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Review

Advancements in artificial intelligence for prostate cancer: Optimizing diagnosis, treatment, and prognostic assessment

Q3 Yuki Arita [a,*], Christian Roest [b], Thomas C. Kwee [b], Ramesh Paudyal [c], Alfonso Lema-Dopico [c], Stefan Fransen [b], Daisuke Hirahara [d], Eichi Takaya [d], Ryo Ueda [e], Lisa Ruby [a], Noam Nissan [a], Lawrence H. Schwartz [a], Amita Shukla-Dave [a,c], Oguz Akin [a,**]

[a] *Departments of Radiology, Memorial Sloan Kettering Cancer Center, New York, NY, USA*
[b] *Department of Radiology, Nuclear Medicine and Molecular Imaging, University Medical Center Groningen, Groningen, the Netherlands*
[c] *Department of Medical Physics, Memorial Sloan Kettering Cancer Center, New York, NY, USA*
[d] *Department of Advanced Biomedical Imaging Informatics, St. Marianna University School of Medicine, Kawasaki, Japan*
[e] *Office of Radiation Technology, Keio University Hospital, Tokyo, Japan*

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Abstract *Objective:* To provide a comprehensive overview of the current research landscape on artificial intelligence (AI) in prostate cancer management, highlighting its potential to enhance diagnosis, improve medical image quality, facilitate risk stratification, and aid prognosis. The review also identifies opportunities and challenges associated with integrating AI into clinical practice.
Methods: This review synthesizes findings from recent studies on AI applications in prostate cancer management. It examines the use of machine learning and deep learning techniques in diagnostic imaging, surgical skill assessment, and outcome prediction. The analysis emphasizes empirical evidence demonstrating the efficacy and limitations of AI models in clinical settings.
Results: AI, particularly machine learning and deep learning algorithms, is improving diagnostic accuracy by analyzing medical images with greater efficiency and precision compared to traditional methods. AI-based tools are also being developed for surgical skill assessment, offering objective evaluations and feedback to surgeons. Additionally, AI applications in

* Corresponding author. Departments of Radiology, Memorial Sloan Kettering Cancer Center, NY, USA.
** Corresponding author. Departments of Radiology, Memorial Sloan Kettering Cancer Center, NY, USA.
E-mail address: yukiarita1113@gmail.com (Y. Arita), akino@mskcc.org (O. Akin).
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predicting patient outcomes are facilitating the creation of personalized treatment plans. Empirical evidence shows that AI models exhibit higher sensitivity and specificity in detecting clinically significant prostate cancer, outperforming conventional diagnostic techniques.

Conclusion: AI holds significant promise for transforming prostate cancer management by improving diagnostic accuracy, personalizing treatment plans, and enhancing patient outcomes. While the evidence underscores its potential, challenges such as the need for larger, more diverse datasets and addressing implementation barriers remain critical. Despite these hurdles, the benefits of AI in prostate cancer management represent a compelling area for future research and clinical integration.

1. Introduction

Artificial intelligence (AI) constitutes a rapidly evolving discipline poised to transform a myriad of sectors, including healthcare. AI entails the development of sophisticated models that can be optimized for tasks that normally require human intellect, making them especially suitable for pattern recognition and decision-making tasks. AI includes the subfield of machine learning (ML), which can be further divided into deep learning (DL) and traditional ML techniques, each representing different categories of algorithms capable of learning by observing large amounts of training data. Traditional ML encompasses techniques such as decision trees, support vector machines, and logistic regression [1]. In contrast, DL is based on complex neural networks consisting of millions of parameters optimized during training. In recent decades, AI has seen increasing implementation in healthcare practices. Within urology, it is being explored as a potential way to improve the diagnostics and therapeutics of prostate cancer (PCa). An important benefit of AI is its ability to rapidly process large volumes of data, including medical imaging and biopsy specimens, to extract diagnostically relevant information and provide risk assessments [2]. In addition, AI may also enhance diagnostic accuracy and improve personalized patient treatment strategies. This review aimed to provide a comprehensive overview of AI research in the context of PCa. It delves into recent advancements in AI using both traditional ML and DL techniques pertaining to the diagnosis, prognosis, and management of PCa. Additionally, it aimed to identify challenges and directions for future research. This manuscript serves as a non-systematic review of the literature on AI applications in PCa, emphasizing key studies that have profoundly impacted the field.

2. Current advances in AI applications for PCa management

The selection of studies for inclusion was based on several critical factors: (a) Pioneering contributions: we prioritized studies that have significantly advanced AI research in PCa. (b) Methodological relevance: the review examines various AI methodologies, including traditional ML and DL techniques, emphasizing their relevance to the diagnosis, treatment, and prognostication of PCa. (c) Clinical impact: we considered the clinical implications of these studies, assessing how they have shaped current practices and influenced future research directions.

