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Artificial intelligence in prostate cancer diagnosis: A systematic review of advances in gleason grade and PI-RADS classification

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ABSTRACT

Artificial intelligence (AI) is reshaping prostate cancer (PCa) diagnosis by integrating advanced imaging modalities such as multi-parametric MRI (mpMRI) and whole-slide imaging (WSI). Leveraging convolutional neural networks (CNNs), these models have demonstrated over 90% accuracy in tasks like tumor localization, gleason grading (GG), and risk stratification. mpMRI modalities—including T2-weighted, diffusion-weighted (DWI), and dynamic contrast-enhanced (DCE) sequences—combined with the standardized prostate imaging reporting and data system (PI-RADS) framework, support consistent clinical interpretation. In pathology, AI methods such as CNNs and U-Net architectures achieve high performance in GG and tumor segmentation, with intersection over union (IoU) scores between 0.75 and 0.85. These systems reduce subjectivity and pathologist workload. Emerging technologies like vision transformers (ViTs) and natural language processing (NLP) further advance large-scale histopathology analysis and clinical data interpretation. Explainable AI contributes to model transparency, fostering clinical trust. This review highlights critical future directions, including multimodal data fusion, real-time diagnostics, image-to-text reporting, and personalized treatment planning—underscoring AI's growing role in improving diagnostic accuracy and patient outcomes in PCa care.

KEYWORDS

artificial intelligence, deep learning, medical imaging, prostate cancer diagnosis, radiologic-pathologic synergy

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1. Introduction

Prostate cancer (PCa) is the second most common cancer among men worldwide, with 1.47 million new cases and 397,430 deaths reported in 2022. The United States recorded the highest incidence with 230,125 cases, followed by China with 134,156 cases, and Brazil with 104,318 cases. Similarly, mortality rates were highest in the United States at 47,522 deaths,

China at 33,746 deaths, and Brazil at 19,958 deaths [1, 2]. These statistics highlight the significant global burden of PCa and the urgent need for improved awareness, early detection, and effective treatment strategies. In India, 37,948 new cases and 18,386 deaths were recorded, ranking it fourth globally in PCa related fatalities. Projections indicate that the global burden will rise to 3 million cases by 2040, driven by aging populations and improved detection [1, 2]. These statistics underscore the urgent need for enhanced awareness, early detection, and effective treatments to address this growing health challenge.

PCa, originating in the gland below the bladder, requires precise diagnostic differentiation from benign conditions like benign prostatic hyperplasia (BPH). While mpMRI has enhanced tumor visualization, interpretation remains subjective. Our AI-driven approach addresses this challenge by integrating three critical data streams: (1) mpMRI for structural/functional tumor assessment, (2) WSI for histopathological correlation, and (3) clinical parameters for contextual analysis. Figure 1 illustrates our optimized pipeline where these multimodal inputs undergo synchronized preprocessing, feature extraction, and intelligent fusion. This synthesis enables more objective international society of urological pathology (ISUP) grade predictions while reducing inter-observer variability. The system's architecture specifically targets current diagnostic pain points - combining radiological imaging with pathological verification and patient-specific clinical data to support personalized therapeutic decisions. This methodological advance demonstrates how AI can standardize PCa grading while maintaining clinical relevance, particularly in distinguishing aggressive from indolent disease.

Current diagnostic techniques for PCa, including mpMRI for PI-RADS scoring and histopathological analysis using WSI for GG, are critical but labor-intensive and susceptible to inter-observer variability. Traditional methods such as digital rectal examination (DRE), prostate-specific antigen (PSA) testing, and transrectal ultrasound (TRUS)-guided biopsies are limited by high false-negative rates, overdiagnosis, and overtreatment of indolent tumors, further complicated by a global shortage of specialized clinicians. The integration of GG and PI-RADS merges histopathological precision with imaging-based localization, improving risk stratification and guiding treatment decisions. AI is transforming PCa diagnosis by automating processes, reducing subjectivity, and enhancing workflow efficiency. These advancements highlight the urgent need for standardized, automated approaches to enhance diagnostic consistency, accuracy, and efficiency in PCa care. GG classifies PCa cells based on their architectural arrangement, ranging from 1 (well-differentiated) to 5 (undifferentiated), with higher patterns indicating greater aggressiveness. The Gleason score (GS), derived by summing the two most prevalent patterns, categorizes cancer into risk groups: low-grade (Gleason 6), intermediate-grade (Gleason 7), and high-grade (Gleason 8–10). Complementing this, the PI-RADS system uses mpMRI to assign a score from 1 (very low likelihood) to 5 (very high likelihood) of clinically significant cancer, guiding targeted biopsies and treatment decisions. Higher PI-RADS scores (4–5) often correlate with higher GS (7–10), reflecting clinically significant disease, while lower PI-RADS scores (1–3) may align with lower GS (6 or less), suggesting less aggressive cancer. Together, GG and PI-RADS provide a synergistic approach to PCa diagnosis, combining histopathological precision with imaging-based localization.

AI, particularly machine learning (ML) and deep learning (DL), has emerged as a transformative force in healthcare, offering unprecedented opportunities to enhance the accuracy, efficiency, and automation of medical diagnostics. Unlike traditional ML, which relies on manually extracted features, DL models can autonomously identify intricate patterns in complex datasets, making them exceptionally suited for medical imaging and pathology tasks. In radiology, AI-driven models are revolutionizing PCa diagnosis by automating PI-RADS scoring based on mpMRI, reducing diagnostic errors, and improving workflow efficiency. Similarly, in pathology, AI algorithms are assisting in GG using WSIs, enabling more precise and reproducible assessments. The integration of AI into these diagnostic frameworks not only reduces subjectivity but also streamlines workflows, ultimately advancing personalized care for PCa patients.

