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Review Article

J Korean Soc Radiol 2025;86(6):858-872
https://doi.org/10.3348/jksr.2025.0062
eISSN 2951-0805

JOURNAL of THE KOREAN SOCIETY of RADIOLOGY

AI in Prostate MRI: A Task-Based Review

전립선 MRI에서의 인공지능: 임무에 따른 고찰

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Received July 13, 2025
Revised August 31, 2025
Accepted September 24, 2025
Published Online November 21, 2025

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Prostate MRI is widely employed across the clinical pathway of prostate cancer, including detection, staging, treatment planning, and surveillance. With the increasing demand for consistent and efficient image interpretation, AI has gained considerable attention as a supportive tool in prostate MRI. This review provides a task-based overview of AI applications in prostate MRI, addressing key areas such as prostate gland segmentation, cancer detection and risk stratification, local staging, disease monitoring during active surveillance, recurrence detection, and image quality assessment. Across these tasks, AI, particularly deep learning, has demonstrated promising results. Although only a limited number of AI tools for prostate MRI are commercially available, it remains essential for radiologists to understand how AI can support clinical practice, particularly as further advances are anticipated.

Index terms Magnetic Resonance Imaging; Prostate; Artificial Intelligence; Deep Learning; Diagnosis

INTRODUCTION

Prostate MRI has become an essential tool across the clinical care continuum of patients with prostate cancer (PCa), encompassing cancer detection, staging, treatment planning, and monitoring for recurrence or progression. In particular, its role in the prebiopsy setting has received increasing attention in recent years. Owing to its high sensitivity for detecting clinically significant PCa (csPCa), MRI enables accurate localization of suspicious lesions, thereby improving the precision of targeted biopsies. MRI-guided biopsy enhances the detection of csPCa while reducing the detection of clinically insignificant PCa (ciPCa), thereby helping to minimize overdiagnosis and overtreatment (1-3). In addition, the superior soft tissue contrast of MRI allows for accurate assessment of local tumor staging, including extracapsular extension and seminal vesicle invasion, thereby supporting optimal treatment planning (4). MRI also plays a key role in detecting disease progression during active surveillance (AS) and evaluating recurrence after definitive therapy (5, 6). These multifaceted clinical applications have driven the widespread adoption of prostate MRI in routine clinical practice.

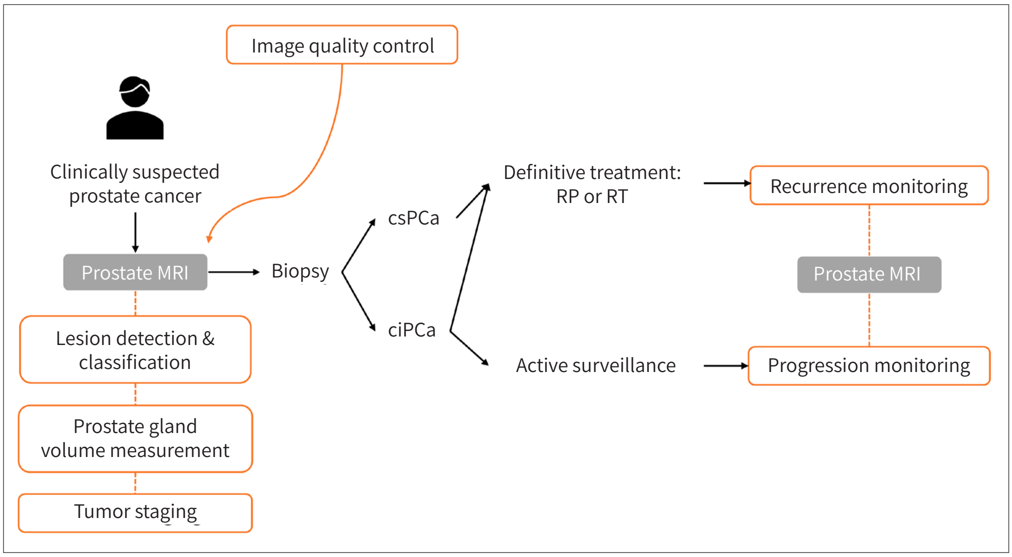
To standardize image acquisition and interpretation, the Prostate Imaging Reporting and Data System (PI-RADS) was introduced and has since been updated to version 2.1 (7, 8). PI-RADS recommends multiparametric MRI (mpMRI)—which includes T2-weighted imaging (T2WI), diffusion-weighted imaging (DWI), and dynamic contrast-enhanced imaging (DCE)—over biparametric MRI (bpMRI), which excludes DCE but requires higher image quality and reader expertise. The PI-RADS framework applies a five-point scale, ranging from 1 (very low) to 5 (very high), to assess the likelihood of csPCa and provides technical guidance for image acquisition to ensure diagnostic quality. However, PI-RADS primarily focuses on lesion detection in biopsy-naïve or previously biopsied patients before definitive treatment. To address other clinical contexts and unmet needs, additional standardized systems have been developed, including prostate imaging quality (PI-QUAL) for evaluating technical adequacy, prostate cancer radiological estimation of change in sequential evaluation (PRECISE) for monitoring disease during AS, and prostate imaging for recurrence reporting (PI-RR) for assessing recurrence after treatment (9-12). Despite these advances in standardization, key challenges remain, including interreader variability, inconsistent image quality, and the rising demand for prostate MRI in clinical practice (13-15).

