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The performance of artificial intelligence in prostate magnetic resonance imaging screening

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ABSTRACT

Prostate cancer is the predominant form of cancer observed in men worldwide. The application of magnetic resonance imaging (MRI) as a guidance tool for conducting biopsies has been established as a reliable and well-established approach in the diagnosis of prostate cancer. The diagnostic performance of MRI-guided prostate cancer diagnosis exhibits significant heterogeneity due to the intricate and multi-step nature of the diagnostic pathway. The development of artificial intelligence (AI) models, specifically through the utilization of machine learning techniques such as deep learning, is assuming an increasingly significant role in the field of radiology. In the realm of prostate MRI, a considerable body of literature has been dedicated to the development of various AI algorithms. These algorithms have been specifically designed for tasks such as prostate segmentation, lesion identification, and classification. The overarching objective of these endeavors is to enhance diagnostic performance and foster greater agreement among different observers within MRI scans for the prostate. This review article aims to provide a concise overview of the application of AI in the field of radiology, with a specific focus on its utilization in prostate MRI.

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1. INTRODUCTION

Magnetic resonance imaging (MRI) is frequently employed in the diagnosis and management of prostate cancers that possess clinical significance. Although reports of MRI's usefulness exist, the diagnostic performance seen in large-scale academic investigations cannot be reliably reproduced outside of research hospitals [1]–[5]. The application of prostate MRI for the diagnosis of prostate cancer through MRI-guided biopsy entails a series of sequential quality control measures. These measures encompass the acquisition of MRI scans, the interpretation and reporting of the MRI findings, the processing of MRI data for biopsy purposes, and the registration of MRI images with transrectal ultrasonography during the biopsy procedure [6]–[8]. The prostate imaging and reporting data system (PI-RADS) was formulated and introduced in 2015 [9] by a consortium of global experts with the aim of enhancing uniformity in the application of MRI for prostate assessment. The most recent iteration currently employed is version 2.1 [10]. However, the essential features of PI-RADS are still subjective, which can weaken the reliability of prostate MRI, especially in the community context, despite the fact that it has been shown to increase the use of prostate MRI in prostate cancer clinical treatment. The application of artificial intelligence (AI) in medical imaging, encompassing radiography and pathological conditions, has demonstrated advancements in tasks [11], [12].

Machine learning is a specialized domain within the field of AI that facilitates the acquisition of knowledge by computers through the analysis of data provided by human experts. This acquired knowledge is then utilized to generate predictions and make informed decisions [13], [14]. Machine learning algorithms can be categorized into three distinct groups as shown in Figure 1. Initially, it is imperative to note that algorithms can solely be instructed through the utilization of a training data set that encompasses ground truth information that has been meticulously annotated by experts in the respective field. This particular approach is commonly referred to as supervised learning. Furthermore, within the domain of unsupervised learning, algorithms have the capability to undergo training without relying on human-labelled data. Thirdly, reinforcement learning places significant emphasis on the algorithm's previous failures and successes as influential factors in shaping its subsequent learning processes [15]–[18].

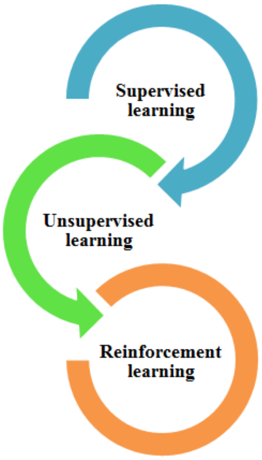

Figure 1. The machine learning categories

The significance of machine learning strategies is increasing in the field of radiology due to the substantial volume of data generated on a regular basis. Machine learning techniques offer the capability to analyze and utilize large-scale datasets for training AI models, which is more efficient compared to conventional statistical methods [19], [20]. Convolutional neural networks (CNNs) represent a specific class of algorithms employed within the realm of deep learning, which constitutes a subfield of supervised machine learning. These neural networks possess concealed layers and are structured in a manner that mimics the organization of human neurons [21], [22].

