Indonesian Journal of Computer Science
ISSN 2549-7286 (*online*)
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Prostate Cancer: MRI Image Detection Based on Deep Learning: A Review

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Article Information

Submitted : 18 May 2024
Reviewed : 23 May 2024
Accepted : 15 Jun 2024

Keywords

Prostate Cancer, MRI, Deep Learning.

Abstract

This comprehensive study delves into the transformative role of artificial intelligence (AI) and deep learning (DL) in the realm of prostate cancer care, an issue of paramount importance in men's health worldwide. Prostate cancer, marked by the unchecked growth of cells in the prostate gland, poses risks of tumor formation and eventual metastasis. The crux of combating this disease lies in its early detection and precise diagnosis, for which traditional screening methodologies like Prostate-Specific Antigen (PSA) tests and multiparametric Magnetic Resonance Imaging (mp-MRI) are fundamental. The introduction of AI and DL into these diagnostic avenues has been nothing short of revolutionary, enhancing the precision of medical imaging and significantly reducing the rates of unnecessary biopsies. The advancements in DL, particularly through the use of convolutional neural networks (CNNs) and the application of multiparametric MRI, have been instrumental in improving the accuracy of diagnoses, foreseeing the progression of the disease, and tailoring individualized treatment regimens. This paper meticulously examines various DL models and their successful application in the detection, classification, and segmentation of prostate cancer, establishing their superiority over conventional diagnostic techniques. Despite the promising horizon these technologies offer, their implementation is not without challenges. The requisite for specialized expertise to handle these advanced tools and the ethical dilemmas they present, such as data privacy and potential biases, are significant hurdles. Nevertheless, the potential of AI and DL to inaugurate a new chapter in prostate cancer management is undeniable. The emphasis on interdisciplinary collaboration among scientists, clinicians, and technologists is crucial for pushing the boundaries of current research and clinical practice, ensuring the ethical deployment of AI and DL technologies. This collaborative effort is vital for realizing the full potential of these innovations in providing more accurate, efficient, and patient-centric care in the fight against prostate cancer, heralding a future where the burden of this disease is significantly mitigated.

A. Introduction

Prostate cancer stands as a paramount concern in men's health, with its origins in the prostate gland—an essential part of the male reproductive system [1]. This type of cancer is distinguished by the abnormal proliferation of cells within the prostate, which can lead to the formation of tumors. If these tumors are not adequately managed, they possess the potential to metastasize [2], or spread, to various other parts of the body [3]. Despite the possibility of rapid advancement in some cases, the progression of prostate cancer [4] is generally slow, offering a window for effective intervention and management. Globally, the impact of prostate cancer is profound, with it being the most common non-skin cancer among men. Statistics underscore its prevalence, with around 1.1 million men diagnosed each year. This alarming figure represents nearly 20% of all cancer diagnoses in men [5], making it the leading type of cancer among males in many countries. In 2018 alone, an estimated 1.3 million new cases were reported, along with 359,000 deaths, highlighting the critical need for effective diagnostic and treatment strategies [2], [6].

The journey towards diagnosing prostate cancer begins with initial screening methods, such as the Prostate-Specific Antigen (PSA) test and Digital Rectal Examination (DRE). Abnormal results from these screenings often lead to further evaluations [7], including transrectal ultrasound (TRUS) guided biopsies, as per recommendations from leading urological associations. The introduction of multi-parametric magnetic resonance imaging (mp-MRI) has significantly improved the diagnostic process by enhancing sensitivity [8], thereby potentially reducing unnecessary biopsies and minimizing the risk of over-diagnosis when compared to the traditional TRUS-guided approach. However [9], the mp-MRI technique requires significant expertise and is time-consuming, which challenges its adoption in everyday clinical practice [10].

The emergence of artificial intelligence (AI) and deep learning (DL) technologies presents innovative solutions to these challenges. These advancements have been instrumental in improving the analysis and interpretation of medical images [11], [12], aiding in the accurate differentiation between benign and malignant conditions of the prostate. Notably, the development of bi-parametric MRI (bp-MRI) marks a significant breakthrough, considerably reducing scanning times without sacrificing diagnostic accuracy. Such technological progress enables more efficient screening processes [13], [40], facilitating the early detection and treatment of prostate cancer. Deep learning's application in medical imaging analysis extends beyond MRI, encompassing a broad spectrum of medical conditions and diagnostic techniques [14]. For instance, both DL and non-DL algorithms have been successfully applied in differentiating between benign and malignant prostate lesions using axial T2-weighted MR images. These algorithms have demonstrated high accuracy in their predictive capabilities [15], illustrating the potential of DL in enhancing diagnostic precision. Additionally, multimodal diagnostic approaches utilizing DL have shown to outperform traditional unimodal methods in classifying radiology and pathology images, further showcasing AI's transformative potential in prostate cancer diagnosis and treatment [16].