2.1. Overview of medical imaging AI

AI can quickly generate interpretations of cross-sectional medical images, including MRI and CT scans. Two primary categories can be identified within medical imaging AI: radiomics and DL-based approaches. Radiomics refers to the process of deriving quantitative biomarkers from medical imaging [3]. Radiomics features are designed to capture various tumor characteristics, including its dimensions, morphology, texture, and signal intensity. DL refers to a category of AI techniques leveraging large neural networks to directly model the relationship between images and clinical endpoints without the need for radiomics feature extraction. DL has become a popular technique due to its potential to achieve high accuracy, and ability to operate autonomously without needing manual region-of-interest delineation. These features make it suitable for automatic medical image segmentation, detection, and diagnosis. Its main drawbacks include substantial computational and dataset requirements, as well as limited insight into the model's inner workings ("black box").

Within the context of PCa management, ML models have been designed to provide objective and data-driven analyses of tumors [4,5], which can assist urologists to improve the efficacy of therapeutic interventions and to forecast clinical outcomes, potentially enabling healthcare providers to tailor personalized treatment regimens to patients' risk profiles. Fig. 1 illustrates the AI-driven radiomics workflows in PCa diagnosis. Supplementary Figure 1 shows the treatment schema for primary PCa. Table 1 shows the current PCa risk stratification according to the European Association of Urology and National Comprehensive Cancer Network guidelines. Supplementary Figure 1 shows the treatment schema for primary PCa.

Tables 2 and 3 summarize the current research trends of AI in PCa diagnosis and risk stratification, respectively. The remainder of this section discusses the current state of AI across all parts of the PCa care continuum and covers the role of AI in MRI-based detection and monitoring of PCa,

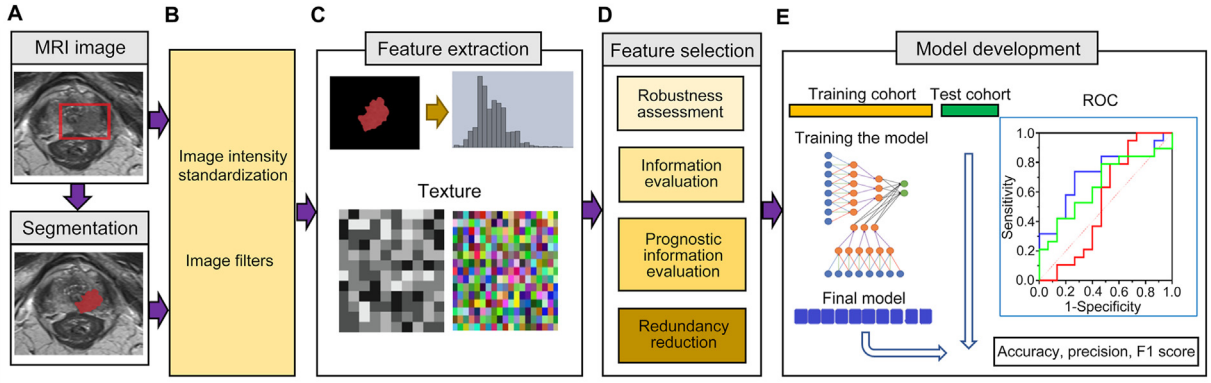

Figure 1 Radiomics for primary prostate cancer. (A) The segmentation of prostate tumor (bounding rectangle in red) on the T2w image; (B) Image standardization—a preprocessing step; (C) Feature extraction from the region of interest with the schematic representation of histogram and textural image features; (D) Feature selection approaches; (E) The model development for clinical endpoint. ROC, receiver operating characteristic curve. T2w, T2-weighted.

Table 1 PCa risk stratification according to the EAU and NCCN guidelines.

Guideline	Very low-risk	Low-risk	Intermediate-risk	High-risk	Very high-risk
EAU [67]	• NA	• cT1-2a, and PSA <10 ng/mL, and ISUP grade 1 (GS <7)	• cT2b, or PSA 10 −20 ng/mL, or ISUP grade 2 or 3 (GS=7)	• cT2c or PSA >20 ng/mL or ISUP grade 4/5 (GS >7); cT3-4 or cN+, any PSA, any ISUP grade (any GS)	• NA
NCCN [68]	• cT1c, and PSA <10 ng/mL, and ISUP grade 1 and <3 positive biopsy cores, ≤50 % cancer per core	• cT1-2a, and PSA <10 ng/mL, and ISUP grade 1	• Favorable: ISUP grade 1/2, and <50 % positive biopsy cores, and 1 risk factor: cT2b-c, PSA 10 −20 ng/mL or ISUP grade 2/3; • Unfavorable: ISUP grade 3, and/or ≥50 % positive biopsy cores, and/or 2 or 3 risk factors: cT2b-c, PSA 10 −20 ng/mL or ISUP grade 2/3	• cT3a, or PSA >20 ng/mL, or ISUP grade 4/5	• cT3b-cT4, and/or primary Gleason pattern 5 and/or >4 cores with ISUP grade 4/5, and/or 2 or 3 high-risk features

cN+, clinical node positive; cT, clinical T stage; EAU, European Association of Urology; GS, Gleason score; ISUP, International Society of Urological Pathology; NCCN, National Comprehensive Cancer Network; PSA, prostate-specific antigen; PCa, prostate cancer; NA, not available.

ultrasound (US), pathology interpretation, radiotherapy, and prognosis.

