Tasks for artificial intelligence in prostate MRI

Mason J. Belue and Baris Turkbey*

Abstract

The advent of precision medicine, increasing clinical needs, and imaging availability among many other factors in the prostate cancer diagnostic pathway has engendered the utilization of artificial intelligence (AI). AI carries a vast number of potential applications in every step of the prostate cancer diagnostic pathway from classifying/improving prostate multiparametric magnetic resonance image quality, prostate segmentation, anatomically segmenting cancer suspicious foci, detecting and differentiating clinically insignificant cancers from clinically significant cancers on a voxel-level, and classifying entire lesions into Prostate Imaging Reporting and Data System categories/Gleason scores. Multiple studies in all these areas have shown many promising results approximating accuracies of radiologists. Despite this flourishing research, more prospective multicenter studies are needed to uncover the full impact and utility of AI on improving radiologist performance and clinical management of prostate cancer. In this narrative review, we aim to introduce emerging medical imaging AI paper quality metrics such as the Checklist for Artificial Intelligence in Medical Imaging (CLAIM) and Field-Weighted Citation Impact (FWCI), dive into some of the top AI models for segmentation, detection, and classification.

Keywords: Artificial intelligence, Deep learning, Machine learning, Magnetic resonance imaging, Prostatic neoplasms

Background

Artificial Intelligence (AI) is an umbrella term that encompasses both machine learning (ML) and deep learning (DL). Traditional ML methods usually require several preprocessing steps which include anatomical segmentation and feature extraction whereas DL is a subfield of ML that does not necessarily depend on handcrafted features and independently identifies features to generate desired output predictions [1, 2]. DL, more commonly than ML, makes use of artificial neural networks that use statistical models inspired and partially modeled on biological neural networks. The use of artificial neural networks allows for the approximation of nonlinear relationships between the inputs and outputs [3]. A major challenge for prostate cancer (PCa) management is the lack of non-invasive tools that can differentiate clinically significant PCas (csPCas) and clinically insignificant PCas (cisPCas), resulting in overdiagnosis and overtreatment. There are many different definitions of csPCas ranging from Gleason score $\geq 6$ or $\geq 7$ permuted with various clinical factors including prostate-specific antigen (PSA) cutoffs, presence of extra-prostatic extension,
and biopsy-core cancer percentage [4]. The most common definition of csPCa across most studies is Gleason score ≥ 7.

Many challenges and potential improvements remain in the prostate cancer diagnostic pathway that may be addressed by AI with the common goal of potentially reducing csPCa overdiagnosis and csPCa underdiagnosis. AI may help accomplish improved cancer detection and/or classification across benign and malignant entities and it may aid in segmentation of suspicious foci and normal anatomy on magnetic resonance imaging (MRI) scans for tasks such as volume estimation or treatment planning utilizing transrectal ultrasound-guided biopsy [5]. AI can also help with the initial evaluation or triaging of prostate multiparametric MRI (mpMRI) cases (i.e., picking/identifying prostate MRI examinations with more atypical image characteristics) and of image quality (i.e., classifying mpMRI scans as diagnostic versus non-diagnostic) [6–8]. All these steps in the PCa diagnostic pathway may suffer from low inter-reader agreement of various sources which AI may also be able to improve upon. Once clinical efficacy of AI systems is demonstrated, clinical deployment can be envisioned as a companion system that creates attention boxes/maps for the radiologist during their clinical read, serves as a second reader providing independent diagnoses, or can be utilized as patient triage systems [9].

In this narrative review, we introduce emerging medical imaging AI paper quality metrics such as the Checklist for Artificial Intelligence in Medical Imaging (CLAIM) and Field-Weighted Citation Impact (FWCI), dive into some of the top AI models for segmentation, detection, and classification (Fig. 1), and also mention potential areas of impact in the radiologist workflow (Fig. 2).