The integration of AI and DL into the realm of prostate cancer research and diagnostics signifies a major leap towards more accurate, efficient, and patient-focused healthcare. By harnessing the power of these technologies, healthcare professionals can improve diagnostic accuracy, refine treatment strategies, and ultimately enhance patient outcomes [17]. The ongoing exploration and development of AI and DL applications within this field promise to propel our understanding and management of prostate cancer forward, heralding a new era in the battle against this pervasive disease. Moreover, the potential of AI and DL in prostate cancer care extends into prognostication and treatment personalization [18]. AI models are increasingly being explored for their capability to predict disease progression, patient response to various treatments, and likelihood of recurrence. This predictive power enables clinicians to tailor treatment plans more closely to individual patient needs, potentially improving the efficacy of interventions and minimizing side effects [13], [19].

In addition to enhancing diagnostic and prognostic capabilities, AI and DL technologies are paving the way for the development of novel therapeutic approaches [20]. For example, AI-driven platforms are being used to design and optimize targeted therapies and immunotherapies, offering new hope for patients with advanced or treatment-resistant forms of prostate cancer. These technologies also play a crucial role in streamlining clinical trials, from patient selection to monitoring treatment responses [21], thereby accelerating the pace of innovation in prostate cancer treatment. The ethical considerations and challenges associated with the integration of AI into healthcare, particularly in sensitive areas such as cancer diagnosis and treatment, are also of paramount importance. Issues related to data privacy, informed consent, and the potential for algorithmic bias necessitate careful attention and rigorous ethical frameworks. Ensuring transparency, accountability, and equity in AI applications is essential to fostering trust and acceptance among patients [22], clinicians, and the wider community. As we stand on the cusp of a revolution in prostate cancer care, the promise of AI and DL technologies is undeniable. However, the realization of their full potential requires a concerted effort among researchers, clinicians, technology developers, and policymakers. Collaborative initiatives aimed at advancing AI research, ensuring ethical standards, and facilitating technology adoption in clinical settings are critical to unlocking new frontiers in prostate cancer diagnosis, treatment, and patient care [23].

B. Research Methodology

The landscape of prostate cancer diagnosis and treatment has been significantly transformed by advancements in artificial intelligence (AI) and neural networks, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs). These technologies have ushered in a new era of precision medicine, offering powerful tools for the detection and classification of prostate cancer from medical images and patient data [24].

CNNs, known for their prowess in analyzing visual imagery, have become a cornerstone in the interpretation of medical imaging such as MRI and ultrasound. Their ability to automatically and hierarchically extract features from images makes them particularly effective for identifying subtle patterns indicative of prostate cancer. Research has demonstrated that CNNs can significantly enhance the accuracy of prostate cancer detection, often outperforming traditional methods in terms of sensitivity and specificity [25]. This has implications not only for early diagnosis but also for the accurate assessment of tumor aggressiveness, which is crucial for treatment planning [26].

RNNs, which excel in processing sequential data, have found their application in the analysis of temporal or sequence-based medical data, such as patient histories or genetic sequences. Although less commonly applied to prostate cancer detection than CNNs [27], RNNs offer promising avenues for predicting disease progression and response to treatment by learning from the sequential patterns and dependencies in the data. ANNs, a broader category encompassing various network architectures including CNNs and RNNs, have been instrumental in modeling complex relationships within large datasets. In prostate cancer research, ANNs have been used to integrate diverse data types [28], including clinical variables, imaging features, and molecular markers, to predict patient outcomes and personalize treatment approaches. Their versatility allows for the development of comprehensive models that can adapt and learn from new information, potentially improving decision-making in clinical practice.

The integration of AI, through the use of CNNs, RNNs [29], and ANNs, into prostate cancer care represents a paradigm shift towards data-driven diagnostics and personalized medicine. These technologies enhance our ability to detect prostate cancer earlier and more accurately [30], [31], predict disease course, and tailor treatments to individual patients. As AI continues to evolve, it holds the promise of further advancements in our fight against prostate cancer, improving both survival rates and quality of life for patients. The reliability of each deep learning algorithm [32] is demonstrated in Figure 1.

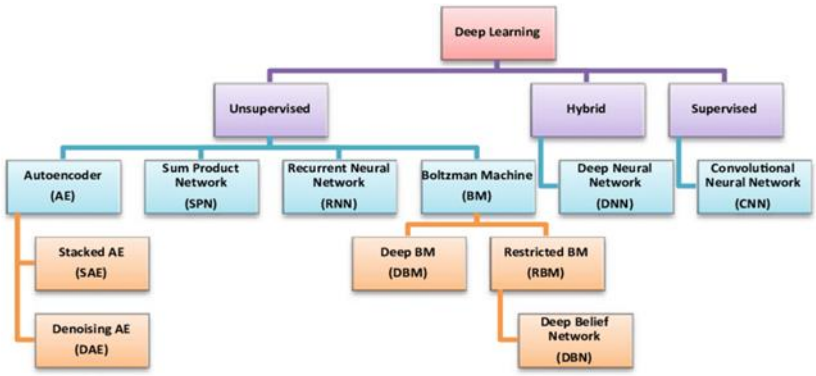

Figure 1. Classification of deep learning techniques

A. Convolutional Neural Networks (CNN) and Artificial Neural Network (ANN) and another Methods for Detecting prostate Cancer (PC):

Advanced technologies are transforming prostate cancer detection and treatment: Convolutional Neural Networks (CNNs) analyze medical imaging for precise tumor identification [33], Artificial Neural Networks (ANNs) evaluate complex patient data for accurate diagnoses; Image-guided radiation therapy

(IGRT) targets tumors accurately with minimal harm to healthy tissue; Generative Adversarial Networks (GANs) enhance image quality for better analysis; and XGBoost leverages clinical data for predictive insights. These innovations offer a comprehensive approach for early detection and personalized treatment of prostate cancer.