2.2. Diagnosis for primary PCa

2.2.1. AI for the detection of clinically significant PCa (csPCa)

Multiparametric MRI (mpMRI) of the prostate, which includes T2-weighted (T2w) imaging, diffusion-weighted imaging (DWI), and dynamic contrast-enhanced (DCE) imaging, has been widely adopted for the detection of csPCa. The Prostate Imaging-Reporting and Data System (PI-RADS) serves as the global benchmark for the acquisition, interpretation, and communication of prostate MRI findings [6]. MRI lesions categorized as PI-RADS 1 and 2 represent a lower likelihood of csPCa, whereas lesions rated as PI-RADS 4 and 5 indicate a higher likelihood of csPCa. The PI-RADS 3 category represents an equivocal likelihood of csPCa,

Table 2 AI for diagnosis of PCa (major papers last 5 years).

Study	Population, *n*	Modality	AI technique	Outcome and diagnosis	AUC and influence
Antonelli et al., 2019 [4]	164 (119 PZ, 45 TZ) training, 30 testing	mpMRI	• LR, NB, RF, SVM, and FFNN	• Gleason 4 component	• Peripheral zone model: AUC 0.83 • Transitional zone model: AUC 0.75 (best model)
Schelb et al., 2019 [7]	250 training, 62 testing	mpMRI	• U-Net	• csPCa	• Sensitivity 88 %, specificity 50 % for PI-RADS ≥4 *vs.* U-Net (similar performance)
Min et al., 2019 [62]	187 training, 93 testing	mpMRI	• LASSO	• csPCa *vs.* insignificant PCa	• Training data set: AUC 0.872 • Testing data set: AUC 0.823
Cao et al., 2019 [63]	417	bpMRI	• FocalNet (*i.e.*, multi-class CNNs)	• csPCa and GS ≥ 4+3	• csPCa: AUC 0.81 • PCa (Gleason ≥4+3): AUC 0.79
Woźnicki et al., 2020 [11]	191	mpMRI	• LR, RF, SVM, and XGboost	• csPCa *vs.* insignificant PCa	• Differentiation of malignant from benign lesions: AUC 0.889 • csPCa from insignificant PCa: AUC 0.844 (best model)
Winkel et al., 2020 [64]	48	bpMRI	• CanLoc and CanQual (a coupled deep neural network)	• PCa screening	• The sensitivity was 87 %, and the specificity was 50 % (κ=0.42). • Detection rates were as follows: PI-RADS 3 lesions showed a 43 % detection rate, PI-RADS 4 lesions a 73 % detection rate, and PI-RADS 5 lesions a 100 % detection rate.
Wildeboer et al., 2020 [25]	48	Ultrasound	• RF	• Multiparametric classification of PCa	• All PCa: AUC 0.75, • Significant PCa (GS> 3+4): AUC 0.90
Saha et al., 2021 [8]	1950 training, 486 testing	bpMRI	• 3D CNNs	• PI-RADS≥4 and csPCa	• PCa (PI-RADS≥4): AUC 0.88 • csPCa: 0.86
Hectors et al., 2021 [9]	188 training, 52 testing	mpMRI	• LR and XGboost	• csPCa	• AUC 0.76 (best model)
Roest et al., 2023 [22]	73	Serial bpMRI	• U-Net and SVM	• csPCa at follow-up	• AUC 0.86 (best model)
Bosma et al., 2023 [65]	300	bpMRI	• SSL	• csPCa	• AUC 0.89 (best model)

Note: this table compiles detailed information on various studies focusing on AI in the context of PCa diagnosis, summarizing key details such as reference, year, population, modality, AI technique, outcome or diagnosis, and AUC or performance metrics.
AI, artificial intelligence; AUC, area under the curve; bpMR, biparametric MRI; CanLoc, Candidate Localization Network; CanQual, Candidate Qualification Network; PCa, prostate cancer; CNN, convolutional neural network; csPCa, clinically significant PCa; FFNN, feedforward neural network; κ, Cohen's kappa; LASSO, least absolute shrinkage and selection operator; LR, logistic regression; mpMRI, multiparametric MRI; NB, naive Bayes; PI-RADS, Prostate Imaging-Reporting and Data System; PZ, peripheral zone; RF, random forest; SSL, semisupervised learning; SVM, support vector machine; TZ, transitional zone; XGboost, extreme gradient boosting; GC, Gleanson score.