CLAIM and FWCI

CLAIM was developed in 2020 [10] to aid authors in presenting research and reviewers in reviewing already published AI manuscripts in medical imaging. The CLAIM checklist, modified after the Standards for Reporting of Diagnostic Accuracy Studies, STARD, guidelines, was specifically designed to address applications of AI in medical imaging that include classification, detection, reconstruction, and workflow optimization. The checklist consists of 42 criteria that should be considered or viewed as “best practice” for presenting medical imaging AI research [10]. This CLAIM checklist can easily be turned into a percentage of CLAIM fulfillment, an objective assessment based on if a paper reports in a way that is considered “best practice” via fulfilling the applicable CLAIM requirements versus if they do not.

FWCI, a common Scopus article metric, is the ratio of the total citations received by the total citations that would be expected based on the average of the subject field. A FWCI of 1 means that the paper performs just as expected for the global average whereas more than 1 means that the paper is more cited than expected according to the global average (a FWCI of 1.48 means 48% more cited than expected) and less than 1 means that the paper is cited less than expected according to the global average. Both CLAIM and FWCI can both be used as markers as of article/research impact and rigor and are encouraged to be used in AI manuscript reporting and evaluation.

Overall, there were 29 classification/detection papers: 18 detection papers, 4 detection and classification papers, and 2 which did not indicate. When comparing papers that created classification models (n = 29) versus those that created detection models (n = 18), the mean AUC was 0.843 for classification models (n = 25 of 29 reporting) and 0.832 for detection models (n = 15 of 18 reporting), while the mean field-weighted impact factor was 4.79 for classification models (n = 26 of 29 reporting) and 3.64 for detection models (n = 18 of 18 reporting), and the mean CLAIM percentage fulfillment was 77.8% (n = 29 of 29 reporting) for classification papers and 71.2% for detection papers (n = 18 of 18 reporting).

The classification and detection papers that were in the top 25% with respect to field-weighted impact factor of the sampled papers and those which have the largest sample sizes and highest CLAIM percentage fulfillment are discussed below as we believe these papers will represent the most impactful and potentially generalizable. Additionally, emerging segmentation AI papers are also introduced which were not covered in this prior review (Table 1).

AI-based prostate segmentation

Prostate segmentation AI is developed to extract out anatomical/lesion regions-of-interest similarly to manual segmentation but attempts to address the variability of segmentations that result from readers of different experiences and MRI scans of varying quality [18]. A typical anatomical AI segmentation training/inference workflow is shown in Fig. 3 from a prostate urethra segmentation AI model [19]. Segmentation AI will attempt to output the exact outline of the desired object/volume of interest (Fig. 1b). Segmentation of the prostate and its related structures is very important for identifying its capsule, prostatic zones, urethra tract, and intraprostatic lesion locations. Identification of these areas allows for improved the treatment of benign prostate hyperplasia, surgical and targeted-biopsy planning, radiotherapy dosage/toxicity calculations, and predicting cancer-specific survival and prognosis [5, 20].
Segmentation of prostate MRI has critical clinical uses such as accurate estimation of the entire prostate gland volume for calculating the serum prostate-specific antigen (PSA) density and MRI data preparation for biopsy guidance in transrectal ultrasound/MRI fusion guided biopsy systems and for radiotherapy planning. Manual segmentation of the prostate and its sub-organs such as the urethra is a time-consuming task and is very much prone to interoperator variations [21]. AI has been commonly used for prostate segmentation and currently there are few commercial solutions for this time-consuming process [7].

