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A Review of Research Progress and Challenges in Deep Learning for Magnetic Resonance Imaging in the Diagnosis and Treatment of Prostate Cancer

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Abstract: Prostate cancer is a highly prevalent malignant tumor among men worldwide, and its precise diagnosis and treatment are crucial for improving patient prognosis. Multiparametric magnetic resonance imaging, as a core imaging modality, is widely used in clinical practice. In recent years, breakthroughs in deep learning technology have provided powerful tools for the intelligent analysis of MRI images, promoting the development of automated and precise diagnosis and treatment for prostate cancer. This article aims to systematically review the current applications of deep learning in the field of prostate cancer MRI, covering key directions such as lesion detection and segmentation, diagnosis and grading, prognosis prediction, and imaging genomics correlation. The article provides an in-depth analysis of current mainstream models, the challenges related to data and validation, and offers insights into future trends, with the goal of providing references for related research and clinical practice.

Keywords: Prostate cancer; Magnetic resonance imaging; Deep learning; Computer-aided diagnosis

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1. Introduction

Prostate cancer (PCa) is a malignant tumor with a high incidence among men globally, and its precise diagnosis and treatment heavily rely on imaging evaluation. Multiparametric magnetic resonance imaging (mpMRI), with its excellent soft tissue resolution and ability to fuse multi-sequence information, has become a core tool for the detection, localization, and risk stratification of prostate cancer. It can effectively identify clinically significant cancer foci (csPCa) and help many patients avoid unnecessary biopsy [1]. However, the traditional interpretation of prostate mpMRI faces significant challenges. Its assessment is highly dependent on the subjective experience of radiologists, leading to substantial inter-observer and intra-observer variability in interpretation. Moreover, analyzing vast amounts of imaging data is time-consuming and labor-intensive, increasing the clinical workload. Additionally, although mpMRI has a high negative predictive value, it still has a false-negative rate of approximately 15–20%, potentially missing some aggressive tumors. These limitations have driven the clinical search for more objective, efficient, and reproducible analysis methods [2].

Artificial intelligence (AI), particularly its important branch, deep learning (DL), provides a new tool for prostate cancer MRI analysis. Deep learning models can automatically learn complex feature patterns from large-scale, high-quality annotated medical imaging data that are difficult for the human eye to recognize. Compared to traditional machine learning methods, deep learning does not require manual feature design; instead, it extracts abstract representations directly from raw pixel data through multi-layer neural network architectures, demonstrating superior performance in image segmentation, classification, and prediction tasks [3]. Specifically in the field of prostate cancer, deep learning technology has been widely applied to several key aspects. In image segmentation, models based on U-Net and its variants can achieve automatic or semi-automatic delineation of the prostate gland, zones (such as the peripheral zone and transition zone), and suspicious lesions, laying the foundation for subsequent quantitative analysis [4]. One study used the SegNet model, combined with T2-weighted imaging (T2WI), diffusion-weighted imaging (DWI), and apparent diffusion coefficient (ADC) maps, to achieve automatic segmentation of prostate zones and cancerous areas. In lesion detection and qualitative diagnosis, deep learning architectures such as convolutional neural networks (CNN) can distinguish between benign and cancerous tissues and further differentiate between clinically insignificant and significant prostate cancer [5]. Their diagnostic performance has shown potential comparable to or even superior to that of experienced genitourinary radiologists in multiple studies. One study developed the FocalNet algorithm, which showed no statistically significant difference in sensitivity compared to a group of genitourinary radiologists in detecting clinically significant index lesions [6]. Furthermore, some studies have indicated that deep learning models based on biparametric MRI (bpMRI) can achieve diagnostic accuracy comparable to standard mpMRI, providing greater assistance to less experienced physicians [7]. In the field of prognosis assessment, deep learning models, by integrating MRI imaging features with clinical data (such as PSA, age), have demonstrated potential in predicting biochemical recurrence, pathological stage, and even the risk of progression to castration-resistant prostate cancer (CRPC). [8] These applications suggest that deep learning not only holds promise for improving the objectivity and efficiency of diagnosis, reducing human variability, but may also advance prostate cancer diagnosis and treatment toward a more precise, individualized model [9]. This review will systematically outline the full landscape of deep learning applications in prostate cancer MRI, delving into specific application scenarios, current challenges, and future development directions, aiming to provide references for research and clinical practice in this field.