introducing a diagnostic challenge due to its indeterminate nature. Recent studies showed that ML models could match or surpass the diagnostic efficacy of PI-RADS in evaluating MRI lesions for the detection of csPCa [7]. They may be instrumental in differentiating between csPCa and clinically insignificant PCa. AI models based on DL for automatically detecting PCa lesions on prostate MRI have been explored in several studies. Saha et al. [8] explored an autonomous DL model based on the U-Net architecture and demonstrated a promising diagnostic accuracy of 0.88 area

Table 3 AI for risk stratification and prognosis in PCa (major papers last 5 years).

Study	Population, *n*	Modality	AI technique	Outcome and Prediction	AUC and Influence
Varghese et al., 2019 [66]	68	mpMRI	• LR, LDA, RF, LSVM, CSVM, GSVM, and QSVM	• PCa risk stratification	• AUC 0.92 (best model)
Cysouw et al., 2021 [14]	76	PSMA PET-CT	• RF	• Metastatic disease or high-risk features	• LNI AUC 0.86, nodal or distant metastasis AUC 0.86, Gleason score AUC 0.81, ECE AUC 0.76
Papp et al., 2021 [15]	52	PET/MRI	• RF	• Prostate lesion-specific low- *vs.* high-risk	• Low- *vs.* high-risk lesion prediction model AUC: 0.86 • Biochemical recurrence model AUC: 0.9 • Overall patient risk model AUC: 0.94
Khosravi et al., 2021 [18]	400	mpMRI	• CAM using GAP in CNNs	• Benign *vs.* cancer and high- *vs.* low-risk PCa	• Cancer *vs.* benign: 0.89 (95 % CI 0.86 −0.92) • High- *vs.* low-risk PCa: 0.78 (95 % CI 0.74 −0.82)
Akatsuka et al., 2022 [24]	772 (2899 ultrasound images)	Ultrasound	• LR and SVM	• High-grade PCa	• Using clinical data: AUC 0.691 • Using clinical data and ultrasound imaging data: AUC 0.835 (best model)

Note: This table compiles detailed information on various studies focusing on AI in the context of PCa risk stratification and prognosis, summarizing key details such as reference, year, population, modality, AI technique, outcome or prediction, and AUC or performance metrics.

AI, artificial intelligence; AUC, area under the curve; bpMRI, biparametric MRI; CAM, class activation map; CI, confidence interval; PCa, prostate cancer; insignificant PCa, clinically insignificant PCa; CNN, convolutional neural network; csPCa, clinically significant PCa; CSVM, cubic support vector machine; ECE, extracapsular extension; GAP, global average pooling; GSVM, gaussian support vector machine; LDA, linear discriminant analysis; LNI, lymph node involvement; LR, logistic regression; LSVM, linear support vector machine; mpMRI, multiparametric MRI; PI-RADS, Prostate Imaging-Reporting and Data System; PSMA, prostate-specific membrane antigen; QSVM, quadratic support vector machine; RF, random forest.

under the receiver operating characteristic curve (AUC) for detecting csPCa on MRI.

Radiomics-based approaches involving quantitative features extraction from radiologists' delineations, making them suitable for providing suspicion scores for radiologist-detected lesions and effectively assisting radiologists. These systems may help to deal with challenging or equivocal cases, such as PI-RADS 3 lesions. Hectors et al. [9] developed and validated an ML model to provide secondary readings for PI-RADS 3 lesions, reclassifying them as csPCa or insignificant PCa from radiomics features extracted from T2w. Using a training cohort of 188 individuals and a validation group of 52, their random forest classifier achieved an AUC of 0.76 for detecting csPCa in the validation data. Mian et al. [10] trained a Least Absolute Shrinkage and Selection Operator algorithm incorporating nine radiomic parameters to discriminate between csPCa and insignificant PCa. They obtained an AUC of 0.82, with a sensitivity of 0.84 and specificity of 0.73 in the validation cohort. Woźnicki et al. [11] developed and assessed ML models against radiologist evaluations using PI-RADS to ascertain their efficacy in distinguishing malignant from benign lesions and csPCa from insignificant PCa. Their ensemble model combined radiomics and clinical predictors, and attained an AUC of 0.899 in differentiating malignant from benign prostate lesions and an AUC of 0.844 in

differentiating csPCa from insignificant PCa in the test cohort [11]. Radiomics may also have value for predicting the upgrading of PCa lesions from grade group (GG) $\leq$2 at biopsy to GG $\geq$3 at histopathological assessment after radical prostatectomy, as demonstrated by Xie et al. [12] in a test set comprising 11 cases (best model: AUC 0.72).