(Iqbal et al. 2021) Highlighted the superiority of deep learning, specifically ResNet-101, in detecting prostate cancer, outshining both traditional and non-deep learning methods such as SVM and LSTM in diagnostic accuracy. While SVM was utilized for the initial training and classification of prostate cancer images, and non-deep learning techniques with GLCM features achieved commendable accuracy, LSTM demonstrated notable sensitivity, specificity, and accuracy. Ultimately, ResNet-101 emerged as the most effective approach, surpassing the performance of non-deep learning methods and LSTM, underscoring the significant advantage of deep learning models in medical diagnostics, as shown in Figure 2 [34].

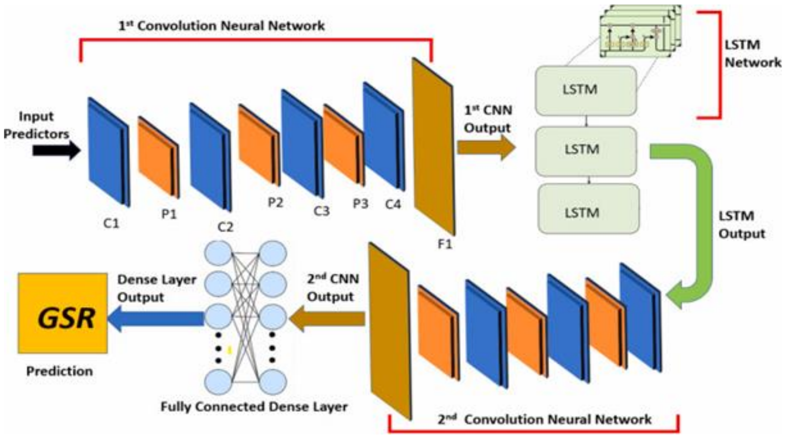

Figure 2. ANN + RNN + LTSM + CNN Architectures [31]

(Labiadh, et.al. 2022) The approach detected prostate cancer by integrating Local Binary Patterns (LBP), skewness coefficients, morphological transformations, and Convolutional Neural Networks (CNNs), without specifying any limitations within the provided contexts. This proposed methodology effectively identified prostate cancer tumors utilizing deep learning architectures, demonstrating superior classification accuracy when benchmarked against existing techniques. Future research directions include exploring tumor surface detection in images with blurring, highlighting the potential for further advancements in accurate cancer detection through innovative deep learning applications [35].

(Falana, et.al. 2023b) Applied deep learning to prostate cancer classification using biparametric MRI, with a focus on DenseNet-201 and ResNet-50 models for detecting clinically significant prostate cancer (csPCa). Axial T2-weighted imaging was identified as the most accurate for csPCa classification, despite challenges like variability in Gleason scores from biopsies and the discomfort these invasive procedures cause. ResNet-50 showed exceptional performance in DWI and T2W sequences, whereas DenseNet-201 was particularly effective in ADC imaging, underlining the potential of deep learning in enhancing non-invasive cancer detection accuracy [36].

(Barra et al. 2021) Developed an automatic prostate segmentation method using U-Net for MRI-based cancer detection, achieving a Dice similarity coefficient of over 85% in both internal and external validations. The algorithm was noted for its ability to optimize computational efforts in detecting prostate cancer. However, segmentation accuracy was lower at the prostate's base and apex, attributed to boundary delineation challenges. Experienced operators also faced difficulty in manually segmenting the apex, with the issue of an unbalanced dataset due to the small size of some prostates. The repeated mention of the Dice similarity coefficient exceeding 85% highlights the method's effectiveness, while also acknowledging the specific challenges in identifying prostate boundaries, particularly in the first and last slices [37].

(Mosleh, et.al. 2022) Highlighted the use of transfer learning models, including Inception-v3, Inception-v4, Xception, and PolyNet, for automated prostate cancer detection from MRI images, achieving high accuracy rates. It addressed the shortcomings of traditional diagnostic methods and the data dependency and manual intervention issues in CAD systems. Through transfer learning, the models improved feature extraction and classification efficiency, significantly reducing manual feature selection effort. The study reported that these models outperformed previous studies in reliability and performance, effectively distinguishing prostate cancer cases with high accuracy and reliability [38].

(Haritha et al. 2023) Introduced a prostate cancer classification method combining Cat Swarm Optimization (CSO) with Deep Learning, utilizing MRI images for precise diagnoses and treatment planning. This automated classification achieved high accuracy by employing CSO and Deep Learning for effective prostate cancer identification. It integrated a NASNet feature extractor and the CSO algorithm for optimal performance, alongside an ALSTM model for classification, thereby enhancing patient outcomes in prostate cancer management. The PCC-CSODL approach accurately classified prostate and brachytherapy classes on MRI, achieving high ROC values and demonstrating its effectiveness in prostate cancer classification [39].