In parallel, rapid advances in AI have driven significant progress in medical imaging. AI models have been developed to perform tasks such as anatomical segmentation, lesion detection and classification, and prediction of treatment response (16, 17). These models have demonstrated promising performance across diverse imaging modalities and clinical settings. As AI technologies continue to mature, their integration into clinical workflows is becoming increasingly feasible. Among imaging domains, prostate MRI presents a particularly promising and impactful area for AI application due to its inherent complexity, interpretive subjectivity, and the need for reproducible assessment (18-20). Given the diverse roles of MRI in the diagnosis, treatment, and surveillance of PCa, AI has the potential to support clinical decision-making at multiple stages (21). This review provides a task-based overview of AI research in prostate MRI, aiming to summarize existing studies according to clinical tasks and offer an updated understanding of the current state of AI in this field (Fig. 1).

PROSTATE GLAND SEGMENTATION

Prostate gland segmentation is a fundamental task in AI-based prostate MRI analysis, serving as the initial step for identifying and delineating the gland's boundaries. Accurate segmentation provides essential clinical information, most notably through precise calculation of prostate volume. Compared with traditional estimation using the ellipsoid formula, which relies on three orthogonal diameters, AI-based segmentation enables more reliable measurements, as the prostate often deviates from an ideal ellipsoid shape and may enlarge asymmetrically. This improved volumetric accuracy is particularly important for evaluating benign prostatic hyperplasia and monitoring volume changes over time. In the context of PCa, precise prostate volume measurement is also critical for calculating the prostate-specific antigen density (PSAD), defined as the serum PSA level divided by prostate volume. PSAD im-

Fig. 1. Schematic illustration of the clinical pathway in patients with suspected prostate cancer.
Orange-outlined boxes indicate specific tasks where AI applications for prostate MRI are explored or proposed. ciPCa = clinically insignificant prostate cancer, csPCa = clinically significant prostate cancer, RP = radical prostatectomy, RT = radiotherapy



proves risk stratification, particularly in patients with negative or indeterminate MRI findings, and can guide biopsy decisions (22, 23). Furthermore, prostate segmentation masks can support downstream applications such as MRI-guided biopsy and radiotherapy (RT) planning (18).

Numerous AI algorithms for prostate segmentation have been developed using deep learning networks. A systematic review identified 48 studies that addressed segmentation of the whole gland and its anatomical zones using deep learning methods (24). The most commonly used performance metric was the Dice similarity coefficient (DSC), which quantifies the spatial overlap between segmentation results from different sources. A DSC of 1.0 indicates perfect agreement, whereas a score of 0 indicates no overlap. Expert radiologists achieved a mean DSC of 0.86 for whole-gland segmentation in one study (25). Many deep learning models have reported comparable or superior performance, with some achieving DSC values as high as 0.98. For zonal segmentation, the mean DSCs were lower: 0.787 ± 0.059 for the peripheral zone and 0.874 ± 0.052 for the transition zone, compared with 0.905 ± 0.039 for whole-gland segmentation. Notably, no statistically significant differences in DSC were observed across MRI vendors. While most studies relied on T2WI alone, some incorporated multiple MRI sequences; however, the inclusion of additional sequences does not consistently improve segmentation performance.