This review uniquely integrates radiology and pathology in PCa diagnosis by bridging mpMRI and WSI through AI. Figure 2 presents the AI pipeline that illustrates the

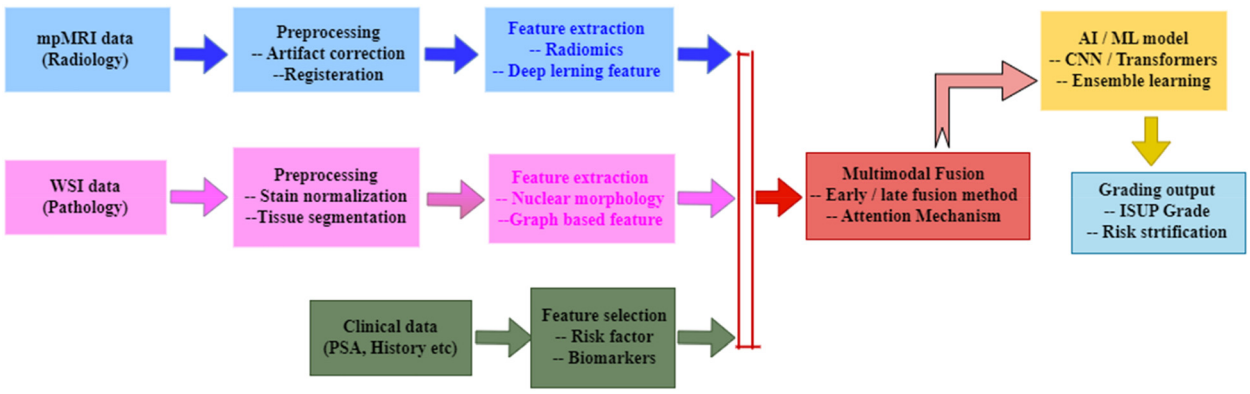

Fig. 1. AI workflow for prostate cancer grading integrating mpMRI, pathology and clinical data

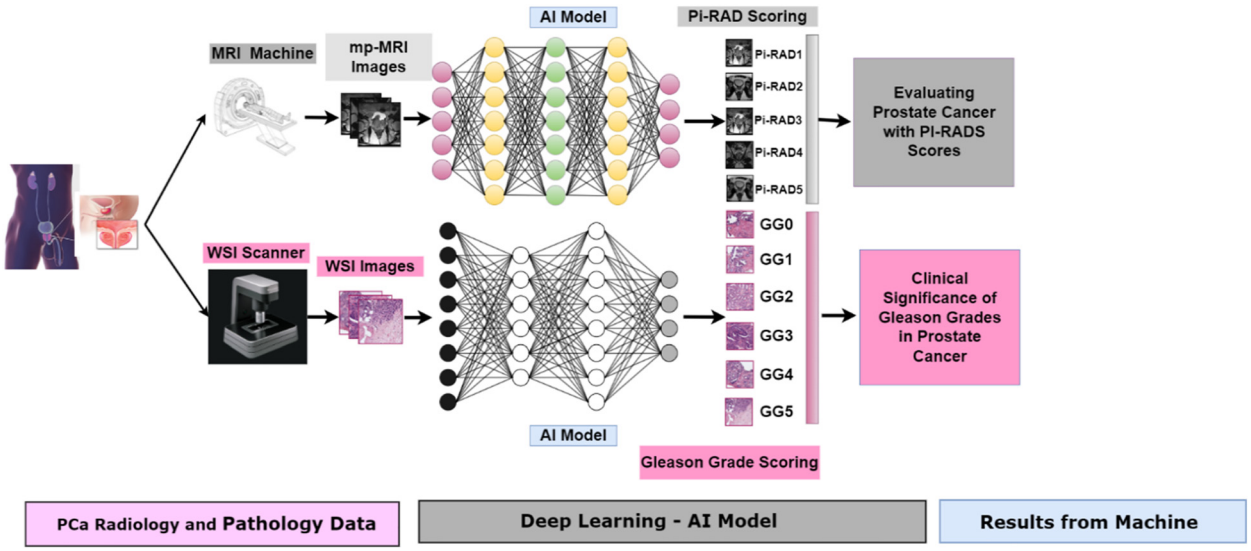

Fig. 2. AI-enhanced pipeline for accurate PCa diagnosis: Integrating prostate imaging and gleason grading

integration of radiological and pathological data. Unlike others that treat these separately, it explores how AI synergizes radiological and histopathological data for better grading and detection. It highlights the shift from traditional ML to NLP-based models like transformers, now used for clinical notes and radiology reports. Vision transformers (ViTs) offer a scalable solution for large-scale WSI analysis. A key focus is explainable AI, ensuring transparency and trust in clinical decisions. Future directions include multimodal integration, real-time diagnostics, and personalized care, making this review a valuable resource for researchers and clinicians.

1.1. Advancing PCa diagnosis through AI and integrated metrics

This paper examines the integration of GG and PI-RADS in PCa diagnosis, emphasizing their complementary roles in risk stratification and decision-making. By addressing the limitations of traditional methods and leveraging advanced technologies, the study contributes to precision medicine in PCa care.

This review analyzes 78 studies on AI in PCa, covering image pre-processing, segmentation, and classification, evaluated using accuracy, AUC, sensitivity, and specificity. Challenges like explainability and data requirements are addressed, with future directions including generative AI for synthetic data, NLP for clinical interpretation, and hybrid radiology-pathology models. Peer-reviewed articles from PubMed, IEEE Xplore, Elsevier, and Springer were included. The paper is structured into the following sections: Introduction, Methodology, PCa Detection Evolution, AI in PCa Management, Future Work, and Conclusion.

2. Advancing PCa diagnosis with AI and imaging

Over the past decade, mpMRI and AI integration have significantly advanced PCa diagnosis and treatment, enhancing detection accuracy, risk stratification, and clinical decision-making. These innovations are transforming prostate cancer care, as illustrated in Fig. 3.