2. Research progress in deep learning for prostate cancer detection, segmentation, and localization

2.1. Automatic segmentation of the prostate gland and zones

Accurate segmentation of the entire prostate gland is the foundation for subsequent analysis, and deep learning models (especially the U-Net series) have achieved near-expert-level accuracy in this task. Studies have shown that models based on the U-Net architecture can efficiently segment the glandular region from prostate magnetic resonance imaging (MRI), with performance metrics such as the Dice similarity coefficient (DSC) generally showing excellent results. One study developed a model based on an attention-guided U-Net for prostate region segmentation in biparametric MRI (bpMRI) images, achieving a DSC of 0.82 [10]. Another study focusing on diffusion-weighted imaging (DWI) apparent diffusion coefficient (ADC) maps also confirmed that the U-Net model has high accuracy in prostate cancer lesion segmentation, with internal and external validation Dice scores reaching 0.822 and 0.7776, respectively [11]. These achievements provide a reliable anatomical basis for subsequent lesion detection and risk stratification.

2.2. Detection and segmentation of clinically significant prostate cancer lesions

Distinguishing between "clinically significant" and "insignificant" cancer is a core clinical need. Deep learning models, through end-to-end training, can directly detect and delineate suspected lesions from MRI, and their performance is relatively good for lesions with a PI-RADS score ≥ 3. Multiple studies have confirmed the potential of deep learning in this task. For example, a cascaded deep learning algorithm based on biparametric MRI (bpMRI) demonstrated performance comparable to that of experienced radiologists in detecting suspicious cancerous lesions and could reliably predict biopsy-confirmed clinically significant prostate cancer (csPCa). Another study developed a diagnostic support system based on a 3D deep convolutional neural network (3DCNN) for identifying high-grade prostate cancer, achieving a sensitivity and area under the curve (AUC) of 85% and 0.82, respectively [12]. By learning complex patterns in images, these models can effectively distinguish significant cancer foci requiring clinical intervention from indolent lesions.

Recent advances include the development of weakly supervised or semi-supervised learning models to reduce reliance on pixel-level fine annotations, and the development of uncertainty estimation modules to provide confidence levels for model predictions, assisting physicians in decision-making. Acquiring large amounts of pixel-level annotated medical images is time-consuming and expensive, making weakly supervised or semi-supervised learning a research hotspot. One study proposed a dual-modal model that combines imaging data and clinical data (such as PSA level, prostate volume, and age). This model not only improved diagnostic performance (AUC reaching 0.82) but also introduced uncertainty analysis, enabling the identification of high-confidence predictions, thereby enhancing the reliability of automated medical decisions [13]. Furthermore, the development of explainable artificial intelligence (XAI) models is crucial. They can provide visual and textual explanations for classification decisions using PI-RADS features, improving model transparency and clinical doctors' trust, especially aiding non-expert doctors in assessing PI-RADS category 3 lesions [14].

Although deep learning models excel in detecting typical peripheral zone lesions, their sensitivity still needs improvement for some challenging cases. Multifocal cancer foci may be missed due to small size or atypical signal, and cancer foci located in the anterior fibromuscular stroma or transition zone are more difficult to detect due to their special anatomical location and potential signal overlap with benign hyperplastic tissue. To address these challenges, future research trends involve developing multimodal fusion models that not only integrate multi-sequence MRI information (such as T2WI, DWI, and dynamic contrast-enhanced) but also incorporate clinical parameters (such as PSA density), pathological information, and even genomic data into the analysis framework to build more comprehensive and precise personalized diagnostic and risk assessment systems.