Recently, DL-based AI solutions are reported commonly to provide robust performance for segmenting the prostate gland and its zones. In a study by Wang et al. [11], a three-dimensional (3D) fully convolutional network with deep supervision was used to develop a fully automated prostate segmentation model for T2-weighted MRI. The authors reported a mean Dice similarity coefficient of 0.88 (range 0.83–0.93) between AI model and manual segmentations for the whole prostate. Wang et al. [11] utilized a combined loss function of both cross-entropy loss and cosine loss in order to take advantage of their individual strengths and attempt to
achieve better quantitative and qualitative performance. The cross-entropy loss is generally optimized for voxel-level accuracy, while other loss functions such as cosine similarity loss are helpful for improving the segmentation quality. In another study, Ushinsky et al. [12] developed a hybrid 3D-two dimensional (2D) U-net based segmentation algorithm for automatic localization and segmentation of prostate gland at T2-weighted MRI of 299 patients. The AI-based whole prostate segmentation model achieved a mean Dice similarity coefficient of 0.898 (range, 0.890–0.908) when compared with manual segmentations. The model Ushinsky et al. developed leverages features from multiple axial slices simultaneously to better construct a single 2D image. They say this architecture imitates a radiologist who will typically interpret multiple axial images before making decisions on one 2D image. Finally, in a study by Sanford et al. [13], a DL approach combining 2D and 3D architectures with transfer learning incorporation was used to develop a whole prostate and transition zone segmentation algorithm in 648 patients. The study reported mean Dice similarity coefficients of 0.931 and 0.89 for whole prostate and transition zone, respectively. This study utilized a data augmentation strategy which was specific to the gland deformations, intensity variations and alterations in image acquisition for MRI data from five different centers and this novel strategy improved the whole prostate and transition zone segmentation performances 2.2% and 3%, respectively. Prostate segmentation AI is the most studied part of prostate MRI workflow and current research indicates that 3D DL-based applications can offer state of the art solutions for this time-consuming task during prostate MRI read out and biopsy planning for radiologists. Figure 3 illustrates how segmentation AI might improve and supplement the workflow of a radiologist. Many of these strategies discussed above for anatomical segmentation of the prostate and its sub-organs also apply to suspicious lesion segmentation as well.

**Intraprostatic lesion AI detection**

AI for prostate cancer detection is mainly used to identify cancer suspicious areas within a prostate MRI scan and do not require prior lesion annotation by radiologists [8]. AI-based detection models may range from two-class...
lesion detection (csPCa versus cisPCa) systems to multiclass lesion detection systems such as the International Society of Urological Pathology (ISUP) score [22] or the Prostate Imaging Reporting and Data System (PI-RADS) score [16]. In contrast to segmentation, which generally provides the exact outline of an object within an image, AI-based detection helps to create bounding boxes around suspicious objects (Fig. 1a). To date, several studies have evaluated AI algorithms developed for prostate cancer detection on mpMRI. Despite the many differences in feature extraction, MRI techniques, and study populations, these studies demonstrate a robust detection rate: 75 to 80% or more. Notably, this is within the range of reported radiologist performance [1].

For AI-based detection there have been several validation studies investigating if these AI truly have an impact on the radiologist workflow. In a recent multireader, multi-institutional study, Gaur et al. [23] showed that AI-based detection improved specificity when combined with PI-RADS v2 [24] categorization. This AI-based detection also slightly improved radiologist efficiency and found an index lesion sensitivity for PI-RADS v2 ≥3 of 78% [23]. Litjens et al. [25] and Song et al. [26] have also demonstrated the improved detection of cancer and discrimination of csPCa from cisPCa when combining AI-based prediction and PI-RADS v2 [25, 26].

The top AI studies developing detection AI are further discussed. One DL paper with a CLAIM percentage fulfillment of 68.3% and a FWI of 6.04 by Cao et al. [14] developed a joint prostate cancer detection and Gleason score prediction model on a dataset of 417 patients who underwent mpMRI [14]. The model combined T2-weighted turbo spin-echo imaging and maps of the apparent diffusion coefficient (ADC) using diffusion-weighted echo-planar imaging and stacked them as different imaging channels before feeding into FocalNet, an end-to-end multi-class CNN. One unique addition that Cao et al. [14] made is what they call mutual finding loss. It tries to address the challenge that different components of mpMRI (T2-weighted and diffusion weighted sequences, ADC maps, dynamic contrast-enhanced sequences) capture distinct information and only a portion of the information is shared across all components when stacked in a multichannel AI detection (Fig. 1a). As a result of this, findings which are observable in one component may be partially observable or non-observable in the other components. During the end-to-end AI model training, a CNN with stacked components as proposed by Cao et al. [14] can learn the common features across components, effectively emulating the normal process of a radiologist’s reading mpMRI, based on a combination of the various imaging findings on the subcomponents of mpMRI. For the detection of histopathology-proven