2.1. Transforming prostate cancer grading (PCG): from traditional methods to AI-enhanced imaging

By integrating T2-weighted imaging, diffusion-weighted imaging (DWI), and dynamic contrast-enhanced MRI, mpMRI improves detection of clinically significant PCa (ISUP Grade ≥2) with 42–66% accuracy for identifying extra

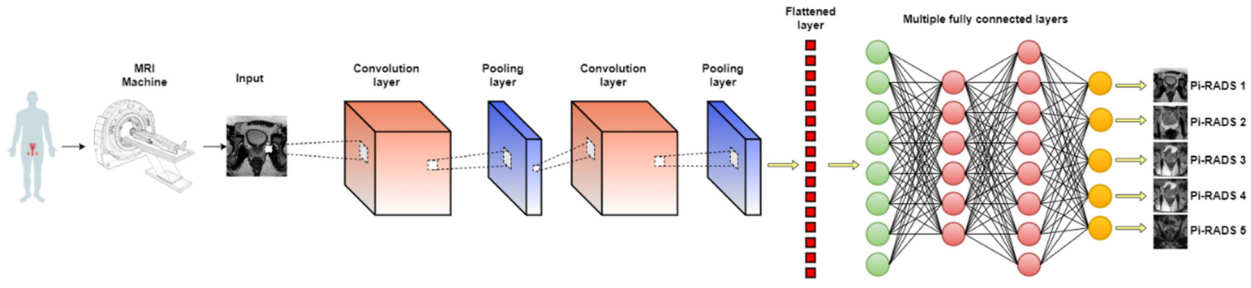

Fig. 3. AI into prostate imaging reporting and data system classification

prostatic extension. Standardized PI-RADS scoring (1–5) enhances risk stratification, guiding targeted biopsies that reduce the overdiagnosis of indolent tumors by 27% compared to systematic biopsies. mpMRI demonstrates higher sensitivity for aggressive cancers (66% for ISUP Grade ≥2 vs. <30% for Grade 1 in sub-0.5 cm lesions), while correlating with surgical GS upgrades (43% vs. 27% for MRI-negative cases).

2.2. AI enters the scene: enhancing mpMRI interpretation

The integration of AI into mpMRI analysis has been transformative. Early AI models, such as those developed by Li et al. [3], used DL to improve tumor detection and segmentation accuracy by leveraging whole-mount histopathology as ground truth. These models demonstrated high diagnostic accuracy (AUC >0.85), reducing unnecessary biopsies and improving patient outcomes. As AI technology advanced, researchers like Talyshinskii et al. [4] explored its role in precision medicine, focusing on AI-driven diagnostic tools, treatment planning, and patient management. AI models began to outperform traditional methods, such as the PI-RADS, in detecting clinically significant prostate cancer. For instance, Yang et al. [17] developed a DL model that achieved an AUC of 0.94, outperforming PI-RADS in accuracy, sensitivity, and risk stratification.

2.3. From semi-automated to fully automated

The transition from semi-automated to fully automated AI systems has been a major milestone. Sushentsev et al. [8] systematically compared fully-automated and semi-automated AI methods for detecting clinically significant prostate cancer on MRI. Their findings revealed that fully-automated systems achieved AUCs between 0.85 and 0.93, with sensitivities ranging from 80% to 92%. These systems not only enhanced diagnostic accuracy but also improved workflow efficiency, reducing the radiologist's workload.

Fully automated DL models, such as those developed in [16], demonstrated high accuracy in lesion detection and biopsy avoidance. These models, integrated with clinical nomograms, provided a comprehensive risk assessment, further reducing unnecessary biopsies and improving patient outcomes.

2.4. Radiomics and hybrid models: the next frontier

Radiomics—the extraction of quantitative features from medical images—has become a powerful tool in prostate cancer grading (PCG). Zhuang et al. [37] demonstrated that using an enlarged region of interest (ROI) on mpMRI significantly improves the accuracy of GS prediction. Similarly, Liu et al. [25] proposed a hybrid model combining radiomics features with CNNs, achieving an AUC of 0.96 for differentiating high- and low-grade PCa, outperforming conventional methods and supporting informed treatment decisions.

Building upon these advances, recent AI-driven approaches have begun integrating mpMRI data with morphometric features from WSIs to provide a more comprehensive tumor characterization. These multi-modal models leverage the complementary nature of radiological and pathological data—capturing both macro-level anatomical structures and micro-level cellular details. Radiogenomic frameworks, which correlate imaging features with histologic and molecular profiles, further enhance this integration by offering insights into tumor heterogeneity.

Advanced architectures, such as transformer-based fusion networks and graph neural networks, are being explored to align spatially corresponding features across modalities. These hybrid systems support more accurate biopsy guidance, GG, and risk stratification. By bridging the gap between imaging and pathology, AI-enabled multi-modal fusion holds significant promise for reducing diagnostic uncertainty and advancing precision oncology in prostate cancer care.

2.5. AI-enhanced MRI-targeted biopsies: the future of PCa diagnosis

The future of PCa grading lies in the integration of AI-enhanced MRI-targeted biopsies and advanced imaging techniques. Chan et al. [24] reviewed the role of AI in optimizing prostate biopsies and imaging, emphasizing the potential of MRI-ultrasound fusion-guided biopsies to improve diagnostic accuracy and reduce unnecessary procedures. Moreover, the use of AI in PSMA PET/CT imaging, as explored by Belal et al. [20], has shown promise in improving lesion detection, segmentation, and disease staging. These advancements highlight the potential of AI to further enhance the accuracy and efficiency of PCa grading.

2.6. Challenges and opportunities in AI-driven PCG

Despite these advancements, challenges remain. Belue et al. [15] highlighted the poor adherence of AI-based prostate MRI algorithms to standardized reporting guidelines, emphasizing the need for improved transparency, reproducibility, and regulatory compliance. Additionally, the variability in datasets and the need for external validation pose significant hurdles in the clinical adoption of AI models.

However, the opportunities are immense. The integration of radiological and clinical data using machine learning techniques, as demonstrated by Esteban et al. [38], has the potential to further enhance the detection of clinically significant PCa. Similarly, the development of non-invasive biomarkers, such as surface luminance distribution measurements [28], offers new avenues for PCa detection and grading.

2.7. Standardization and harmonization for generalizable AI in prostate MRI

Dataset variability remains a major hurdle for developing generalizable AI models in prostate MRI. Variations in scanner hardware, field strength, and imaging protocols reduce model transferability across institutions. As noted by

Sunoqrot et al. [9], standardized datasets like PI-CAI and PROSTATEx are essential to improve reproducibility and benchmark progress.

Guidelines such as PI-RADS v2.1 promote uniform acquisition and reporting, while pre-processing techniques —e.g., rescaling, histogram equalization, and N4 bias correction—help reduce inter-scanner variability. Cuocolo et al. [13] reported strong diagnostic performance of ML models (AUC 0.88–0.96) but highlighted the need for external validation due to dataset heterogeneity.