While radiomics models are normally trained to use lesion delineations, Han et al. [13] explored a fully automated radiomics system by using segmentation algorithms to delineate regions of interest for the prostate. A comparison to the radical prostatectomy histopathological assessment revealed no significant differences in diagnostic accuracy between radiomics (best model: AUC 0.73) and transrectal US-guided biopsy (best model: AUC 0.79) for detecting high-grade PCa.

Several studies have explored diagnostic AI models leveraging data beyond MRI. A study by Cysouw et al. [14] used preoperative ^{18}F-DCFPyL PET-CT scans from 76 patients identified as intermediate-to high-risk for PCa to train random forest models to simultaneously predict lymph node metastasis, a Gleason score greater than 8 and extracapsular extension, achieving predictive AUCs ranging from 0.76 to 0.86 for each prognostic indicator. Papp et al. [15] leveraged a combination of PET and MRI data to detect csPCa lesions, determine the likelihood of biochemical recurrence, and assess the overall risk profile of patients, showcasing the potential of ML in refining PCa risk stratification and subsequently guiding clinical decision-making. The use of PET scans is also investigated for the detection of lesions that may not be visible on conventional imaging [16] and the detection of metastatic lymph node [17]. The detection of these lesions could lead to improved staging and treatment planning. Lastly, Khosravi et al. [18] evaluated an AI-based strategy incorporating MRI and histopathological data into a multimodal AI system to refine the precision of PI-RADS assessments.

2.2.2. AI for active surveillance

Several recent studies have explored the potential role of AI in active surveillance, focusing on two primary tasks: PCa progression detection and risk stratification [19–22]. On the topic of progression and detection, Sushentsev et al. [19] conducted an exploratory analysis of radiomics-based risk prediction in active surveillance patients with MRI-visible lesions. Of a total of 252 models trained, their highest performing classifier based on T2w radiomics and clinical parameters achieved an AUC of 0.75 in differentiating between patients with and without disease progression over a minimum of 2-year follow-up (defined as radiological or histopathological progression or switch to active treatment). The study by Sushentsev et al. [19] explored MRI-based follow-up during active surveillance. Three different ML classifiers were optimized to predict grade group progression based on changes in the radiomics signatures of lesions across baseline and follow-up MRI scans (referred to as delta radiomics). Their best model achieved an AUC of 0.82 for detecting grade group progression, while the radiologist using PRECISE performed only marginally better at an AUC of 0.84. In a subsequent study by this group, neural networks were applied to allow the model to incorporate more than two MRI time points [20]. Combining serial MRI and serial prostate-specific antigen (PSA) density levels into this model resulted in the highest performance at 0.86 AUC, outperforming the delta radiomics baseline model. Midya et al. [21] also assessed the predictive value of delta radiomics in an active surveillance cohort and reported similar diagnostic performances for their model combining delta radiomics and clinical predictors (AUC 0.84). Roest et al. [22] developed a sequential AI model using a hybrid approach based on DL and support-vector machines to detect progression to csPCa on sequential MRI scans by comparing differential likelihood and volumetric features, reaching an AUC of 0.81, which increased to 0.86 by incorporating clinical predictors. Overall, the diagnostic accuracy reported for AI-based prognostication and follow-up is promising, particularly when combining imaging and clinical predictors, suggesting the potential for AI to enhance patient selection and the follow-up for active surveillance in the future. However, available evidence on this subject is currently limited by small cohort size and relatively short follow-up time. Further exploration with larger sample sizes is thus needed to validate these results.

Besides diagnostic use cases, AI is also being explored to enhance the quality and efficiency of prostate MRI through DL reconstruction algorithms using raw MRI scans [23]. DL reconstruction can be applied to optimize scanning efficiency, facilitating shorter scan times while maintaining comparable levels of signal-to-noise and image quality. However, well-powered studies comparing DL reconstructed scans' diagnostic outcomes are currently unavailable. Nevertheless, the efficiency gained from DL reconstruction may be vital to allow more patients to undergo prostate MRI and meet increasing imaging demands in the future.

2.2.3. US

US imaging represents an economical modality that yields valuable insights into PCa diagnostics [24,25]. Recent studies have explored the integration of ML and US imaging data to identify high-grade PCa (Gleason score $\geq$4+3) [24,25]. Wildeboer et al. [25] trained a random forest classifier to enhance the localization of csPCa on US images and reached an AUC of 0.75 for the localization of PCa lesions. Furthermore, Akatsuka et al. [24] explored a multimodal approach combining US images with clinical data to detect the high-grade PCa.

It is well established that conventional US imaging has inherent limitations in detecting anterior lesions within large prostates, as well as in addressing the potential impact of calcifications. These constraints significantly influence diagnostic performance [26,27], emphasizing the necessity for multimodal approaches including MRI, in AI applications for PCa diagnosis. The integration of radiomics with US imaging represents an emerging and promising pathway in the realm of urological AI applications. This approach has the potential to complement traditional imaging modalities, such as MRI and CT, ultimately enabling clinicians to perform more targeted biopsies and enhance diagnostic precision.