(He et al. 2023) Revolutionized prostate cancer diagnosis and treatment using MRI by improving lesion identification, grading, and prognostic assessments. With automatic operation and high accuracy, deep learning significantly advanced prostate cancer diagnosis within urology, especially in MRI-based approaches. A review outlined the progress of deep learning-based systems for prostate cancer diagnosis and treatment, highlighting their role in grading and prognostic evaluations. These models showed promise in tumor identification, lesion segmentation, and grading, promising considerable enhancements in clinical outcomes [40].

(Rovcanin et al. 2022) Artificial Intelligence (AI) and neural networks have significantly advanced prostate cancer diagnosis and therapy, leveraging biomarkers and MRI for stratification and treatment assessment. An Artificial Neural Network (ANN) developed for this purpose showed 80% accuracy in identifying diseased subjects, with the potential of AI in diagnosis and prediction being a major highlight. AI's use in analyzing serum PSA levels and distinguishing between benign and malignant biopsy nuclei improved the sensitivity and specificity of prostate cancer detection. Highlighting the invasiveness and limitations of current diagnostic methods, AI promises to reduce the reliance on expensive and complicated prostate biopsies by enabling early detection and minimizing the need for invasive procedures. The developed ANN achieved a testing accuracy of 92.7%, underscoring AI's potential to revolutionize prostate cancer diagnosis and treatment [41].

Table 1. Overview of the literature on detecting Prostate Cancer based on CNN, ANN, GAN, And other Type Of DL.

Authors	Year	Dataset	Algorithm	Limitations	Advantages	Results
Iqbal et al. **[34]**	2021	MRI medical images	ANN(LSTM), CNN(ResNet-101)	The paper lacks discussion on computational complexity and model interpretability.	Optimal performance achieved with ResNet-101 and Deep Learning LSTM.	LSTM method showed high accuracy, specificity, and AUC.
Labiadh, Seddik, and Boubchir **[35]**	2022	Microscopic cells and MRI imaging	Local Binary Patterns (LBP)+CNN	(LBP) method include its sensitivity to noise and variations in illumination,	The CNN model used in the study can easily identify the discriminative regions of an image	Proposed methods effectively detect prostate cancer tumors using deep learning architectures
Falana, Serener, and Serte **[36]**	2023 b	MRI (Axial T2w+ADC + DWI)	CNN (DenseNet-201 and ResNet-50)	Invasive procedures like biopsies can be uncomfortable for patients.	Deep learning models, such as DenseNet-201 and ResNet-50, have shown promise in accurately detecting	ResNet-50 excels in DWI and T2W, DenseNet-201 in ADC.
Barra et al. **[37]**	2021	MRI (T2w)	CNN (U-Net, ResNet-18)	Difficulty in manually segmenting apex among experienced operators.	The algorithm can be integrated into a Computer-Aided Diagnosis (CAD) system	Dice similarity coefficient >85% in internal and external validation datasets.
Mosleh, Hamoud, and Alsabri **[38]**	2022	MRI (ADC)	CNN	Inaccuracy results and complications reported in traditional diagnosis methods.	Deep learning models detect prostate cancer with high accuracy rates.	High accuracy rates achieved by transfer learning models for PCa detection.
Haritha et al. **[39]**	2023	MRI medical images	RNN(ALSTM)	The effectiveness of the PCC-CSODL technique may depend on the quality and resolution of the MRI images used for classification	Automated Prostate Cancer Classification with high accuracy on MRI images.	PCC-CSODL accurately classified prostate and brachytherapy classes on MRI.

He et al. **[40]**	2023	(mpMRI) images	CNN, GAN	Scarcity of research on 3D DL applications in prostate MRI.	Deep learning enhances lesion identification, detection, segmentation, grading in prostate cancer.	DL models show promise in tumor identification, lesion segmentation, and PCa grading.
Rovcanin et al. **[41]**	2022	MRI medical images	ANN	AI can reduce expensive and complicated prostate biopsies.	AI aids in prostate cancer diagnosis and therapy through biomarkers.	Developed ANN achieved an accuracy of 92.7% in testing.

B. Deep Learning (DL) for Detecting prostate Cancer (PC):

Deep learning significantly advances prostate cancer detection by analyzing medical images with high accuracy. This technology surpasses traditional methods, enabling earlier, precise diagnoses and improving patient outcomes through its ability to learn and identify cancer indicators efficiently.

(Yang et al. 2024) Demonstrated that a deep learning (DL) model significantly outperformed the PI-RADS grading system in detecting clinically significant prostate cancer (csPCa) on multiparametric MRI (mpMRI). An ensemble DL model achieved high accuracy in prostate cancer (PCa) classification, benefitting from the integration of multiple MRI sequences to enhance diagnosis. These DL-based mpMRI networks exhibited superior sensitivity and specificity without any specific limitations mentioned. DL models showed higher csPCa detection rates compared to PI-RADS categorization, with the ensemble approach using multiple MRI sequences surpassing single-sequence models in PCa diagnosis. The ensemble DL model notably excelled in csPCa detection, highlighting its superiority over the conventional PI-RADS grading system [42].