Harmonization methods like ComBat and domain adaptation enable alignment across sites. Transfer learning and fine-tuning on local data further support generalization. Ultimately, multi-center, prospective validation—particularly across diverse populations—is critical for real-world deployment. Public resources such as TCIA and PROSTATEx facilitate robust external benchmarking.

2.8. The role of pre-biopsy MRI and advanced imaging techniques

Pre-biopsy MRI has emerged as a valuable tool in PCa screening. Tesfai et al. [29] evaluated the impact of pre-biopsy MRI and additional diagnostic tests, demonstrating improved detection accuracy and reduced unnecessary biopsies. Similarly, Scherer et al. [33] highlighted the effectiveness of pre-biopsy mpMRI in improving diagnostic accuracy and reducing unnecessary biopsies in Switzerland.

Advanced imaging techniques, such as biparametric MRI (bpMRI), have also gained traction. Caglic et al. [35] evaluated the safety and reliability of bpMRI for monitoring prostate cancer during active surveillance, demonstrating its comparability to mpMRI. Additionally, Balaha et al. [36] explored the use of intravoxel incoherent motion (IVIM)-based parametric estimation from diffusion-weighted MRI (DW-MRI) to improve the precision of PCa assessment.

In summary, the integration of pathology and radiology data has been a significant advancement in PCa diagnosis. AI-assisted PCa diagnosis was presented [14]. It has explored by integrating radiologic and pathologic data, enhancing detection accuracy and treatment planning. Similarly, a non-local Mask R-CNN model [39] was presented with histopathological ground truth to improve PCa detection and segmentation on MRI. They have achieved high diagnostic accuracy and lesion localization.

3. The future: AI-driven precision medicine

The future of PCa grading lies in AI-driven precision medicine. The role of AI in PCa diagnosis and prognosis highlights its potential to automate pathology workflows, enhance diagnostic accuracy, and improve patient outcomes [19]. An in-depth review of DL approaches for automated GG was presented [30] to emphasize the need for standardized validation and improved reproducibility.

Emerging technologies, such as fusion MRI/ultrasound-guided transperineal biopsy, have shown significant promise. Giannakodimos et al. [27] demonstrated that this technique improves targeting precision, reduces infection risks, and offers superior accuracy compared to conventional biopsy methods. Additionally, Tang et al. [31] explored a CAD system leveraging multi-parameter MRI for early-stage PCa detection, demonstrating high accuracy and potential for improved diagnostic precision.

3.1. AI in bone metastasis imaging

AI and radiomics have also been applied to imaging PCa bone metastases. Pawan et al. [34] reviewed advancements in automated detection, classification, and prognosis prediction, highlighting the potential of AI to improve personalized treatment planning for advanced PCa. AI-driven mpMRI and radiology integration have enhanced PCa grading, improving diagnostic accuracy, reducing biopsies, and enabling personalized care. Table 1 summarizes key insights and implications, while Table 2 reviews 38 studies on AI in GG grading, tumor detection, segmentation, and classification, highlighting ML, DL, and CNNs. Hybrid AI models show superior performance, with emerging trends in radiomics and precision medicine driving a shift toward data-driven, personalized PCa treatment.

4. The evolution of AI in PCa diagnosis and management

The evolution of AI in PCa diagnosis and management has been transformative, progressing from early applications in histopathology and GG to the integration of multi-modal imaging and advanced AI systems reshaping clinical workflows, Fig. 4.

Table 1. Comparison of AI-based models for prostate cancer diagnosis using mpMRI: methods, performance, and clinical relevance

AI Model	Application	Performance	Clinical Impact	Limitations
CNN (ResNet, VGG) [41]	Lesion detection	High sens/spec [42]	Improves accuracy [43]	Large datasets [44]
Radiomics + ML [45]	GG classification	Mod-high acc [46]	Early diagnosis [47]	Poor generalization [48]
Hybrid AI [49]	Combined analysis	Improved precision [50]	Integrates knowledge [51]	Computationally heavy [52]
Transformers [53]	Tumor localization	Emerging superiority [54]	Auto-reporting [55]	Needs validation [56]
GANs [57]	Data augmentation	Enhances diversity [58]	Balances datasets [59]	Artificial features [60]