2.2.4. Pathology

Pathomics leverages AI to conduct molecular-level analyses of tissue specimens, such as biopsies, to detect PCa [28]. While the Gleason grading system remains an important

predictor of PCa outcomes, ML systems may help to reduce the inter-observer variability while enhancing diagnostic precision and streamlining the biopsy grading process [29]. Automated Gleason grading promises to yield more objective and consistent scoring, matching the proficiency of pathologists, and could serve as either a primary screening mechanism or as a second reader [30]. Recent research trends on ML methods in pathology have been primarily focused on DL [30], using convolutional neural networks (CNNs) to grade and delineate malignancies, with several studies reporting promising diagnostic accuracy in discriminating Gleason patterns and grades [30–33]. Kott et al. [31] evaluated a DL-based AI for PCa detection, achieving an accuracy of 91.5 % in categorizing slides as benign or malignant and an accuracy of 85.4 % in more granular distinctions between benign tissues and between Gleason grades. Bulten et al. [30] trained a CNN to delineate individual glands and assign Gleason scores automatically. They evaluated the model in a test set of 535 biopsies and achieved an AUC of 0.99 in discriminating benign and malignant samples. Moreover, the model significantly outperformed pathologists with <15 years of experience while performing similar to more experienced pathologists. Lucas et al. [32] trained a CNN to grade biopsy samples and attained an accuracy of 90 % in differentiating between Gleason grades 3 and 4. Another CNN-based algorithm displayed proficiency in identifying Gleason grades 3 and 4, albeit with diminished accuracy for Gleason grade 5 [33]. Furthermore, AI has enabled the conversion of two-dimensional histopathology slides into three-dimensional models, aiming to improve visualization and risk stratification for PCa patients [34]. Besides improving diagnostic accuracy, AI may also enhance workflow efficiency. In a research conducted by da Silva et al. [35], integrating AI in the histopathological analysis workflow reportedly reduced the time required for analysis and diagnosis by approximately 65.5 % while simultaneously detecting PCa in patients that were previously missed by three histopathologists.

2.2.5. Surgery

Traditionally, surgical skill assessment has been marked by manual evaluations carried out by humans, a process often hindered by time inefficiencies and susceptibility to subjective biases. AI presents a sophisticated solution to these challenges [36]. By training on rich datasets, including surgical video recordings and the kinematics of surgical instruments, AI is pioneering a transformative approach to surgical skill assessment. Integrating AI with quantifiable surgical metrics enables a nuanced assessment of surgical abilities. For instance, Hung et al. [37] exploited kinematic metrics extracted from surgical robots of 78 radical prostatectomy cases, using features including path length and instrument velocity, to categorize skill levels and prognosticate patients' lengths of stay following robotic-assisted radical prostatectomy. AI-enhanced skill assessment systems have demonstrated an ability to accurately predict surgeons' experience levels that correlate with immediate postoperative metrics, such as the duration of hospital stays and longer-term recovery outcomes, including urinary continence [37–40].

AI's role extends to the direct analysis of surgical footage through vision recognition technologies, enabling the accurate identification of specific surgical maneuvers (*e.g.*, needle passing, suturing, and knot tying) and the classification of surgeons' expertise levels [41]. Furthermore, Baghdadi et al. [42] employed AI to analyze the color and texture within a dataset of 20 surgical videos for recognizing anatomical structures during pelvic lymph node dissection, and using regression to correlate these features to established pelvic lymphadenectomy appropriateness and completion evaluation scores provided by a panel of expert surgeons, offering a quantifiable measure of dissection quality. These automated assessments closely mirrored expert evaluations in a 30 % test set, suggesting their potential utility in refining surgical education and assessment protocols.

A significant advancement in AI diminishes the time dedicated to surgical video reviews, thereby facilitating the maintenance of an educational repository of surgical procedures. Additionally, AI has demonstrated the ability to detect and categorize individual instrument movements into distinct surgical gestures through the application of recurrent DL models to video recordings [43], providing useful insights into the differences in techniques employed by novice and experienced surgeons. The surgical gesture analysis has also been demonstrated to correlate with long-term patient outcomes, such as erectile function post-surgery, as shown in a study of 80 nerve-sparing prostatectomy cases automatically analyzed using AI by examining video recordings of the procedure [44]. Overall, these studies mark an innovative advancement in surgical evaluation and training.