3. Application of deep learning in prostate cancer diagnosis, grading, and risk stratification

3.1. Cancer vs. non-cancer classification and Gleason score prediction based on MRI

Deep learning models can directly perform automatic classification on multiparametric magnetic resonance imaging (mpMRI) images or segmented lesion regions to predict their probability of malignancy. Studies have shown that deep learning algorithms such as convolutional neural networks (CNNs) demonstrate significant advantages in distinguishing between benign and malignant prostate lesions. A systematic review noted that the median area under the receiver operating characteristic curve (AUC) for machine learning or deep learning models used to distinguish significant from insignificant prostate cancer could reach 0.79 (interquartile range: 0.77-0.87) [15]. Another study, an interpretable machine learning model based on multiparametric MRI radiomics (with the random forest model performing the best), was developed and externally validated. This model can effectively distinguish between benign and malignant prostate masses preoperatively, and its clinical interpretability was enhanced through the SHAP method [16].

3.2. Prognosis prediction and biochemical recurrence risk assessment

Imaging features extracted by deep learning are not only useful for diagnosis but also show value in predicting disease progression and recurrence risk in prostate cancer. These features can be used to predict the risk of disease progression during active surveillance, the risk of biochemical recurrence after radical treatment (such as radical prostatectomy), and the probability of distant metastasis [17]. One study applied deep learning algorithms such as CNN-BiLSTM to establish a biochemical recurrence prediction model based on various clinical information from patients after radical prostatectomy, achieving an accuracy of 76.7%. By integrating pre-treatment MRI image features and clinical information, the model can output individualized risk scores, thereby assisting clinicians in formulating more precise treatment strategies. Survival analysis models have also been used to establish associations between imaging features and patient recurrence-free survival. One study utilized deep learning algorithms for multimodal fusion analysis of clinical and imaging data from prostate cancer patients to promote precise prognosis assessment [18]. However, the results of these prediction models still require rigorous validation in prospective, large-scale clinical cohorts to confirm their general applicability and clinical utility. Furthermore, fusion models combining clinical information, radiomics features, and deep learning features have been shown to further improve predictive performance. One study constructed a clinical-radiomics-deep learning joint model for diagnosing clinically significant prostate cancer, achieving an AUC of 0.91, which outperformed single models or PI-RADS scores from senior physicians [19]. In predicting bone metastasis, a joint model constructed based on clinical, MRI radiomics, and deep learning also demonstrated excellent predictive ability [17].

4. Challenges and limitations analysis

High-quality, large-scale, multi-center annotated datasets are a key bottleneck for the development of deep learning models in prostate cancer diagnosis and treatment. The training and validation of models heavily depend on precise annotations using pathological results as the gold standard. However, obtaining such annotations faces multiple challenges. Additionally, medical data privacy protection regulations are extremely strict, greatly limiting the centralized sharing and integration of data between different institutions, making it difficult to build large-scale, diverse datasets [20].

The inherent "black box" nature of deep learning models is a major obstacle to their widespread clinical acceptance [21]. To enhance model interpretability, current research is focusing on developing and applying various visualization techniques, such as class activation maps (CAM) and gradient-weighted class activation mapping (Grad-CAM). These techniques can intuitively display the image regions that the model focuses on for decision-making, thereby linking the model's "attention" to the visual assessment of radiologists [22]. However, merely improving diagnostic metrics (such as sensitivity and specificity) is insufficient to prove the clinical value of a model. Models must undergo rigorous external validation and prospective clinical trials to demonstrate that they can genuinely improve clinical endpoints. Only when the interpretability of models is enhanced and their clinical utility is confirmed by high-level evidence, can deep learning truly integrate into and revolutionize the prostate cancer diagnosis and treatment workflow.

5. Future directions: Multimodal fusion and clinical translation prospects

5.1. Deep learning multimodal integration

Deeply integrating deep learning with radiomics and genomics is an important future direction to build more powerful predictive models and achieve non-invasive molecular subtyping. "Deep radiomics" represents this trend, combining deep features automatically extracted by deep learning with traditional handcrafted radiomics features to more comprehensively assess tumor heterogeneity and aggressiveness. In imaging genomics, deep learning holds promise for bridging the gap between MRI manifestations and key genomic features. Although current literature has limited studies directly linking MRI to specific gene states, some research has indirectly explored the connection between imaging and tumor biological behavior by analyzing the correlation between MRI features and tumor aggressiveness [23]. In the future, using deep learning to mine deep features from multiparametric MRI and correlating them with genomic data will provide a powerful tool for achieving non-invasive molecular subtyping and individualized treatment of prostate cancer.