Table 2. Summary of AI applications in PCa grading using mpMRI

Reference	AI Model	Datasets	Key Findings	Clinical Relevance
Li et al. [3]	DL (Histopathology Ground Truth)	mpMRI + Histopathology	AUC >0.85, better detection & segmentation.	Non-invasive, avoids biopsies.
Talyshinskii et al. [4]	DL for Precision Medicine	Multi-center Trials	AI improves accuracy & treatment.	Prevents biopsies, improves outcomes.
Thomas et al. [5]	AI-based Detection	Multiple Studies	Systematic review & meta-analysis.	Standardizes AI evaluation.
Harmon et al. [6]	AI Pathology + Radiology	Public Prostate MRI	AUC 0.85–0.96, accuracy 88%–95%.	Limits biopsies, boosts detection.
Turkbey et al. [7]	CNNs, DL for Detection	Public + Private MRI	AUC 0.85–0.97, accuracy 87%–94%.	Enhances consistency, lessens workload.
Sushentsev et al. [8]	Automated vs. Semi-AI	Multi-center Data	AUC 0.85–0.93, sensitivity 80%–92%.	Boosts accuracy, streamlines workflow.
Sunoqrot et al. [9]	AI for Prostate MRI	PROSTATEx, PI-CAI	AUC 0.85–0.96, accuracy 80%–95%.	Calls for standard benchmarks.
Greer et al. [10]	CAD	Multi-center mpMRI	Boosts accuracy & agreement.	Prevents biopsies, ensures consistency.
Saha et al. [11]	AI vs. Radiologists	PI-CAI	AI accuracy 89%, AUC 0.91, sensitivity 87%.	Matches radiologists, cuts workload.
Twilt et al. [12]	AI Classification	ProstateX, PI-CAI	Accuracy 85%–92%, AUC 0.89–0.94.	Boosts detection, minimizes errors.
Cuocolo et al. [13]	ML for Cancer	ProstateX, MRI Data	AUC 0.88–0.96, accuracy 82%–94%.	Helps detect early, stratifies risk.
Mata et al. [14]	AI for Radiology + Pathology	ProstateX, Pathology Data	AUC 0.91–0.97, accuracy 85%–95%.	Enhances lesion localization and treatment.
Belue et al. [15]	Prostate MRI AI	Multi MRI Studies	Low CLAIM adherence (30%).	Demands better transparency and reproducibility.
Schrader et al. [16]	DL Risk Assessment	1,500 MRI Cases	AUC 0.93, sensitivity 90%, specificity 85%.	Minimizes biopsies and enhances risk stratification.
Yang et al. [17]	DL for PCa	Institutional + Public	AUC 0.94, accuracy 90%, better than PI-RADS.	Improves detection and biopsy decisions.
Lin et al. [18]	Cascaded DL for bpMRI	1,200 bpMRI Scans	AUC 0.91, IoU 0.75, sensitivity 87%.	Enhances detection and reduces workload.
Satturwar et al. [19]	AI for Diagnosis	TCGA, ProstateX	AUC 0.94, accuracy 92%.	Streamlines workflows and improves outcomes.
Belal et al. [20]	AI for PSMA PET/CT	Clinical Trials	AUC 0.96, accuracy 91%.	Enhances detection and staging.
Gavade et al. [21]	Automated DL Segmentation	Public MRI	Comparison: V-net, U-net, nnU-net, CNN.	Reduces biopsies and refines risk stratification.
Cai et al. [22]	MRI-Ultrasound Biopsy	5,000+ Patients	Sensitivity 85%, specificity 80%, AUC 0.92.	PZ and CZ localization.
Watts et al. [23]	AI MRI Biopsies	Clinical Trials	AUC 0.94, sensitivity 88%, specificity 85%.	Outperforms cognitive biopsy, minimizing errors.
Chan et al. [24]	Hybrid Radiomics + CNN	1,000+ mpMRI	AUC 0.96, accuracy 90%, best approach.	Reduces procedures and enhances detection.
Liu et al. [25]	AI for Noise Correction	1,500 MRI Cases	Sensitivity 90%, specificity 87%.	Guides treatment and reduces biopsies.
Coelho et al. [26]	DL (Histopathology GT)	mpMRI + Histopathology	AUC >0.85, better detection & segmentation.	Improves accuracy and lowers false positives.
Giannakodimos et al. [27]	DL for Precision Medicine	Multi-center Trials	AI improves accuracy & treatment.	Lowers infection risk and enhances targeting.
Tereszkiewicz et al. [28]	AI-based Detection	Multiple Studies	Systematic review & meta-analysis.	Non-invasive PCa detection.
Tesfai et al. [29]	AI Pathology + Radiology	Public Prostate MRI	AUC 0.85–0.96, accuracy 88%–95%.	Limits overdiagnosis and biopsies.

(continued)

Table 2. Continued

Reference	AI Model	Datasets	Key Findings	Clinical Relevance
Patel et al. [30]	CNNs, DL for Detection	Public + Private MRI	AUC 0.85–0.97, accuracy 87%–94%.	Standardizes GG and enhances consistency.
Tang et al. [31]	Automated vs. Semi-AI	Multi-center Data	AUC 0.85–0.93, sensitivity 80%–92%.	Enhances early PCa detection.
Kaneko et al. [32]	AI for Prostate MRI	PROSTATEx, PI-CAI	AUC 0.85–0.96, accuracy 80%–95%.	Refines tumor boundaries and cuts manual effort.
Scherer et al. [33]	CAD	Multi-center mpMRI	Boosts accuracy & agreement.	Creates 3D PCa maps for precise targeting.
Pawan et al. [34]	AI vs. Radiologists	PI-CAI	AI accuracy 89%, AUC 0.91, sensitivity 87%.	Enhances accuracy and outcomes.
Caglic et al. [35]	AI Classification	ProstateX, PI-CAI	Accuracy 85%–92%, AUC 0.89–0.94.	Enhances treatment planning.
Balaha et al. [36]	ML for Cancer	ProstateX, MRI Data	AUC 0.88–0.96, accuracy 82%–94%.	Safe, cost-effective PCa monitoring.
Zhuang et al. [37]	AI for Radiology + Pathology	ProstateX, Pathology Data	AUC 0.91–0.97, accuracy 85%–95%.	Non-invasive PCa characterization.
Esteban et al. [38]	Prostate MRI AI	Multi MRI Studies	Low CLAIM adherence (30%).	Enhances risk stratification and biopsy decisions.
Dai et al. [39]	DL Risk Assessment	1,500 MRI Cases	AUC 0.93, sensitivity 90%, specificity 85%.	Improves detection of significant PCa.
Samaratunga et al. [40]	DL for PCa	Institutional + Public	AUC 0.94, accuracy 90%, better than PI-RADS.	Enhances PCa segmentation and localization.

4.1. Evolution of PCG with WSI and AI

PCa grading is essential for prognosis and treatment. Since the 1960s, the GS has been pivotal, but AI-enhanced WSI now enables precise, efficient, and reproducible grading. The shift from glass slides to digital WSI has revolutionized pathology, allowing high-resolution analysis and AI-driven automation. Tabesh et al. [58] pioneered computational pathology by integrating color, texture, and morphometric features for PCa diagnosis and GG, advancing AI applications in pathology.

The integration of AI and ML into WSI analysis has significantly enhanced the accuracy and efficiency of PCa grading. Faryna et al. [41] utilized CNNs and transformer models to achieve high accuracy in GG classification, despite variability in datasets from multiple hospitals. Similarly, Kong et al. [43] proposed a federated learning framework with attention consistency, achieving high diagnostic accuracy while preserving data privacy across different centers. These studies underscore the potential of AI to handle diverse datasets and improve diagnostic consistency.

The comparison between hand-crafted and machine-driven features has also been a focal point. Baqain and Al-Kadi [44] found that machine-driven features outperformed hand-crafted ones in accuracy and IoU, although hand-crafted features offered better interpretability. This highlights the trade-off between performance and transparency in AI models.

4.2. Challenges in dataset variability and generalization

Variability in datasets remains a major obstacle to the clinical deployment of AI models for PCa grading. In histopathology, differences in staining protocols, tissue preparation, and scanner hardware introduce inconsistencies in color, resolution, and contrast across WSIs. These variations hinder the reproducibility and robustness of AI models across institutions. Techniques such as stain normalization (e.g., Macenko, Reinhard), stain augmentation, and standardization of scanning parameters (e.g., resolution, tile size, calibration) are crucial for mitigating these effects.