The size and shape of the prostate can vary considerably due to individual anatomy or prior interventions, such as transurethral resection of the prostate or abdominal perineal resection. Artifacts from metallic implants, such as hip prostheses, may also degrade image quality and complicate segmentation. One study specifically evaluated deep learning-based segmentation in these challenging cases (26); the results demonstrated a DSC of 0.916 compared with radiologist-defined ground truth, slightly lower than that of typical cases but still indicating high performance (27). The presence of signal distortion or anatomical irregularities negatively affects segmentation accuracy.

In summary, deep learning–based prostate gland segmentation has consistently achieved high performance across multiple studies. These algorithms remain robust even in challenging cases, where traditional volume estimation methods using the ellipsoid formula are more prone to error. AI-based segmentation enables accurate, efficient, and reproducible measurements without the need for time-consuming manual contouring, providing clear advantages across a range of clinical applications.

CANCER DETECTION AND RISK STRATIFICATION

In patients with clinically suspicious PCa, such as those with elevated PSA or suspicious findings on other imaging modalities, the primary goal of prebiopsy MRI is cancer detection. However, the reliability of prostate MRI is often limited by interreader variability in lesion detection and classification. In particular, the clinical management of PI-RADS 3 lesions, indicating an indeterminate likelihood of csPCa, remains controversial, with reported proportions of PI-RADS 3 findings varying across studies (28, 29). If AI algorithms can demonstrate reliable performance in interpreting prostate MRI in biopsy-naïve patients, they could serve as triage tools or assist as second readers. A major focus of AI research in prostate MRI has been the detection of focal lesions and classification of cancer risk, tasks central to prostate MRI interpretation. AI algorithms in this domain vary widely in their design, including differences in input data (bpMRI vs. mpMRI), model architecture, and output objectives. Some models are trained to detect suspicious lesions, whereas others perform binary risk classification (e.g., PCa vs. non-PCa or ciPCa vs. csPCa) or provide multiclass predictions based on PI-RADS scores, the International Society of Urological Pathology (ISUP) grade of PCa. Fig. 2 presents the output of representative commercial AI software (Prostate AI, Siemens Healthineers, Forchheim, Germany), demonstrating bpMRI-based focal lesion detection, PI-RADS classification, and automated prostate gland segmentation.

A systematic review of deep learning approaches for PCa detection included 29 studies published between 2019 and 2023. Most were retrospective (93.1%) or single-center (62.0%) studies (30). The majority of models used T2WI and/or DWI with an apparent diffusion coefficient (ADC) map as input. These studies addressed diverse objectives, including cancer detection, risk stratification, and lesion localization. Deep learning-based models demonstrated promising performance in detecting and segmenting csPCa on MRI, often matching or surpassing the accuracy of radiologists' PI-RADS-based assessments. Reported sensitivities ranged from 56.1% to 96%, and specificities ranged from 31% to 87.1%, depending on factors such as probability thresholds, test datasets, and reference standards (e.g., radiologists or histopathology) (31-38). For example, models trained on T2WI and DWI achieved diagnostic performance comparable to PI-RADS ≥4 classifications by radiologists. In some studies, deep learning models demonstrated noninferior sensitivity to radiologists when whole-mount histopathology was used as the gold standard, with no statistically significant differences. Furthermore, deep learning systems outperformed general or junior radiologists in terms of sensitivity or specificity while achieving results comparable to those of expert readers (38, 39). One study applying a deep learning algorithm for PI-RADS-based cancer risk as-