5.2. Clinical decision support systems

The future success of deep learning models lies in their integration with existing clinical workflows and the development of decision support capabilities. An ideal clinical support system should automatically analyze images after scanning and present the analysis results to radiologists in real-time in the form of standardized reports or intuitive heatmap overlays, assisting in diagnosis. One study has already developed a deep learning-based multiparametric MRI artificial intelligence analysis system that can quickly provide diagnostic results. When combined with PET imaging, it can significantly improve the sensitivity and accuracy of prostate cancer diagnosis. This indicates that AI-assisted systems have the potential to enhance clinical diagnostic efficiency. On the other hand, developing AI navigation systems for ultrasound-MRI fusion targeted biopsy is another key direction. Such systems use deep learning algorithms to achieve real-time, precise registration of MRI and ultrasound images, thereby guiding the biopsy needle accurately to suspicious lesions identified on MRI, significantly improving biopsy precision and positive rate [24]. Research has confirmed that combining PSMA PET/CT with multiparametric MRI image fusion technology can more precisely locate tumors and guide biopsy, thereby improving diagnostic accuracy. In the future, such real-time navigation systems will make targeted biopsy for small or difficult lesions more reliable, reduce unnecessary repeat biopsies, and optimize clinical decision-making pathways.

6. Conclusion

The application of deep learning in the field of prostate cancer MRI analysis marks a new era in imaging diagnosis, driven by data and intelligence. From automatic segmentation to prognosis prediction, existing technologies have demonstrated their potential to assist, and in some specific tasks, even match expert interpretation. Current research trends clearly point towards two directions of deep integration: first, model architectures themselves are evolving from performing isolated single tasks to integrated multi-task, end-to-end comprehensive systems that combine segmentation, detection, diagnosis, and prediction, aiming to simulate the comprehensive decision-making process of clinicians; second, integration with multi-omics data such as radiomics and genomics, which goes beyond merely improving diagnostic accuracy and strives to uncover the deep biological characteristics reflected by imaging features, such as the tumor microenvironment and gene expression profiles, laying the foundation for achieving true precision medicine.

However, transitioning from excellent research results to widespread clinical routine application involves challenges that must be carefully addressed. Data heterogeneity and annotation bottlenecks are fundamental obstacles limiting model generalization. Differences in data generated by different centers, scanning equipment, and protocols, as well as the significant reliance on expert time and effort for high-quality annotation, all test the robustness of models. More critically, many high-performance deep learning models are considered "black boxes," lacking intuitive explanations for their decision logic, which is a major concern in clinical practice that emphasizes diagnostic reasoning and doctor-patient communication. Furthermore, the vast majority of current evidence comes from retrospective studies, lacking prospective, multi-center randomized controlled trials to confirm whether these tools can genuinely improve key clinical endpoints for patients (such as survival rate, quality of life), which is the final pass for clinical translation.

Looking ahead, the healthy development of this field requires a balance between technological innovation and clinical validation. Building large-scale, standardized, high-quality multi-center collaborative datasets is the cornerstone, requiring industry consensus, standardized acquisition protocols, and potentially new paradigms like weak supervision or self-supervised learning to break through annotation bottlenecks. Moreover, algorithm development must balance performance with interpretability. Integrating attention mechanisms and explainable artificial intelligence (XAI) techniques into model design, making the AI decision-making process transparent and traceable for doctors, is essential to establishing solid clinical trust. Additionally, all technological pathways must be validated through rigorous clinical trials, using evidence-based medicine to assess their clinical utility, cost-effectiveness, and impact on existing workflows.

In summary, deep learning is not intended to replace radiologists but to evolve into a powerful intelligent assistant. By integrating multi-source information, quantifying imaging features, reducing inter-observer variability, and providing objective decision support, it holds the potential to free doctors from heavy repetitive tasks, allowing them to focus more on complex decision-making, patient communication, and the formulation of personalized treatment plans. The future prostate cancer diagnosis and treatment system will be a synergistic system deeply integrating physician experience with artificial intelligence computational capabilities, jointly advancing the goal of more precise, efficient, and personalized disease management.

Disclosure statement

The author declares no conflict of interest.

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