Table 1 Summary of the artificial intelligence (AI) development papers discussed in detail

| First author [reference number] | Overall sample size | AI family | AI method | Public/external datasets used | Images used | Loss functions | AUC | Dice similarity coefficient |
|-------------------------------|---------------------|-----------|-----------|-----------------------------|------------|---------------|-----|-----------------------------|
| Wang [11]                     | 90                  | Whole gland segmentation | 3D CNN + skip connections | PROMISE12 | T2-weighted | Cross-entropy + cosine loss | 0.86—0.88 |
| Ushinsky [12]                 | 299                 | Whole gland segmentation | Hybrid 2D-3D CNN + skip connections | T2-weighted | Adam loss | 0.88 |
| Sanford [13]                  | 648                 | Whole gland segmentation | Hybrid 2D-3D CNN | Five separate unaffiliated institutional independent datasets | T2-weighted | Dice similarity coefficient loss | 0.931 |
| Cao et al. [14]               | 417                 | Lesion detection | 3D CNN FocalNet | T2-weighted, ADC maps, echo-planar | Mutual finding loss | 0.81 |
| Ishioka [15]                  | 335                 | Lesion detection | U-net + ResNet50 (skip connections) | T2-weighted | Adam loss | 0.64—0.65 |
| Le [16]                       | 364                 | Lesion classification | Two parallel 2D CNNs | The Cancer Imaging Database (TCIA) | T2, ADC maps | Similarity loss | 0.91 |
| Liu et al. [17]               | 341                 | Lesion classification | 3D CNN XmasNet | PROSTATE-x | T2, ADC, diffusion-weighted, K\textsubscript{trans} | Adam loss | 0.84 |

2D Two-dimensional, 3D Three-dimensional, ADC Apparent diffusion coefficient, AUC Area under the curve, CNN Convolutional neural network
index lesions and clinically significant lesions, their FocalNet achieved 89.7% and 87.9% sensitivity at one false positive per patient and showed a sensitivity only 3.4% and 1.5% lower than that of experienced radiologists using PI-RADS v2 [14]. Another DL detection paper with a CLAIM percentage fulfillment of 75% and FWI
of 7.69 by Ishioka et al. [15] shows the power of AI network ensembling by combining a U-net with ResNet50 and introduces neural network interpretability and probability maps. U-net has the potential to distinguish whole and local pelvic structures and ResNet can then reformulate the CNN layers to learn them as residual functions instead of learning unreferenced functions. It is generally understood that residual functions help to eliminate the vanishing gradient problem in AI by allowing it to communicate with intermediate CNN layers. One unique contribution from Ishioka et al. [15] is the visualization of the feature and probability maps within the CNN as a way of interpreting which imaging features the AI is using the most for predictions [15]. These feature maps are paramount in attempting to explain the logical structure of a neural network, which is often expressed as a “black box” and may take form as feature maps, saliency maps, or probability maps [see Fig. 4 showing probability maps for AI detection]. Overall, intraprostatic lesion detection is one of the most critical steps of prostate MRI read outs and it requires significant expertise and is prone to interobserver variation commonly. Currently, quite a few research-based AI models exist for this task however, to document their actual impact on improving clinical management, which is mainly including biopsy decisions, prospective and multicenter studies are needed.