Data harmonization methods, including federated learning and domain generalization, further support robust model training across diverse, decentralized datasets while preserving patient privacy. Initiatives such as the PANDA and CAMELYON challenges provide standardized annotations that help improve the consistency and generalizability of models. Egevad et al. [42] emphasized the clinical impact of dataset variability, demonstrating wide differences in 10-year PCa mortality risk across GS combinations using a nationwide biopsy dataset. Similarly, Schmidt et al. [49] highlighted the importance of external validation, showing that while AI models for GG perform well, their generalization across institutions remains a challenge. Prospective, multi-center validations on population-based datasets are key to building clinical trust and enabling regulatory adoption of AI tools in PCa care.

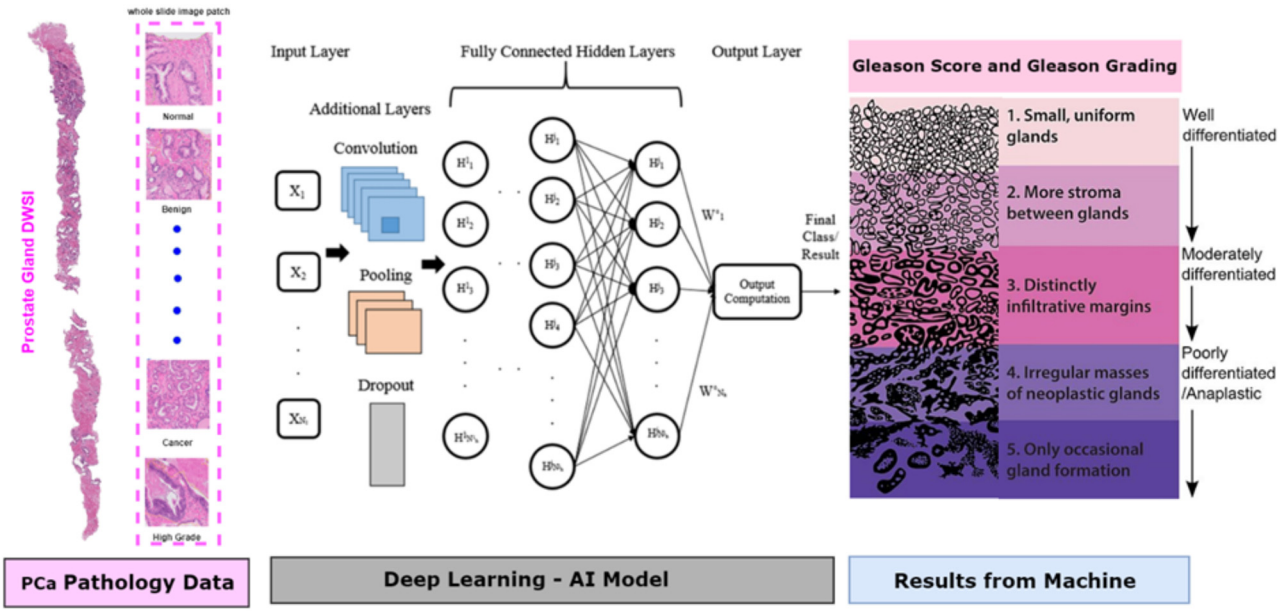

Fig. 4. Gleason grading in the AI Era: Precision and automation in pathology

4.3. Advancements in federated learning and privacy-preserving techniques

Federated learning has emerged as a promising approach to address data privacy concerns while leveraging multi-center datasets. Kong et al. [43] demonstrated the effectiveness of federated learning in achieving high diagnostic accuracy while preserving privacy across different data sources. This approach is particularly relevant in the context of PCa, where data sharing across institutions is often restricted due to privacy regulations.

4.4. The role of explainable AI in PCG

XAI has gained traction as a means to enhance the interpretability of AI models in pathology. Gunashekar et al. [65] developed an XAI approach for CNN-based prostate tumor segmentation in mpMRI, achieving high accuracy and AUC. By providing transparent segmentation results, this approach aids pathologists in understanding and trusting AI-driven diagnoses.

Similarly, Eminaga et al. [73] introduced an AI model that provides interpretable malignancy grades for PCa using histology images, achieving high accuracy and AUC values. These advancements in XAI are crucial for bridging the gap between AI and clinical practice, ensuring that AI models are not only accurate but also interpretable by pathologists.

4.5. The impact of AI on clinical workflows

AI is reshaping clinical workflows in PCa diagnosis by improving diagnostic efficiency, consistency, and decision-making. Integration of AI tools into picture archiving and communication systems (PACS) and digital pathology platforms allows real-time support for radiologists and pathologists.

In radiology, Salman et al. [46] developed an automated PCa grading system using the YOLO deep learning algorithm, demonstrating high accuracy in detecting and grading lesions from mpMRI. This enables faster interpretations, reduces inter-reader variability, and aids biopsy targeting.

In pathology, AI improves WSI analysis through tasks such as GG, tumor segmentation, and mitotic count estimation. Eloy et al. [63] demonstrated that AI-assisted workflows significantly enhanced diagnostic accuracy and efficiency in evaluating PCa biopsy samples.

Moreover, hybrid models that combine radiomics from mpMRI with morphometric features from histopathology have shown superior performance. Liu et al. [25] achieved an AUC of 0.96 using a combined radiomics–CNN model to classify PCa aggressiveness. Zhuang et al. [37] reported improved GS prediction using radiomics features extracted from enlarged regions of interest.