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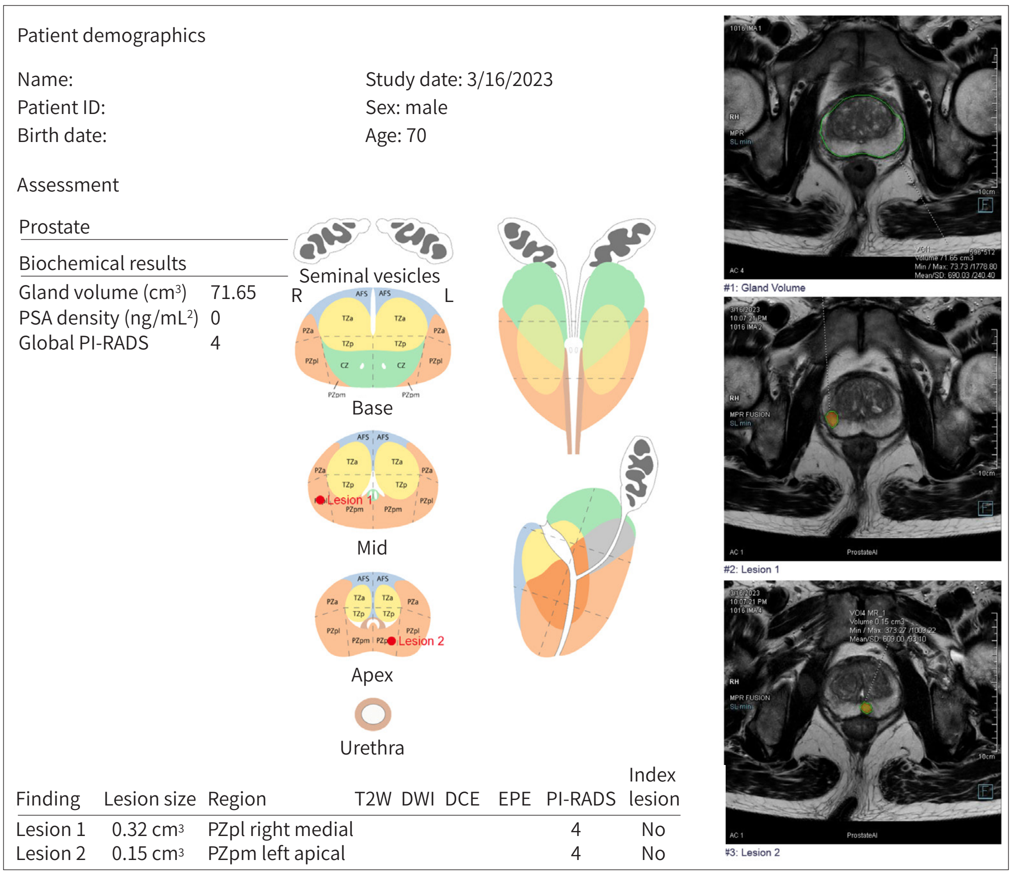
Fig. 2. An example of a deep learning–based algorithm applied to prostate MRI.
An exemplary AI software (MR Prostate on syngo.via, Siemens Healthineers) generates MRI reports, including a prostate sector map annotated with the locations of detected lesions. The algorithm detects focal lesions, classifies prostate cancer risk according to the PI-RADS, and performs segmentation of the prostate gland and lesions, approximately providing prostate volume and lesion volume.
DCE = dynamic contrast-enhanced imaging, DWI = diffusion-weighted imaging, EPE = extraprostatic extension, PI-RADS = Prostate Imaging Reporting and Data System, PSA = prostate-specific antigen, PZpl = peripheral zone posteromedial, PZpm = peripheral xone posterolateral, T2W = T2-weighted imaging


Patient demographics

Name:
Patient ID:
Birth date:

Study date: 3/16/2023
Sex: male
Age: 70

Assessment

Prostate

Biochemical results

Gland volume (cm^3)	71.65
PSA density (ng/mL^2)	0
Global PI-RADS	4

Finding	Lesion size	Region	T2W	DWI	DCE	EPE	PI-RADS	Index lesion
Lesion 1	0.32 cm^3	PZpl right medial					4	No
Lesion 2	0.15 cm^3	PZpm left apical					4	No

sessment reported a notably low proportion of PI-RADS 3 classifications, reflecting reduced diagnostic uncertainty. In contrast, the least experienced radiologists assigned PI-RADS 3 to 24% of cases (39). Another study demonstrated that AI assistance reduced interreader variability among seven radiologists with varying levels of experience and also shortened MRI reading times (40). Similarly, the diagnostic performance of less experienced radiologists in detecting and classifying focal lesions significantly improved when aided by AI support (38).