Intraprostatic lesion AI classification

Intraprostatic lesion classification AI models are used to classify either full images or to classify preannotated regions-of-interest ranging from two classes (csPCa versus cisPCa) to multiple separate classes (histopathological grading also known as ISUP score or PI-RADS score) as seen in Fig. 1. AI lesion classification typically does not perform voxel-level predictions but is commonly entire image/region-of-interest based. Patients with cisPCa are those with ISUP 2 or lower and are usually eligible for active surveillance whereas men with higher grade lesions such ISUP greater than 2 are typically advised to undergo active treatment such as focal therapy, radical prostatectomy, or radiotherapy [8]. Accurate lesion classification is important for selecting appropriate management options as any one therapy has a mosaic of side effects. Reductions in unnecessary biopsies is important in preventing common biopsy complications including infections, hematuria, rectal bleeding, hematospemria, lower urinary tract symptoms, and temporary erectile dysfunction [4]. Suarez-Ibarrola et al. [2] found within the literature that lesion classification accuracy of the algorithms they looked at was comparable to that provided by radiologists using PI-RADS [2]. An original research study [16] with a percentage CLAIM fulfillment of 68.3% and a FWI of 6.81 developed a classification CNN for (i) detecting cancerous versus noncancerous lesions and (ii) differentiating csPCa versus indolent cisPCa. This paper designed a new similarity loss function like mutual finding loss utilized by Cao et al. [23], allowing for the fusion of common and consistent features from ADC maps and T2-weighed images. This allows the CNN to “see” the true visual patterns of PCa across the spectrum of imaging sequences. Otherwise, without similarity loss functions,
imaging features from different mpMRI sequences such as those being T2-weighted will not be able to fill in the information gaps that arise from other functional sequences such as ADC maps, diffusion-weighted images, or vice versa.

Le et al. [16] then combined the classification results of the multimodal CNN with results based on hand-crafted features using a support vector machine classifier. Experimental results from an extensive clinical dataset from 364 patients with a total of 463 PCa lesions and 450 noncancerous lesions demonstrate that their system can achieve a sensitivity of 89.9% and a specificity of 95.8% for distinguishing cancerous from noncancerous tissues. With respect to csPCa versus cisPCa, they achieved a sensitivity of 100.0% and a specificity of 76.9%. This paper also demonstrated superior performance compared to the state-of-the-art method relying on handcrafted features alone [16]. Another original research study [17] with a percentage CLAIM fulfillment of 70.6% and an FWI of 23.12 developed XmasNet, a novel deep learning architecture based on CNNs, for classification of prostate lesions on MRI. This study showed that with the strength of data augmentation via 3D rotations and slicing, their XmasNet outperformed traditional ML models based on engineered features. Their XmasNet outperformed 69 methods from 33 participating groups and had the second highest AUC (0.84) in the 2017 PROSTATEx challenge. Like intraprostatic lesion detection AI models, several research-based AI algorithms are defined for intraprostatic lesion classification task and further research is needed to depict the benefit of these AI models in radiologists’ performance.

Moving forward with prospective AI studies

AI can potentially play a major role in further improving prostate MRI contribution to the clinical management of localized PCa. The majority of the work in prostate MRI AI reveals promising results for various tasks of prostate MRI interpretation and data processing for biopsy; however quite a limited amount of this work has reached to actual translation phase to clinics so that a clear benefit of AI on prostate MRI workflow is yet to be demonstrated. For this to happen, one of the “musts” is proving the benefit(s) of AI in prospective clinical trials. The potential benefits can be listed as improved performance in comparison with radiologists’ and reduction in read out times and inter-reader variation. Moving forward comfortably with AI will require this critical prospective multicenter evaluation.

Conclusions

AI is a commonly studied topic for prostate MRI and several groups report AI models for prostate segmentation, intraprostatic lesion detection and classification tasks with promising results. Some of the best models across the applications discussed utilize 3D AI models and special loss functions that attempt to combine the findings and fill in gaps introduced by different mpMRI sequences. Prospective studies with multi-center design will be needed to depict the impact of AI on radiologist performance and clinical management of prostate cancer.

Abbreviations

2D: Two-dimensional; 3D: Three-dimensional; ADC: Apparent diffusion coefficient; AI: Artificial intelligence; AUC: Area under the curve; cisPCa: Clinically insignificant prostate cancer; CLAIM: Checklist for Artificial Intelligence in Medical Imaging; CNN: Convolutional neural network; csPCa: Clinically significant prostate cancer; DL: Deep learning; FWCI: Field-weighted citation impact; ISUP: International Society of Urological Pathology; ML: Machine learning; mpMRI: Multiparametric magnetic resonance imaging; MRI: Magnetic resonance imaging; PCa: Prostate cancer; PI-RADS: Prostate Imaging Reporting and Data System; PSA: Prostate-specific antigen.

Authors’ contributions

Literature search: MB, BT. Article drafting: MB, BT. Draft editing: MB, BT. Both authors read and approved the final manuscript.