(Maimone et al. 2022) An automated CAD system study compared Machine Learning (ML) and Deep Learning (DL) for prostate cancer segmentation, finding DL superior in reducing false positives and negatives, thus enhancing accuracy. It used evaluation metrics like Dice Similarity Coefficient, Precision, and Recall but cited the lack of a large validation set as a limitation for improvement. The research emphasized the absence of comparative studies on DL and ML across the same patient subsets, with DL demonstrating slightly higher accuracy and effectiveness in reducing false negatives through a 3-channel model. This highlighted DL's advantage over ML in segmentation accuracy [43].

(Pellicer-Valero et al. 2022) The deep learning system effectively automated prostate cancer detection and Gleason grading, surpassing radiologists' PI-RADS scores and demonstrating high sensitivity and specificity in lesion detection. Utilizing mpMRI datasets, the model outperformed expert radiologists in lesion detection and segmentation, showing excellent concordance in prostate zonal segmentation. Achieving high AUC, sensitivity, and specificity for PCa lesion detection, it exhibited superior performance across different Gleason Grade Group significance criteria [44].

(Singh et al. 2024) Deep learning was employed to detect prostate cancer using MRI with a high level of accuracy. A 3D CNN network was utilized for Gleason grading and segmentation, achieving notable specificity, accuracy, and sensitivity rates of 85%, 87%, and 89%, respectively. The research concentrated on leveraging deep learning techniques for the detection of prostate cancer, emphasizing the importance of Gleason grading and MRI image analysis in the process. The proposed technique demonstrated segmentation accuracy of 92% on MR images, ultimately predicting prostate cancer with high precision and reliability [45].

Table 2. Overview of the literature on detecting Prostate Cancer based on Deep Learning (DL).

Authors	Year	Dataset	Algorithm	Limitations	Advantages	Results
Yang et al. **[42]**	2024	MRI (T2w+ADC + DWI)	DL (PI-RADS in csPCa detection).	The DL model's performance may vary depending on the specific clinical factors considered	DL-based models exhibited higher detection rates of clinically significant prostate cancer (csPCa)	DL models had higher csPCa detection rates than PI-RADS categorization.
Maimone et al. **[43]**	2022	MRI (T2w+ADC)	DL techniques	Lack of large validation set impacts system improvement.	DL techniques greatly decrease the volume of False Positives (FPs) and the number of False Negatives (FNs)	DL methods achieve slightly higher accuracy than ML.
Pellicer-Valero et al. **[44]**	2022	MRI medical images	DL	Difficulty in comparing results due to dataset inconsistencies.	Fully automatic system for PCa detection, segmentation, and Gleason grade estimation.	Achieved high AUC, sensitivity, and specificity for PCa lesion detection.
Singh et al. **[45]**	2024	MRI (BVAL+ADC+Ktrans)	DL	The performance of the proposed method was evaluated using 3D CNN networks	Early detection of prostate cancer is crucial for long-term survival	Achieved specificity of 85%, accuracy of 87%, and sensitivity of 89%.

C. Convolutional Neural Networks (CNN) for Detecting prostate Cancer (PC):

Convolutional Neural Networks (CNNs) significantly improve prostate cancer detection by efficiently analyzing medical images, such as MRIs. Their advanced pattern recognition capabilities enable early and accurate identification of cancer indicators, surpassing traditional diagnostic methods and facilitating prompt, effective treatment strategies. This technology marks a crucial advancement in enhancing patient care and outcomes in prostate cancer management.

(Y. Liu et al. 2020) Proposed a system for prostate cancer classification that utilized deep learning, specifically combining features extracted by Convolutional Neural Networks (CNN) with handcrafted features for enhanced classification accuracy. This approach achieved an accuracy of 0.947, thereby outperforming other methods in the field. It demonstrated how deep learning, through the integration of CNN models and handcrafted features, significantly improved the sensitivity and accuracy of image feature detection in medical imaging. The experiment provided clear evidence of the model's superiority in terms of both accuracy and the Area Under the Curve (AUC) when compared to other methods, specifically noting the improved performance of the ST-ResNet model [46].

(W. Wang et al. 2024) Advanced MRI-based prostate cancer segmentation by combining CNNs with tokenized MLPs and a hybrid attention module, significantly improving segmentation precision and addressing challenges like unclear lesion boundaries. It underscored the utility of MRI and ultrasound fusion, achieving remarkable accuracy over existing methods through a hybrid loss function and an interactive attention mechanism. This network proved superior in segmenting the prostate gland and clinically significant prostate cancer, offering a credible and generalizable solution that outperformed state-of-the-art techniques [47].

(F. Liu et al. 2024) Explored the identification of pathological groups in prostate cancer through MRI, employing graph representation learning for effective MRI data analysis. It relied on feature extraction via a pretrained ResNet-50 model, trained on RGB images, and utilized a graph convolutional network with limited depth to prevent overfitting. The MMIGRL model, described as a 'black box,' posed challenges in interpretability. The evaluation of the MMIGRL model's performance, alongside ablation studies, was conducted to assess its efficacy [48].