The Prostate Imaging: Cancer AI (PI-CAI) challenge was a large-scale international study designed to compare the performance of AI algorithms and radiologists in detecting csPCa (41). It represented a global effort, involving the largest cohort of radiologists ($n = 62$) and numerous AI submissions from around the world. In this study, an ensemble AI model, formed by combining the top five performing algorithms, demonstrated superior diagnostic performance compared with the average performance of the participating radiologists, using PI-RADS ≥3 as the threshold for positivity. Specifically, the ensemble AI achieved a positive predictive value (PPV) of 68.0% versus 53.2% for radiologists and a negative predictive value of

93.8% versus 90.2%. However, the AI model did not meet the noninferiority threshold compared with expert interpretation in a multidisciplinary practice, showing slightly lower specificity (68.9% vs. 69.0%) at matched sensitivity (96.1%). A subsequent study based on the PI-CAI algorithm compared the diagnostic performance of 61 radiologists reading bpMRI, both with and without AI assistance (42). AI support significantly improved performance, increasing the area under the receiver operating characteristic curve (AUC) from 0.882 to 0.916 (+3.3%), with corresponding gains in sensitivity (+2.5%) and specificity (+3.4%). Notably, the benefit of AI assistance was particularly prominent among nonexpert readers.

These findings collectively highlight the potential of deep learning algorithms for PCa detection and risk stratification. In particular, AI assistance enhances radiologists' diagnostic performance, particularly among less experienced readers, and reduces interreader variability. Many algorithms have demonstrated strong performance using only bpMRI, without the need for DCE. Although studies have reported that bpMRI can achieve diagnostic accuracy comparable to that of mpMRI, the omission of DCE remains controversial (43, 44). Several reports have demonstrated the added value of DCE in lesion detection and improving radiologists' diagnostic confidence (45, 46). Nevertheless, given the increasing demand for prostate MRI examinations, bpMRI offers significant practical advantages, including reduced scan time, lower cost, and avoidance of gadolinium-based contrast agents, which raise concerns regarding safety and long-term brain retention. With continued advances in deep learning techniques, AI algorithms for detecting csPCa are expected to play an increasingly impactful role in future prostate MRI workflows.

LOCAL TUMOR STAGING

Accurate staging of PCa is essential for selecting the optimal treatment strategy, planning surgery, and predicting patient prognosis. MRI is regarded as the most effective imaging modality for local staging because of its superior soft-tissue contrast. Tumor T stage is classified as follows: T2 for organ-confined disease; T3a for extracapsular extension, including neurovascular bundle invasion; T3b for seminal vesicle invasion; and T4 for invasion into adjacent organs.

Several AI algorithms have been developed to perform local tumor staging using radiomics-based machine learning (ML) or deep learning networks on prostate MRI (47). While many early studies required manual tumor segmentation by radiologists, they still demonstrated high diagnostic performance, with AUC values ranging from 0.61 to 0.88. For example, one study applied texture analysis and ML to predict histopathologically confirmed extraprostatic extension (EPE), encompassing both T3a and T3b stages, using bpMRI (48). Radiomics features were extracted from a two-dimensional region of interest (ROI) of the index lesion, and various feature selection and classification techniques were evaluated. The best-performing classifier achieved an AUC of 0.88 for EPE prediction. Another study implemented a deep learning–based pipeline for automated EPE grading from bpMRI (49). This approach leveraged pretrained AI models for prostate gland and lesion segmentation, from which extracted features were used to train a random forest classifier to predict EPE, with grades ranging from 0 to 3. Using a threshold of EPE grade $\geq$1, the AI model achieved performance comparable to that of radiologists (sensitivity: 67% vs. 81%; specificity: 73% vs. 62%; accuracy: 72%

vs. 66%). In a separate study, a pretrained convolutional neural network was used for prostate segmentation and cancer detection, followed by rule-based classification to estimate the likelihood of EPE (47). At a threshold of 0.35, the algorithm achieved 80.0% sensitivity and 28.2% specificity at the patient level, whereas the radiologists' sensitivity and specificity was 50.0% and 76.9%, respectively. As research has progressed from models requiring manual lesion segmentation to those utilizing automated lesion and gland segmentation, AI algorithms have demonstrated the advantage of providing clinically relevant information with less time and effort from radiologists.