Funding

Open Access funding provided by the National Institutes of Health (NIH). This project has been funded in whole or in part with federal funds from the National Cancer Institute, National Institutes of Health (NIH), USA. The content of this publication does not necessarily reflect the views or policies of the Department of Health and Human Services, nor does mention of trade names, commercial products, or organizations imply endorsement by the U.S. Government. Additional research support was provided by the NIH Medical Research Scholars Program, a public-private partnership supported jointly by the NIH and contributions to the Foundation for the NIH from the Doris Duke Charitable Foundation, the American Association for Dental Research, and the Colgate-Palmolive Company.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

Mason Belue: none to be declared; Baris Turkbey: NVIDIA (Cooperative Research and Development Agreement); Philips (Cooperative Research and Development Agreement); Royalties from National Institutes of Health, USA; patents in the field of artificial intelligence (US 20170176565 A1-Automated Cancer detection using MRI).

Received: 2 February 2022 Accepted: 18 May 2022

Published online: 31 July 2022

References

1. Harmon SA, Tuncer S, Sanford T et al (2019) Artificial intelligence at the intersection of pathology and radiology in prostate cancer. Diagn Interv Radiol. 25:183–188. https://doi.org/10.5152/dir.2019.19125

2. Suarez-Ibarrola R, Sigle A, Eklund M et al (2021) Artificial intelligence in magnetic resonance imaging-based prostate cancer diagnosis: where do we stand in 2021? Eur Urol Focus 52405–4569.00099–00097. https://doi.org/10.1016/j.euf.2021.03.020

3. Van Booven DJ, Kuchakulla M, Pai R et al (2021) A systematic review of artificial intelligence in prostate cancer. Res Rep Urol 13:31–39. https://doi.org/10.2147/RRU.S268596
Belue and Turkbey  European Radiology Experimental  (2022) 6:33

4. Ahmed HU, Bosaily AE-S, Brown LC et al (2017) Diagnostic accuracy of multi-parametric MRI and TRUS biopsy in prostate cancer (PROMIS): a paired validating confirmatory study. Lancet 389:815–822. https://doi.org/10.1016/S0140-6736(16)32401-1

5. Bardis MD, Houshyar R, Chiang PD et al (2020) Applications of artificial intelligence to prostate multiparametric MRI (mpMRI): current and emerging trends. Cancers 12:1204. https://doi.org/10.3390/cancers12051204

6. Giganti F, Lindner S, Piper JW et al (2021) Multiparametric prostate MRI quality assessment using a semi-automated PI-QUAL software program. Eur Radiol Exp 5:48. https://doi.org/10.1007/s40539-021-00245-x

7. van Leeuwen KG, Schalekamp S, Rutten MJCM et al (2021) Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. Eur Radiol 31:3797–3804. https://doi.org/10.1007/s00330-021-0882-2

8. Twilt JJ, van Leeuwen KG, Huisman HJ et al (2021) Artificial intelligence based algorithms for prostate cancer classification and detection on magnetic resonance imaging: a narrative review. Diagnostics 11:959. https://doi.org/10.3390/diagnostics11060959

9. Syer T, Mehta P, Antonelli M et al (2021) Artificial intelligence compared to radiologists for the initial diagnosis of prostate cancer on magnetic resonance imaging: a systematic review and recommendations for future studies. Cancers 13:3318. https://doi.org/10.3390/cancers13133318

10. Ongan J, Moy L, Kahn CE (2020) Checklist for artificial intelligence in medical imaging (CLAIM): a guide for authors and reviewers. Radiol Artif Intell 2:e200029. https://doi.org/10.1148/ryai.2020200029

11. Wang B, Lei Y, Tian S et al (2019) Deeply supervised 3D fully convolutional networks with group dilated convolution for automatic MRI prostate segmentation. Med Phys 46:1707–1718. https://doi.org/10.1002/mp.13416

12. Ushinsky A, Bardis M, Glavis-Bloom J et al (2021) A 3D-2D hybrid U-net convolutional neural network approach to prostate organ segmentation of multiparametric MRI. AJR Am J Roentgenol 216:111–116. https://doi.org/10.2214/AJR.19.22168

