has strong support ability, high diagnostic accuracy and wide technical recognition, while the limitations are high data dependence, high model complexity and insufficient interpretability, which limit the universality and feasibility of grass-roots deployment.

4 Future Challenges and Prospects

At present, the clinical transformation of AI imaging technology still faces four major challenges: the first is the bottleneck of data quality and accessibility, the scarcity of rare disease data and the inconsistency of multi-center standards; the second is the lack of model robustness and the weak adaptability of complex clinical scenarios; the third is the lack of inclusiveness, the high cost of grass-roots deployment and the lack of solutions for common diseases; Fourth, the lack of standards and trust system, "black box" characteristics affect clinical acceptance.

In the future, efforts should be made in three aspects: first, strengthen technological innovation, solve data problems through federated learning and small sample learning, integrate Transformer and convolutional neural network to improve model robustness, and develop interpretable technology to enhance trust; second, improve the standard system, unify technical specifications and evaluation standards, and strengthen supervision to ensure application security; Thirdly, people should deepen the collaboration of "AI + medical examination", promote cross-research and development of medical workers, develop lightweight models to help grass-roots promotion, and expand the application scenarios of common diseases.

Looking forward to the future, with the technology iteration and policy improvement, AI imaging technology will gradually transform into an "intelligent decision-making partner", breaking the barriers to the distribution of medical resources, and providing strong support for the strategy of precision medicine and healthy China.

5 Conclusions

AI imaging technology promotes clinical diagnosis and treatment from "experience-driven" to "data intelligence" with the help of two core advantages of multi-modal fusion and special disease modeling. This paper focuses on two core technology routes.

Route A is the subdivision scenario technology adapted for special disease modeling, which optimizes the model for specific diseases such as nerve, lung and breast, and improves the accuracy of subdivision scenario diagnosis by customizing the network and loss function. It has the advantages of strong scenario adaptability and flexible deployment, but has the limitations of a narrow application scope and scattered R & D resources.

Route B is a full-chain diagnosis and treatment technology driven by multi-modal fusion, which integrates multi-source data such as image, pathology and gene, constructs an analysis framework, and realizes full-cycle diagnosis and treatment support for cancer and other diseases. Its advantages lie in comprehensive information and accurate diagnosis, but it faces challenges such as the high cost of data annotation and the high complexity of models.

At present, the clinical transformation of this technology is facing four challenges: data, robustness, inclusiveness and standard system. In the future, people need to promote it to become an intelligent decision-making partner and help the development of precision medicine through technological innovation, improvement of standards and deepening of medical collaboration.

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