DISEASE PROGRESSION MONITORING DURING ACTIVE SURVEILLANCE

AS is the recommended management strategy for patients with low-risk PCa confined to the gland (5, 50). While AS allows patients to avoid immediate aggressive treatment and its associated side effects, it carries the risk of initial misclassification and the possibility of missing disease progression over time. Baseline MRI plays an important role in minimizing misclassification by improving the detection of csPCa (5). During AS, patients typically undergo serial PSA testing, digital rectal examinations, and scheduled control biopsies. Given the utility of MRI in evaluating prostate anatomy and tumor characteristics, some guidelines have incorporated mpMRI into AS monitoring protocols (51, 52). Although using MRI as a potential alternative to repeated biopsies is an attractive approach, the optimal timing and triggers for biopsy remain unclear. Two meta-analyses reported that serial MRI during AS demonstrates moderate sensitivity (0.59–0.61) and good specificity (0.75–0.78), helping to reduce unnecessary biopsies. However, MRI alone may miss up to 12% of true progressions, indicating that it cannot fully replace scheduled repeat biopsies (53, 54). To improve standardization, the PRECISE scoring system was introduced and recently updated to version 2. The PRECISE system provides a 5-point scale for assessing radiologic progression, ranging from 1 (complete regression) to 5 (definite progression). A score of X is assigned when image quality is insufficient for reliable assessment (11).

AI has the potential to address several limitations of MRI in AS by standardizing serial image interpretation, reducing interreader variability, and assisting less experienced radiologists (55). One study evaluated a pretrained deep learning algorithm for detecting csPCa on mpMRI images obtained during AS (excluding MRI examinations for the initial diagnostic biopsy) (56). The AI algorithm provided results in the form of PI-RADS scores. Radiologists detected 83 lesions, 33% of which were csPCa (ISUP grade ≥2). The AI system identified most csPCa cases but missed six significant lesions. At the patient level, AI achieved high sensitivity (96.4%) but low specificity (25%) for detecting ISUP ≥2 disease. These findings suggest that although the AI algorithm has low specificity and may produce false positives, its high sensitivity can complement radiologists by reducing the risk of missing clinically significant progression or PCa. In this context, AI may help ensure timely treatment decisions during AS, where undetected progression could lead to delayed or suboptimal care.

Several studies have investigated the use of ML and deep learning models for monitoring tumor progression during AS, reporting AUC values between 0.72 and 0.86 (57). Notably, incorporating clinicopathological data and their longitudinal changes significantly improved model performance, highlighting the importance of additional input features. However, most studies included small sample sizes, and the findings should be interpreted with caution. Despite these encouraging results, AI implementation in AS still faces key challenges, including inconsistent definitions of disease progression, heterogeneous inclusion criteria, and limited access to large, standardized, and publicly available datasets. Therefore, further research and validation studies are needed to establish stronger evidence before clinical adoption.

RECURRENCE PREDICTION AND DETECTION AFTER TREATMENT

Radical prostatectomy (RP) is the only treatment for localized PCa that has demonstrated a survival benefit in both overall and cancer-specific terms, whereas RT remains one of the primary curative approaches (58). Despite these curative intents, biochemical recurrence (BCR) still occurs. The 15-year cumulative incidence of BCR after RP is reported to be 16%, 30%, and 46% in the low-, intermediate-, and high-risk D'Amico groups, respectively, whereas for RT the corresponding rates are 18%, 24%, and 36%, respectively (59). The use of mpMRI enables the accurate early detection of local recurrence after both RP and RT (6). To standardize imaging and reporting in this context, the PI-RR system was introduced (12). PI-RR employs a five-point scoring system to indicate the level of suspicion for recurrent PCa, with DWI and DCE as key sequences for assessment.

Several studies have developed ML models to predict BCR using pretreatment MRI. One study trained an ML classifier using the most discriminative radiomic features extracted from 2D ROI in cancerous areas on T2W images and ADC maps. This model achieved an AUC of 0.73 for predicting recurrence after RT (60). Another study using radiomic features from T2W images acquired before and after RT reported an AUC of 0.632, with posttreatment radiomics providing the best predictive performance (61).

In contrast to the abundance of deep learning models for PCa detection and risk stratification in treatment-naïve patients, only a few have addressed recurrence detection after definitive therapy. One study evaluated a deep learning model trained on bpMRI images of treatment-naïve lesions to detect recurrent PCa following RT (62). In this study, radiologists achieved per-patient and per-lesion sensitivities of 91.3% and 87.5%, respectively, without AI assistance. The standalone deep learning model showed lower performance, with sensitivities of 76.1% (per-patient) and 71.4% (per-lesion). However, AI-assisted reading modestly improved the PPV compared with unassisted reading (78.4% vs. 70.0%), although the difference was not statistically significant.

Currently, deep learning models for recurrence detection remain limited and are not yet widely accessible. Given the clinical importance of early recurrence detection for treatment planning and prognosis, future studies are warranted to explore and validate AI models in this domain.