13. Sanford TH, Zhang L, Harmon SA et al (2020) Data augmentation and transfer learning to improve generalizability of an automated prostate segmentation model. AJR Am J Roentgenol 215:1403–1410. https://doi.org/10.2214/AJR.19.22347

14. Cao R, Mohammadian Bagirian A, Afshari Mirak S et al (2019) Joint prostate cancer detection and Gleason score prediction in mp-MRI via FocalNet. IEEE Trans Med Imaging 38:2496–2506. https://doi.org/10.1109/TMI.2019.2901928

15. Ishioka J, Matsuoka Y, Uehara S et al (2018) Computer-aided diagnosis of prostate cancer using a convolutional neural network algorithm. BJU Int 122:411–417. https://doi.org/10.1111/bju.14397

16. Le MH, Chen J, Wang L et al (2017) Automated diagnosis of prostate cancer in multi-parametric MRI based on multimodal convolutional neural networks. Phys Med Biol 62:6497–6514. https://doi.org/10.1088/1361-6560/aa7731

17. Liu S, Zheng H, Feng Y, Li W (2017) Prostate cancer diagnosis using magnetic resonance imaging and artificial intelligence. Open Access J Cancer Res 7:286–293. https://doi.org/10.2174/1874059071607010001

18. Nelson CR, Ekberg J, Fridell K (2020) Prostate cancer detection in screening using magnetic resonance imaging and artificial intelligence. Open Artif Intell J 6. https://doi.org/10.17147/issn.2020.060101

19. Belue MJ, Harmon SA, Patel K et al (2022) Development of a 3D CNN-based AI model for automated segmentation of the prostatic urethra. Acad Radiol S1076-6332:00057–00055. https://doi.org/10.1016/j.acra.2022.01.009

20. Tataru OS, Vartolomei MD, Rassweiler JJ et al (2021) Artificial intelligence and machine learning in prostate cancer patient management—current trends and future perspectives. Diagnostics 11:354. https://doi.org/10.3390/diagnostics11020354

21. Garvey B, Türkbey B, Truong H et al (2014) Clinical value of prostate segmentation and volume determination on MRI in benign prostatic hyperplasia. Diagn Interv Radiol 20:229–233. https://doi.org/10.1512/dir.2014.13322

22. van Leenders GJLH, van der Kwast TH, Grignon DJ et al (2020) The 2019 International Society of Urological Pathology (ISUP) consensus conference on grading of prostatic carcinoma. Am J Surg Pathol 44:e87–e99. https://doi.org/10.1097/PAS.0000000000001497

23. Gaur S, Lay N, Harmon SA et al (2018) Can computer-aided diagnosis assist in the identification of prostate cancer on prostate MRI? A multi-center, multi-reader investigation. Oncotarget 9:33804–33817. https://doi.org/10.18632/oncotarget.26100

24. Türkbey B, Rosenkranz AB, Haider MA et al (2019) Prostate imaging reporting and data system version 2.1: 2019 update of prostate imaging reporting and data system version 2. Eur Urol 76:340–351. https://doi.org/10.1016/j.eururo.2019.02.033

25. Litjens GS, Barentsz JO, Karssemeijer N, Huisman HJ (2015) Clinical evaluation of a computer-aided diagnosis system for determining cancer aggressiveness in prostate MRI. Eur Radiol 25:3187–3199. https://doi.org/10.1007/s00330-015-3743-y

26. Song Y, Zhang Y-D, Yan X et al (2018) Computer-aided diagnosis of prostate cancer using a deep convolutional neural network from multiparametric MRI. PCA classification using CNN from mp-MRI. J Magn Res Imaging 48:1570–1577. https://doi.org/10.1002/jmi.26047

Publisher’s Note
Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Submit your manuscript to a SpringerOpen journal and benefit from:

► Convenient online submission
► Rigorous peer review
► Open access: articles freely available online
► High visibility within the field
► Retaining the copyright to your article

Submit your next manuscript at ► springeropen.com