2.2.6. Radiation therapy (RT) including brachytherapy

AI has also been explored in non-surgical treatment planning for PCa. In an investigation conducted by McIntosh et al. [45], an ML model was devised to formulate plans for external RT. They extended a previously developed ML model capable of estimating the dose-per-voxel based on radiomics features by adding an atlas regression forest to find previous patients with similar characteristics relevant to dose distribution. Upon evaluation by an independent, blinded clinician, 89 % of the RT plans generated by the ML algorithm were judged as clinically viable, with 72 % being preferred over plans created by radiotherapists. Remarkably, the implementation of the ML model resulted in a 60.2 % reduction in the time required for the complete RT planning process, from 118 h to 47 h. However, despite the model's commendable performance in simulations, treating physicians' adoption of ML-optimized RT plans witnessed a 21 % decline during actual clinical deployment. This observation underscores the discrepancy between the theoretical efficacy of ML models and their acceptance in clinical practice, emphasizing the need for cautious integration of AI technologies into patient care.

In low-dose-rate prostate brachytherapy, a treatment characterized by the implantation of small radioactive seeds within or near the prostate gland, precise planning is paramount. Traditional methods require manual contouring of the prostate boundary on transrectal US images, a labor-intensive process that suffers from considerable inter-observer variability. To address this challenge, Nouranian et al. [46] introduced a sophisticated ML-based multi-label segmentation algorithm designed to generate

instantaneous and clinically useful segmentations for the planning of seed implantation. This innovation signifies an important advancement in brachytherapy planning that could mitigate the subjectivity and inefficiencies associated with manual contouring.

2.3. Patient prognosis

2.3.1. Survival and mortality prediction

The field of precision oncology is witnessing a shift toward a more personalized approach to disease management that aligns more closely with the unique profiles of individual patients. AI models exhibit proficiency in analyzing large clinical datasets and provide a data-driven method for developing prognostic models [47]. Such models are trained on time-to-event datasets, with features known at baseline serving as input data and longitudinal outcomes (*e.g.*, survival) obtained at the follow-up as target labels. By learning from large datasets, such models may provide accurate the risk levels for future events. Bibault et al. [48] evaluated an AI algorithm capable of forecasting the risk of PCa mortality within a decade post-diagnosis, incorporating 30 clinical parameters with a reported accuracy of 0.98. In this study, factors including the Gleason score, PSA levels at diagnosis, and patient age were each identified as having a significant influence on the model's prognostications. Koo et al. [49] developed an online support mechanism leveraging a long short-term memory neural network model to project survival rates based on initial treatment approaches. The model was developed using data from 7267 patients to produce precise, personalized survival estimates for 5 years and 10 years [49].

Efforts to elucidate differences in PCa outcomes across different racial demographics have led to investigations on the role of race and other non-biological determinants in PCa-specific mortality [50]. Notably, tumor characteristics at the time of diagnosis emerged as a paramount predictor of mortality, with racial background also identified as a secondary critical factor. Healthcare access and socioeconomic conditions were determined to be equally influential.

Furthermore, Zhang et al. [51] explored a prognostic AI framework to search DNA methylation profiles for gene markers and identified *FOXD1* as a potential therapeutic target for patients with a poor prognosis. Nevertheless, considering the heterogeneity between patients, it is unlikely that a single predictive model can identify all relevant variables influencing mortality. Furthermore, Lee et al. [52] introduced the Survival Quilts model, designed to predict and benchmark its prognostic accuracy against other established models, thereby enhancing the precision of personalized prognostics.

2.3.2. Recurrence prediction

Predicting the risk of recurrence and its correlation with increased mortality is a critical area of investigation in the context of radical prostatectomy. Similar to risk models for the prediction of survival, these models are trained on time-to-event datasets to predict the likelihood of PCa recurrence based on baseline information, including radiomics and clinical parameters. ML algorithms have surpassed traditional nomograms for forecasting the likelihood of PCa recurrence [53]. Tan et al. [54] developed three AI models that outperformed nomograms in predicting biochemical recurrence over intervals of 1 years, 3 years, and 5 years, with the most effective model achieving an AUC of 0.894 for predicting recurrence 5 years post-surgery. Similarly, Huynh et al. [55] explored radiomics features from preoperative MRI to predict PCa recurrence (defined as biochemical or two consecutive PSA levels $\geq$0.2 ng/mL) in patients who had undergone radical prostatectomy. Cross-validation in 225 cases revealed an AUC of 0.89, surpassing two established clinical nomograms: the Memorial Sloan Kettering Cancer Center's "Prediction Tools for Prostate Cancer Nomograms—Pre-Radical Prostatectomy" and the UCSF-CAPRA score [56]. A study by Zhu et al. [57] provides evidence that radiomics features from pretreatment MRI have predictive value for biochemical recurrence (defined as PSA levels $\geq$2 ng/mL above the nadir) following the brachytherapy treatment. The test results in a sample of 16 patients revealed AUCs for the biochemical recurrence-free survival rate between 0.86 and 0.90 for up to 3 years after therapy. Furthermore, Algohary et al. [58] found that pretherapy MRI radiomics features predicted biopsy positivity 24 months after positive biopsy after radiotherapy.