(Wen et al. 2023) Focused on predicting incidental prostate cancer by applying a deep CNN to prostatic MRIs, introducing the iPCa-Net framework that surpassed existing methods in both segmentation and prediction. It tackled challenges such as subtle MRI differences and sample imbalance. The research utilized retrospective data from a single institution, concentrating on T2-weighted sequences and noting fluctuations in model performance due to sensitivity to parameter settings. The quality of manual segmentation significantly influenced the training data. iPCa-Net demonstrated exceptional ability in MRI segmentation and prediction tasks, notably excelling in the early identification of incidental prostate cancer patients [49].

(Aldoj et al. 2020) Developed deep learning model utilizing multi-parametric MR imaging for prostate cancer classification achieved an AUC of 0.89 to 0.91, demonstrating accuracy comparable to experienced radiologists. This model, which did not require manual segmentation but only the lesion's location, showed sensitivity and specificity rates competitive with professional assessments. Employing a multi-channel 3D CNN, the study highlighted that perfusion MR images significantly influenced the model's performance, which remained unaffected by lesion size. This advancement underscores deep learning's potential to match, and possibly enhance, the diagnostic accuracy of prostate cancer using established radiological standards like PI-RADS [50].

(Deniffel et al. 2020) Employed a 3D Convolutional Neural Network (CNN) on multiparametric MRI (mpMRI) for clinically significant prostate cancer (csPCa) risk assessment, demonstrating that a calibrated CNN significantly reduced unnecessary biopsies compared to the PI-RADSv2 standard. It emphasized the importance of CNN calibration for its clinical utility in prostate biopsy decisions, employing decision curve analysis to evaluate the model's clinical utility by balancing the benefits against the risks of true and false positives. Despite the original CNN predictions being severely miscalibrated and potentially leading to net harm, the calibrated CNN showed good discrimination (C = 0.85) and moderate calibration, underlining the crucial role of calibration in enhancing the CNN's utility for biopsy decisions and improving patient outcomes by minimizing unnecessary procedures [51].

(Soni et al. 2022) Introduced for autonomously identifying prostate cancer locations from multiparametric magnetic resonance imaging (MP-MRI) regions. Utilizing two parallel convolutional networks to analyze feature maps from apparent diffusion coefficient (ADC) and T2-weighted (T2W) images, it integrated these to leverage complementary information within MP-MRI. The inclusion of extrusion and excitation blocks allowed for an automatic increase in relevant features in the fusion feature map, aiming to refine the segmentation of prostate cancer lesions. Conducted with 140 instances, the SEMRCNN model achieved a Dice coefficient of 0.654, demonstrating its superiority in segmentation accuracy over models like V net, Resnet50-U-net, Mask-RCNN, and U network model by effectively isolating prostate cancer lesions, minimizing surrounding area interference, and enhancing lesion feature learning [52].

(Bhattacharjee et al. 2020) Introduced that deep learning (DL) techniques were highly effective in classifying benign and malignant tissues, achieving notable accuracies. Specifically, lightweight convolutional neural network (LWCNN) models, tailored for image and feature classification, reported an accuracy of 94%, with a precision of 94.2% and a recall of 92.9%. This demonstrated the potent capability of DL models to predict tissue classification outcomes accurately, underscoring their significant potential in medical diagnostics for distinguishing between benign and malignant tissues with high precision [53].

(Gavade et al. 2023) Developed a deep learning (DL) approach utilizing multiparametric MRI (mpMRI) images for automating prostate cancer diagnosis, significantly outperforming existing methods. By segmenting and classifying regions of interest as cancerous or non-cancerous, this approach, which incorporates U-Net, CNNs, and LSTM models, demonstrates high precision in detecting prostate cancer. Highlighting a gap in the literature for automated diagnosis using mpMRI, the findings suggest a promising direction for future models, potentially including vision transformers, to improve clinical assessments of prostate cancer [54].

(Ushinsky et al. 2021) Focused on using deep learning to automate prostate segmentation from multiparametric MRI (mpMRI), employing a hybrid 3D-2D U-Net convolutional neural network (CNN) architecture. This approach achieved high accuracy, as evidenced by a mean Dice score of 0.898 and a Pearson correlation coefficient of 0.974, indicating precise prostate volume measurements. These results highlight the effectiveness of CNNs, specifically the U-Net architecture, in accurately segmenting the prostate from clinical MR images, showcasing the potential of deep learning in enhancing the precision of medical imaging analyses [55].

(Arif et al. 2020) Developed a deep learning-based method for detecting clinically significant prostate cancer in low-risk patients, utilizing multiparametric MRI (mpMRI) data to achieve high diagnostic accuracy. This computer-aided approach accurately segmented significant from non-significant prostate cancer, excluding patients with PI-RADS score 3 and small lesions. Employing convolutional neural networks (CNN), the model attained an AUC of 0.78, with 85% sensitivity and 72% specificity, demonstrating its effectiveness in identifying

ISUP grade 2 prostate cancer. This indicates the potential of deep learning in improving the precision of prostate cancer diagnosis and treatment planning [56].