IMAGE QUALITY EVALUATION

In prostate MRI, image quality is critical for accurate interpretation and clinical decision-making. Although PI-RADS provides technical recommendations, considerable variation in MRI acquisition parameters has been observed across institutions (15). To address this, the PI-QUAL score was developed as a standardized system for evaluating prostate MRI image quality (10). Many studies have demonstrated that poor image quality is associated with reduced diagnostic performance in cancer detection and staging (63). While interobserver agreement for PI-QUAL scoring has been reported as moderate to substantial, further improvements in interreader consistency remain necessary. Additionally, although PI-QUAL version 2 simplified the scoring system, radiologists are still required to verify whether essential technical criteria are met and perform subjective assessments of image quality (64).

A study introduced a semiautomated image quality assessment system that checks whether the recommended acquisition parameters are met for each MRI sequence (65). Although visual assessment still needs to be performed manually, this tool enables radiologists to quickly and reliably evaluate technical parameters. Similar functionality is also available through freely accessible online tools (66).

AI-based approaches are also being explored to improve workflow efficiency and personalize imaging protocols. One convolutional neural network was developed to determine the necessity of DCE acquisition based on T2WI and DWI, achieving a sensitivity and specificity of 94.4% and 68.8%, respectively (67). To support real-time clinical decision-making, this model was implemented within a server-based system and mobile application, enabling radiologic technologists and radiologists to classify image quality as "approved," "insufficient," or "inconclusive." In approved cases, image acquisition is considered complete without DCE; in insufficient cases, DCE images are acquired; and in inconclusive cases, radiologists are prompted to review and decide on DCE acquisition (68). This AI-driven triage process allows for a streamlined workflow and optimized use of radiology resources.

FUTURE DIRECTIONS AND CONCLUSION

Owing to the rapid recent advances in large language models (LLMs), several studies have explored their use in prostate MRI reporting. In one study, an LLM processed unstructured prostate MRI reports to extract prostate gland dimensions and volume, PSA density, and lesion characteristics, including PI-RADS score and lesion dimensions (69). The LLM demonstrated excellent performance in extracting prostate volume and PSA density, whereas results for extracting lesion characteristics were more variable. Additionally, another study used an LLM to assign PI-RADS categories from clinical free-text MRI reports and reported limited performance (70). Further studies are anticipated, including applications for automatically generated structured reports, extraction of sequence-level metadata, multilingual/generalizable LLMs across institutions, and multimodal LLMs integrating image features with clinical text.

This review summarized the current landscape of AI research by key tasks, including gland segmentation, cancer detection and risk stratification, local staging, disease monitoring during AS, recurrence detection, and image quality evaluation (Table 1). Across these tasks, AI models, particularly deep learning–based approaches, have demonstrated strong performance. Several AI–based software products for prostate MRI have received clearance under Section 510(k) by the United States Food and Drug Administration for applications that assist

Table 1. Clinical Tasks in Prostate MRI: Radiologists' Standard Methods, AI Applications, and Key Results

Clinical Task	Radiologists' Methods	Goals of AI	AI Research	Key Results/Performance
Prostate gland segmentation	Ellipsoid formula for volume estimation	Delineating prostate gland boundaries Calculating prostate volume Aiding PSA density calculation Biopsy and RT planning	DL-based segmentation	DSC up to 0.98 for whole gland
Cancer detection and risk stratification	PI-RADS	Detecting suspicious lesions Classifying cancer risk PI-RADS scoring	DL models with bpMRI and/or DCE	Sensitivity: 56.1%–96% Specificity: 31%–87.1% AI is often comparable or superior to radiologists, especially bpMRI
Local tumor staging	T-staging via MRI	Assessing extracapsular extension or seminal vesicle invasion	Radiomics with ML DL pipelines	AUC: 0.61–0.88
Disease monitoring in AS	PRECISE	Tracking tumor progression in low-risk PCa during AS	DL models for PI-RADS scoring Lesion detection	Sensitivity: 96.4% Specificity: 25% AUC: 0.72–0.86
Recurrence prediction and detection	PI-RR	Identifying local recurrence after RP or RT Predicting biochemical recurrence	Radiomics from pre or post treatment MRI ML classifiers or DL models	AUC up to 0.73 DL-assisted reading improved PPV
Image quality evaluation	PI-QUAL	Ensuring diagnostic quality of MRI	Semi-automated tool DL model for DCE necessity Real-time triage applications	AI can standardize assessments, streamline workflows, and tailor acquisition protocols