Lastly, two studies suggest a role for assessing treatment response to androgen deprivation therapy and for the detection of significant residual tissue after androgen deprivation therapy [59,60].

Once further validated, AI models may facilitate a more personalized approach in the management and multimodal treatment of PCa (longitudinal changes and predictive value of multiparametric MRI features for prostate cancer patients treated with MRI-guided Lattice Extreme Ablative Dose boost radiotherapy). Fig. 2 visually maps AI applications from

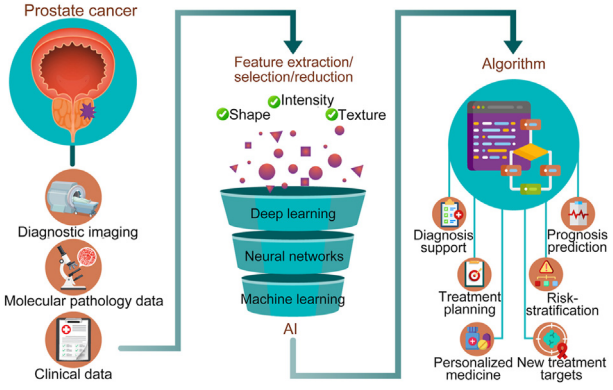

Figure 2 From diagnosis to targeted therapy: a roadmap for AI in prostate cancer care. This figure illustrates the comprehensive pathway from diagnosis to targeted therapy in prostate cancer care, enhanced by the integration of AI. The flowchart outlines the critical steps, including initial screening, diagnostic imaging, and histopathological analysis. It highlights the role of AI in each phase, from improving imaging interpretation and aiding in analyzing histopathological samples to predicting therapeutic outcomes. The roadmap underscores the potential of AI to streamline the diagnostic process, personalize treatment plans, and improve patient outcomes in prostate cancer care. AI, artificial intelligence.

diagnosis to treatment, reinforcing the integration of AI across the patient care continuum.

2.3.3. AI-based patient prognosis web tools

To support urologists, some of these patient prognosis models have been made available as AI-based web tools. These web tools help to bring AI into clinical practice in two different ways. First, these tools may help by offering real-time grading, diagnosis, and treatment suggestions. For example, the UCSF-CAPRA score that aims to aid urologists in making treatment decisions that incorporate the estimated likelihood that a given tumor will recur after treatment, progress, and pose a threat to life [61]. Second, web tools might help newly diagnosed PCa patients with information. For example, Auffenberg et al. [47] developed a web tool (askMUSIC) that offers newly diagnosed men a platform to explore predicted treatment options by comparing their characteristics with those of similar patients. Additionally, recent advancements in large language models (LLMs) show promise in enhancing these tools by improving user interaction and delivering more personalized insights. LLMs can assist clinicians by rapidly processing and analyzing complex medical literature, providing more accurate decision-making support, and facilitating communication between healthcare professionals and patients. By integrating LLMs into AI-based web tools, the accessibility and effectiveness of these platforms can be further enhanced, ultimately helping bridge the gap between research innovations and clinical practice.

3. Conclusion

Integrating AI holds substantial promise to transform PCa management. Previous studies have provided evidence of AI-driven systems' efficacy in accurately identifying PCa and forecasting patient outcomes in medical imaging and pathology samples, showing AI-driven systems' potential to improve clinical care. Nonetheless, several limitations inherent to AI in healthcare need to be considered, including its dependency on the quality and volume of the data on which they are trained. While AI models for csPCa detection have been evaluated in substantial cohorts, AI models for other tasks have mostly been developed and tested in relatively small datasets. This could result in reduced performance or failure in real-world scenarios that deviate from the initial training data. Further research in large and diverse datasets is necessary to explore their potential and limitations and devise strategies to mitigate potential risks associated with AI implementation. Ethical concerns regarding AI deployment in medical decision-making processes and the risk of bias inherent in these algorithms also warrant attention.

Author contributions

Study concept and design: Yuki Arita, Christian Roest, Thomas C. Kwee, Amita Shukla-Dave, Oguz Akin.
Data acquisition: Yuki Arita, Christian Roest, Alfonso Lema-Dopico, Daisuke Hirahara.
Data analysis: Yuki Arita, Christian Roest, Alfonso Lema-Dopico, Eichi Takaya.
Drafting of the manuscript: Yuki Arita, Christian Roest.
Critical revision of the manuscript: Thomas C. Kwee, Ramesh Paudyal, Alfonso Lema-Dopico, Stefan Fransen, Ryo Ueda, Lisa Ruby, Noam Nissan, Lawrence H. Schwartz, Amita Shukla-Dave, Oguz Akin.

Conflicts of interest

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ajur.2024.12.001.

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