(Falana, et.al 2023a) Explored the use of deep learning frameworks to differentiate clinically significant prostate cancer (csPCa) using MRI sequences, finding axial T2-weighted (T2W) imaging to be the most effective for csPCa classification. It noted a lack of comparison with other deep learning models and limited discussion on the impact of image quality on classification accuracy. Despite these gaps, the research confirmed that deep learning models are capable of effectively distinguishing csPCa from non-csPCa, with multi-planar volumes further enhancing prostate segmentation results [57].

(Li et al. 2023) Deep learning was used to detect and segment prostate cancer in MRI scans, employing a 3D Mask RCNN model with high efficacy. With 133 patients included, the focus was on automating the segmentation and detection processes. Ethical approval was secured, and evaluation metrics such as DSC, sensitivity, specificity, and accuracy were employed. Results showed a DSC of 0.856, sensitivity of 0.921, and specificity of 0.961, with similar performance on the test set. The study demonstrated accurate detection and segmentation of prostate cancer, indicating promising potential for clinical application [58].

(Salvi et al. 2022) Utilized deep learning and Active Shape Models for automated prostate segmentation, achieving a mean dice score of 0.851 and a Hausdorff distance of 7.55mm. The proposed method demonstrated excellent performance in segmenting the prostate gland from MR images, employing a standardized approach involving training and intensity histogram mapping. Partial support for the research was provided by Cassa di Risparmio di Cuneo. Testing involved four configurations, varying ASM parameters [59].

(Karagoz et al. 2023) Evaluated for its ability to detect prostate cancer across diverse datasets, demonstrating high performance in identifying clinically significant cases. Large-scale bi-parametric MRI data were employed to train the deep learning model, with the authors utilizing a self-adapting deep network specifically for prostate cancer detection. The study focused on assessing the effectiveness of deep learning in cancer detection, where the nnU-Net model achieved AUROC scores of 0.888 and 0.889. On in-house testing data, the model maintained a performance AUROC of 0.886. However, a slight decrease in performance to 0.870 was observed when employing transfer learning techniques [60].

(Zheng et al. 2024) Enhanced prostate cancer detection by using anatomical information from multiparametric MRI, featuring a design that improved lesion detection. The model's effectiveness in patient-level classification was influenced by clinical factors like PSAD levels. Its use of a single-institution dataset and exclusion of DCE imaging were limitations. However, AtPCa-Net stood out for integrating anatomical priors, which improved detection and classification, reduced false positives, and showed better performance in patients with higher PSAD levels [61].

(Deng et al. 2023) Deep learning models effectively predicted Ki67 expression in prostate cancer, a marker gene indicative of tumor cell proliferation, which is closely associated with cancer aggressiveness, recurrence, and metastasis. Radiomic nomograms provided noninvasive preoperative prognoses for prostate cancer. These deep learning algorithms, renowned for their high accuracy in image recognition, outperformed clinical models in predicting Ki67 expression. Multiple user-friendly models were developed for preoperative prognostication of prostate cancer, enhancing clinical decision-making processes [62].

Table 3. Overview of the literature on detecting Prostate Cancer based on Convolutional Neural Networks (CNN).

Authors	Year	Dataset	Algorithm	Limitations	Advantages	Results
Y. Liu et al. **[46]**	2020	MRI medical images	CNN(ResNet -50)	The paper lacks comparison with more recent deep learning architectures.	Combination of all three handcrafted features leads to highest accuracy.	Model achieves 0.947 accuracy,
W. Wang et al. **[47]**	2024	MRI medical images	CNN	Challenges include unclear boundaries and variations in prostate cancer lesions.	ParaCM-PNet offers superior segmentation for prostate gland and csPCa.	ParaCM-PNet excels in segmenting prostate gland and csPCa in MRI.
F. Liu et al. **[48]**	2024	MRI (T2w+ADC)	CNN (ResGCN)	Graph convolutional network has limited depth to avoid overfitting.	Graph representation learning techniques can handle large-scale datasets efficiently,	Evaluation of MMIGRL model performance and ablation studies conducted.
Wen et al. **[49]**	2023	MRI medical images	CNN (iPCa-Net)	Model performance fluctuations and sensitivity to parameter settings.	iPCa-Net outperforms the top-performing method by 1.23%	Superior performance in early identification of incidental prostate cancer patients.
Aldoj et al. **[50]**	2020	MRI (T2w+ADC + DWI, and K-trans) Image	CNN (3D CNN)	Small dataset with 200 patients, potentially leading to overfitting.	Deep learning model for prostate cancer classification comparable to radiologists	3D CNN achieved AUC of 0.89 to 0.91 for prostate cancer detection.
Deniffel et al. **[51]**	2020	MRI (T2w+ADC + B1600) Image	CNN (3D CNN)	Retrospective single-center study with limited cohort size.	Decision curve analysis confirms net benefit of using calibrated deep learning model.	Calibrated CNN achieved good discrimination (C = 0.85) and moderate calibration
Soni et al. **[52]**	2022	MRI medical images	CNN(SEMRC NN)	Improved segmentation accuracy of prostate cancer lesions in MP-MRI.	The SEMRCNN model outperforms other models like V net	SEMRCNN model achieves Dice coefficient of 0.654, sensitivity of 0.695.
Bhattacharjee et al. **[53]**	2020	MRI medical images	CNN (Two lightweight CNN +	The study did not provide details on the dataset used	Lightweight CNN and ensemble ML achieved high	DL model achieved 94% accuracy with