AUC = area under the receiver operating characteristic curve, AS = active surveillance, bpMRI = biparametric MRI, DCE = dynamic contrast-enhanced imaging, DL = deep learning, DSC = Dice similarity coefficient, ML = machine learning, PCa = prostate cancer, PI-QUAL = Prostate Imaging Quality, PI-RADS = Prostate Imaging Reporting and Data System, PI-RR = prostate imaging for recurrence reporting, PPV = positive predictive value, PRECISE = prostate cancer radiological estimation of change in sequential evaluation, PSA = prostate-specific antigen, RP = radical prostatectomy, RT = radiotherapy

Table 2. Summary of Prostate MRI AI Software with U.S. FDA Clearance

Device	Company	Intended Use/Functions	U.S. FDA Regulatory Status	Date of U.S. FDA Decision
AI-Rad Companion Prostate MR	Siemens Healthineers	Automatic prostate segmentation; quantitative analysis of the prostate gland	Class II, 510(k)-cleared	2020-07-30
qp-Prostate	Quibim S.L.	Quantitative MR analysis; reporting assistance	Class II, 510(k)-cleared	2021-02-04
Avenda Health AI Prostate Cancer Planning Software	Avenda Health, Inc.	Prostate and lesion segmentation; biopsy/ablation tool placement simulation	Class II, 510(k)-cleared	2022-11-22
Quantib Prostate	Quantib BV	Automatic prostate segmentation; semi-automatic lesion segmentation; reporting assistance	Class II, 510(k)-cleared	2023-04-17
Medihub Prostate	JLK	Semi-automatic prostate outlining and volume estimation	Class II, 510(k)-cleared	2024-06-21
Prostate MR AI	Siemens Healthineers	Automatic prostate and zonal segmentation; automatic lesion detection and PI-RADS classification; suspicion map and lesion list generation	Class II, 510(k)-cleared	2025-03-05
QP-Prostate® CAD	Quibim	Lesion detection; two-level suspicion markers (moderate/high)	Class II, 510(k)-cleared	2025-03-18

FDA = Food and Drug Administration, PI-RADS = Prostate Imaging Reporting and Data System

radiologists with MRI interpretation (Table 2) (71).

Despite this progress, several barriers remain before AI can be fully integrated into clinical workflows. Challenges include limited generalizability across institutions, lack of standardization in outcome definitions (particularly for progression or recurrence), and the predominance of small, retrospective datasets. In addition, critical unmet needs persist around model interpretability, regulatory approval, and prospective clinical validation.

Future studies should focus on developing robust, generalizable models through multicenter collaborations and prospective trials. The integration of multimodal inputs, including clinical, pathological, and temporal data, may further enhance AI model performance. Ultimately, successful adoption of AI in routine prostate MRI practice requires not only high diagnostic accuracy but also meaningful improvements in efficiency, consistency, and patient-centered outcomes.

Supplementary Materials

Korean translation of this article is available with the Online-only Data Supplement at http://doi.org/10.3348/jksr.2025.0062.

Conflicts of Interest

The author has no potential conflicts of interest to disclose.

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Funding

None

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전립선 MRI에서의 인공지능: 임무에 따른 고찰

최문형*

전립선 자기공명영상(이하 MRI)은 전립선암의 진단, 병기 설정, 치료 계획 수립, 추적 관찰 등 진단 및 치료 과정 전반에서 널리 활용되고 있다. 영상 판독의 일관성과 효율성에 대한 요구가 증가함에 따라, 전립선 MRI에서 인공지능(이하 AI)의 활용 가능성이 주목받고 있다. 본 고찰에서는 전립선 MRI에서의 AI 적용을 임상적 임무(task) 별로 정리하고, 전립선 분할, 암 탐지 및 위험도 분류, 국소 병기 설정, 능동적 감시 중 질병 진행 평가, 치료 후 재발 평가, 영상 품질 평가 등 주요 영역을 다룬다. 이러한 임무 전반에 걸쳐, 특히 딥러닝 기반 AI는 유망한 성과를 보여주고 있다. 아직까지 전립선 MRI에 특화된 상용 AI 도구는 제한적이지만, 향후 기술 발전에 대비하여 다양한 임무에서 AI 연구의 현황을 이해하는 것이 중요하다.

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