These AI systems are designed to augment, not replace, clinical judgment. By automating routine tasks and providing decision support, AI contributes to faster

Table 3. Comparative analysis of AI models for prostate cancer diagnosis using whole slide imaging (WSI): techniques, performance, and clinical impact

AI Model	Application	Performance	Clinical Impact	Limitations
CNN [61]	Gleason grading	High acc [62]	Reduces workload [63]	Needs annotations [64]
Attention Networks [65]	Tumor localization	Precise detection [66]	Borderline cases [67]	Interpretation limits [68]
Self-Supervised [69]	Feature extraction	Works with less data [70]	Cuts labeling [71]	Early stage [72]
Multi-Modal AI [73]	Data integration	Better confidence [74]	Holistic assessment [75]	Complex fusion [76]
XAI [77]	Transparent decisions	Builds trust [78]	Supports adoption [63]	Needs standards [64]

Table 4. Summary of AI in PCa using WSI

Reference	Datasets	Strengths	Limitations	Results	Clinical Relevance	Future Relevance
Faryna et al. [41]	Histopathology	High accuracy (90%)	Dataset variability	AUC ∼0.90, IoU ∼0.85	Improves GG, treatment	Enhances PCa management
Egevad et al. [42]	Nationwide Biopsy	Comprehensive	Potential bias	PCa death risk: 45%–66%	Aids prognosis	Better risk stratification
Kong et al. [43]	Multi-center PCa	Privacy-preserving	Comm. overhead	Acc 92%, IoU 0.85	Assists GG diagnosis	Federated AI applications
Baqain & Al-Kadi [44]	Public PCa datasets	Machine > Hand-crafted (90% vs. 85%)	Overfitting risk	IoU 0.82 vs. 0.78	Supports pathologists	Enhances automated grading
Olabanjo et al. [45]	MRI, US, ProstateX	High accuracy (>90%)	Dataset limitations	AUC >0.9	Better diagnosis	Boosts early detection
Salman et al. [46]	MRI datasets	Real-time detection	Needs annotations	AUC >0.9	Aids radiologists	Improves automated grading
Bhattacharya et al. [47]	MRI, US, CT	Reduces errors	Data needs	AUC, IoU high	Early detection	Faster clinical decisions
Arvidsson et al. [48]	Biopsy samples	Efficient cancer ID	Small dataset	Acc ∼90%, AUC ∼0.95	Improves detection	Better biopsy interpretation
Schmidt et al. [49]	Prostatectomy data	Reduces variability	Dataset bias	Acc 87–92%, AUC ∼0.94	Aids GG, prognosis	Enhances standardization
Rabaan et al. [50]	MRI, biopsy, clinical	Better accuracy	Limited real-world tests	AUC: 0.92–0.97	Better detection & planning	Clinical AI adoption
Ikromjanov et al. [51]	Histopathology	High segmentation (93%)	Computationally heavy	AUC ∼0.96	Supports pathologists	Advances AI histology
Tătaru et al. [52]	Multiple datasets	Covers AI tools	Lacks original results	Various metrics	Improves PCa care	AI expansion in clinics
Harder et al. [53]	MRI & histopathology	Fewer biopsies	Model depends on MRI	Acc 88–95%, AUC 0.92–0.98	Reduces overtreatment	Refines biopsy guidance
García et al. [54]	Histopathology images	DL > Hand-crafted	Needs large datasets	Acc ∼90% (DL) vs. 75–80%	Automates detection	Boosts pathologist AI use
Hong et al. [55]	Prostate MRI	Better segmentation	Needs big data	Acc ∼92–95%, IoU ∼85–90%	Aids radiologists	Improves AI segmentation
Wang et al. [56]	WSI datasets	Handles weak labels	High computation	Acc 85–95%, IoU 75–85%	Enhances diagnosis	Improves weakly labeled AI
Koziarski et al. [57]	DiagSet	Large diverse dataset	Limited cancer stages	Acc 92%, AUC 0.94	Boosts PCa detection	Expands diagnostic AI
Tabesh et al. [58]	Histological images	Color & texture features	Feature limits	Acc 96.7%, GG 81%	Improves diagnostics	Advances feature-based AI
Rani et al. [59]	PCa hospital data	PSA correlation	Single dataset	Strong PSA-GG link	Predicts progression	Refines PSA screening
Asif et al. [60]	Pathology & imaging	Faster diagnosis	Needs high-quality data	Acc 85–95%, AUC 0.90–0.95	Supports pathologists	Improves AI diagnostics
Wu et al. [61]	WSI datasets	Generalizable AI	High-quality WSI needed	Acc 92–95%, AUC 0.95	Aids metastasis detection	Boosts automated pathology
Zhu et al. [62]	MRI, biopsy, genomics	High precision	Dataset limits	Acc 85–92%, AUC 0.90–0.95	Enhances PCa care	Refines AI management
Eloy et al. [63]	PCa biopsy slides	Faster diagnosis	Data quality limits	Acc 90–95%, AUC 0.92–0.96	Speeds PCa diagnosis	Improves AI pathology
Saha et al. [64]	WSI datasets	Automated detection	Needs high-quality WSI	Acc 90–95%, AUC 0.92–0.96	Supports pathologists	Enhances AI efficiency
Gunashekar et al. [65]	mpMRI, histopathology	Explainability	Data dependency	Acc 85–90%, AUC 0.90–0.94	Aids segmentation	Boosts clinical AI use
Chen et al. [66]	WSI databases	Fast search	Limited complex tasks	Acc 90%, AUC 0.93–0.96	Speeds pathology review	Refines AI indexing
Bulten et al. [67]	PANDA dataset	Reproducible AI	Dataset variability	Acc 94%, IoU 0.76, AUC 0.98	Automates PCa Dx	Refines grading AI
Khened et al. [68]	Histopathology datasets	Diverse adaptability	High computation	Acc >90%, IoU 0.75–0.85, AUC 0.93	Reduces errors	Expands AI segmentation
Singhal et al. [69]	PCa biopsy images	Automated grading	Needs large datasets	Acc 92%, IoU 0.80–0.85, AUC 0.94	Supports PCa Dx	Enhances AI grading
Kosaraju et al. [70]	Histopathology data	High segmentation (93–96%)	Needs large datasets	Acc 93–96%, AUC 0.91	Aids pathologists	Boosts automated Dx
Zhu et al. [71]	Histopathology	High accuracy (90%)	Dataset variability	AUC ∼0.90, IoU ∼0.85	Improves GG, treatment	Enhances PCa management
Mun et al. [72]	Nationwide Biopsy	Comprehensive	Potential bias	PCa death risk: 45%–66%	Aids prognosis	Better risk stratification
Eminaga et al. [73]	Multi-center PCa	Privacy-preserving	Comm. overhead	Acc 92%, IoU 0.85	Assists GG diagnosis	Federated AI applications
Sparks & Madabhushi [74]	Public PCa datasets	Machine > Hand-crafted (90% vs. 85%)	Overfitting risk	IoU 0.82 vs. 0.78	Supports pathologists	Enhances automated grading
Gorelick et al. [75]	MRI, US, ProstateX	High accuracy (>90%)	Dataset limitations	AUC >0.9	Better diagnosis	Boosts early detection
Nagpal et al. [76]	MRI datasets	Real-time detection	Needs annotations	AUC >0.9	Aids radiologists	Improves automated grading
Khosravi et al. [77]	MRI, US, CT	Reduces errors	Data needs	AUC, IoU high	Early detection	Faster clinical decisions
Yu et al. [78]	Biopsy samples	Efficient cancer ID	Small dataset	Acc ∼90%, AUC ∼0.95	Improves detection	Better biopsy interpretation