			LWCNN)	for training and testing the models.	accuracies for tissue classification.	non-handcrafted features.
Gavade et al. **[54]**	2023	(mpMRI) images	CNN (U-Net)	Developed and tested on a single dataset.	DL models provide automated diagnosis of prostate cancer.	Achieved high precision in detecting PCa disease with high potential.
Ushinsky et al. **[55]**	2021	MRI (T2W) Image	CNN (Hybrid 3D-2D U-Net CNN)	Limited generalizability to other centers or MRI equipment.	Deep learning CNN for automatic segmentation of the prostate organ.	Mean Dice score was 0.898, Pearson correlation coefficient for prostate volume 0.974.
Arif et al. **[56]**	2020	MRI (T2w+ADC+ DWI-b800) Image	CNN	Results may vary in different patient cohorts and centers.	Deep learning method accurately detects and segments clinically significant prostate cancer.	Model achieved 0.78 AUC with sensitivity 85% and specificity 72%.
Falana, Serener, and Serte **[57]**	2023 a	MRI (T2w+ADC)	CNN (DenseNet-201, ResNet-50, and VGG-19)	Limited discussion on the impact of image quality on classification.	Image augmentation techniques can be employed to expand the training dataset	xial T2W imaging is most effective for csPCa classification accuracy.
Li et al. **[58]**	2023	MRI (T2W) Image	RCNN	Small sample size affects generalizability.	The study produced promising results, with high accuracy	Achieved DSC of 0.856, sensitivity of 0.921, specificity of 0.961.
Salvi et al. **[59]**	2022	MRI (T2W) Image	CNN (VNet-T2)	Limitations include noisy intensity profiles and lack of standard image scale.	The method achieves excellent segmentation performance.	Achieved excellent segmentation performance with mean dice score of 0.851.
Karagoz et al. **[60]**	2023	MRI medical images	CNN (3D nnU-Net, U-Net)	Small training sample size and standard 2D U-net used.	indicating its potential to improve prostate cancer diagnostics	nnU-Net model achieved AUROC of 0.888 on hidden validation data.
Zheng et al. **[61]**	2024	MRI (T2WI, high-B DWI, and ADC)	CNN	Single-institution dataset affects model evaluations and generalizability	AtPCa-Net integrates anatomical priors, improving PCa detection performance.	AtPCa-Net improves PCa detection and patient-level classification performance.
Deng et al. **[62]**	2023	MRI (T1W + T2W) images	CNN (Resnet101, Inceptionv3,	Limited discussion on potential biases.	Deep learning algorithms offer high recognition	Deep learning models outperformed

	Densenet12 1 for Ki67 prediction)	accuracy in image recognition.	clinical model in predicting Ki67 expression.

C. Result and Discussion

The collected research across various studies highlights the significant advancements in prostate cancer detection and classification using a blend of deep learning technologies, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and transfer learning models. Notably, models like ResNet-101 emerged as particularly effective, surpassing traditional and other non-deep learning methods in diagnostic accuracy. Innovations such as the integration of Local Binary Patterns with CNNs, the application of DenseNet-201 and ResNet-50 for csPCa detection, and the use of U-Net for segmentation underscored the potential of deep learning in addressing challenges like Gleason score variability and the intricacies of tumor boundary delineation. Furthermore, the application of transfer learning models and the combination of Cat Swarm Optimization with Deep Learning illustrated significant improvements in automated detection, reducing manual feature selection efforts and enhancing treatment planning. These studies collectively demonstrate the transformative impact of AI and deep learning on prostate cancer diagnostics, promising more accurate, non-invasive, and efficient methods for early detection and classification, thereby potentially minimizing the need for invasive diagnostic procedures.

D. Conclusion

The integration of artificial intelligence (AI) and deep learning (DL) into the diagnostics and treatment of prostate cancer marks a significant shift toward more advanced healthcare solutions. These technologies empower medical professionals to not only improve the accuracy of diagnoses but also to refine the efficiency of screening procedures and customize treatments for better patient outcomes. Our study highlights the crucial role of AI and DL across multiple stages of prostate cancer management, including the early detection of tumors, forecasting disease progression, and optimizing treatment responses. Despite the hurdles of technological sophistication and ethical considerations, the advantages these digital innovations offer are substantial. Ensuring ongoing collaboration among researchers, clinicians, and ethicists is paramount in leveraging AI and DL's full capabilities. This approach is vital in overcoming challenges and maximizing the beneficial impact on prostate cancer care. Through dedicated interdisciplinary efforts and robust ethical frameworks, the integration of AI and DL is set to redefine the standards of care, leading to more targeted, efficient, and patient-focused treatments. This evolution in care models underscores a promising future where prostate cancer management is significantly enhanced by technological progress.

E. References

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