diagnoses, improved risk stratification, and more personalized treatment pathways. Seamless integration into clinical workflows and validation through multi-center studies will be crucial for broader adoption.

4.6. Future directions and challenges

Looking ahead, near-term impactful developments include AI integration into routine clinical workflows through scalable, interoperable tools embedded in radiology, pathology, and hospital information systems. While AI has made significant strides in PCa grading, several challenges remain. Rabaan et al. [50] discussed barriers to clinical integration, such as data heterogeneity and the need for robust, real-world validation. Asif et al. [60] emphasized the critical importance of high-quality, annotated datasets, interpretability, and transparency to support clinical trust in AI-driven diagnostics.

A particularly promising direction is the multi-modal fusion of imaging data—such as mpMRIand WSIs—with genomic profiles (e.g., gene expression signatures, mutational burden) and clinical records. Technically, such integration can be enabled by advanced DL architectures like multi-branch neural networks and transformer-based fusion models, which are capable of handling heterogeneous data streams and learning shared representations. These approaches offer a more holistic view of prostate cancer, encompassing molecular, radiological, and morphological dimensions.

Beyond diagnosis and grading, AI holds substantial potential in predicting treatment response. By leveraging longitudinal imaging data, therapy outcomes, and biomarker trends, AI models can help guide personalized treatment planning, such as identifying ideal candidates for active surveillance versus those requiring radical interventions. Zhu et al. [62] demonstrated the utility of such AI tools across the spectrum of PCa management, including prognosis and therapy selection.

Advancements in federated learning and privacy-preserving techniques will further enable collaborative model development without compromising patient confidentiality. Explainable AI (XAI) techniques—such as saliency maps and attention-based visualizations—will be crucial for clinician interpretability and regulatory approval. Standardizing datasets, acquisition protocols, and evaluation metrics will improve reproducibility, while optimizing algorithms for computational efficiency ensures accessibility in resource-constrained settings.

In summary, the future of AI in PCa lies in multi-scale, multi-modal, and clinically embedded solutions, validated through prospective multi-center trials and designed to complement human expertise across diagnostic, prognostic, and therapeutic dimensions.

As Table 3 highlights, AI enhances detection, segmentation, and risk stratification, while Table 4 emphasizes its role in GG and pathology workflows, addressing challenges like dataset variability and interpretability. These advancements pave the way for multi-modal AI and real-time diagnostics.

5. Conclusion

This paper explores the applications of AI in PCa grading, with a focus on integrating AI with radiology, particularly mpMRI for PI-RADS grading. We reviewed datasets, segmentation, and classification techniques, highlighting the dominance of CNN architectures in cancer classification and U-Net (including advanced variants like nnU-Net) in segmentation tasks. Notably, segmentation achieved Dice scores exceeding 90%, while classification accuracy surpassed 95%. In WSI-based studies, segmentation achieved Dice scores above 92%, and classification accuracy reached 98%, with U-Net and its advanced variants being the preferred segmentation architectures. For classification, CNNs were widely used, though emerging trends show NLP-based transformers and hybrid models achieving superior accuracy over conventional methods.

The review recommends U-Net and its advanced semantic segmentation architectures for segmentation tasks and CNNs for classification. However, the field is increasingly leaning toward NLP-based transformers, which show promise for future PCa classification. Future research should focus on multi-modal AI integration, combining mpMRI, WSI, and genomic data for enhanced diagnostic precision. Additionally, efforts should address challenges like dataset variability, model interpretability, and computational efficiency. The adoption of XAI and privacy-preserving techniques like federated learning will further bridge the gap between AI and clinical practice, paving the way for more accurate, efficient, and personalized PCa diagnosis and treatment. Another approach would possible to redesign architecture using fractional order activation functions, seen from [79, 80].

Declaration: • This manuscript has not been published and is not being considered for publication elsewhere, in whole or in part, in any language.

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Abbreviations

This paper includes the following abbreviations

mpMRI - Related Abbreviations	**AI** – Artificial Intelligence, **AUC** – Area Under the Curve, **bpMRI** – Bi-Parametric Magnetic Resonance Imaging, **CAD** – Computer-Aided Detection, **CNN** – Convolutional Neural Network, **DCE-MRI** – Dynamic Contrast-Enhanced MRI, **DL** – Deep Learning, **DWI** – Diffusion-Weighted Imaging, **Dice Score** – Dice Similarity Coefficient, **ML** – Machine Learning, **mpMRI** – Multi-Parametric Magnetic Resonance Imaging, **PCa** – Prostate Cancer, **PSA** – Prostate-Specific Antigen, **PSMA-PET/CT** – Prostate-Specific Membrane Antigen Positron Emission Tomography/ Computed Tomography, **ROI** – Region of Interest, **Sensitivity** – True Positive Rate, **Specificity** – True Negative Rate, **T2W-MRI** – **T2**-Weighted Magnetic Resonance Imaging
WSI-Related Abbreviations	**GG** – Gleason Grading, **GS** – Gleason Score, **H&E** – Hematoxylin and Eosin (Staining Technique), **IoU** – Intersection over Union, **MIL** – Multiple Instance Learning, **NLP** – Natural Language Processing, **nnU-Net** – No-New-Net, a Self-Adaptive Segmentation Network, **U-Net** – U-Net Deep Learning Architecture for Image Segmentation, **ViT** – Vision Transformer,- **V-Net** – V-Net Deep Learning Architecture for Medical Image Segmentation, **XAI** – Explainable AI

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