In traditional radiology applications, the input neurons of a network are constructed using integrated feature vectors, and the network subsequently comprises multiple hidden layers consisting of neural nodes. In order to establish a connection with the output neurons that correspond to the model's final result, each node forms connections with nodes in different layers, with the strength of these connections being determined by varying weights [23]–[25]. This review paper aims to provide an overview of the application of AI in radiology applications, specifically for prostate MRI. The field of AI in prostate MRI has garnered significant attention in the past five years, primarily driven by the advancements in deep learning-based AI applications.

2. THE PERFORMANCE OF AI IN PROSTATE CANCER BASED-MRI SCANS

The extensive implementation of prostate MRI has led to a considerable variation in the quality of scans obtained. The factors that contribute to the scanning process encompass various elements such as the presence of a hip prosthesis, patient motion, and rectal gas, as well as the characteristics of the equipment and pulse sequence parameters [26], [27]. The PI-RADS v. 2.1 document provides comprehensive information regarding the suggested technological prerequisites and patient preparation methodologies aimed at enhancing the quality of prostate MRI [10]. Although there is a general correlation between strict adherence to PI-RADS technical criteria and higher-quality prostate MRI scans [28], [29] it is important to note that this relationship is not universally consistent [30] Moreover, the impact of patient preparation measures is highly varied, encompassing procedures such as bowel preparation and the administration of antispasmodic medications [30]–[32]. The European prostate MRI experts have recently released prostate imaging quality (PI-QUAL), which is among several ongoing global initiatives aimed at improving the quality of prostate MRI [33] The primary objective of this system is to evaluate and determine the diagnostic efficacy of various pulse sequences utilized in prostate MRI [33]. A recent study examined the inter reader agreement for PI-QUAL using a sample of 103 patients and two dedicated radiologists. Significant concurrence was observed for each PI-QUAL score ($r = 0.85$, $p < 0.001$, percent agreement = 84%). The diagnostic quality of T2-weighted imaging, dynamic contrast-enhanced MRI, and diffusion-weighted imaging demonstrated a substantial level of agreement, with 92%, 88%, and 78% of the 103 scans, respectively, yielding high-quality results [34]. The forthcoming disclosure will provide insights into the true impact of the PI-QUAL evaluation system on the improvement of prostate MRI quality. Limited scholarly investigation has been conducted pertaining to the utilization of AI for the assessment and enhancement of the caliber of prostate MRI scans. In a preliminary study comprising a cohort of 30 individuals, Gassenmaier *et al.* [35] conducted a comparative analysis between the utilization of a novel deep learning (DL) T2 weighted turbo spin echo imaging sequence and conventional T2 weighted turbo spin echo imaging in prostate MRI. The researchers in this study were able to achieve faster image acquisitions by training the deep learning algorithm using a representative data pool. The methodology employed data consistency inside a parallel imaging signal model following the completion of training. The rapid reconstruction of MR images using the fixed-unrolled technique is based on the principles of data consistency, trainable Nesterov momentum, and regularization using convolutional neural networks (CNN). The regularization approach employs a novel hierarchical iterative network architecture. This network utilizes a technique of iteratively decreasing and increasing the resolution of feature maps, resulting in a lower memory usage compared to conventional CNNs. The network received under sampled k-space data and conventional coil-sensitivity maps. The acquisition time for image capture of the deep learning-based T2 sequence was 1 minute and 38 seconds, in contrast to the conventional T2 sequence, which required 4 minutes and 37 seconds. The performance of lesion identification was enhanced with the implementation of the deep learning-based T2 sequence, as a result of decreased noise levels and improved image quality ratings [35]. Further validation in larger cohorts is necessary for this feasibility study.

The availability of consistently high-quality imaging studies during read-outs would significantly enhance the performance of radiologists in their work. There are several ongoing initiatives aimed at enhancing the standard of prostate MRI, and the utilization of AI in addressing this matter is currently in its nascent stages. Nevertheless, the integration of AI-based MRI quality models within structured frameworks such as PI-QUAL has the potential to augment this process (5).

3. THE PERFORMANCE OF AI IN PROSTATE TISSUE SEGMENTATION

The delineation or partitioning of the prostate using magnetic resonance imaging (MRI) scans has significant physiological and therapeutic consequences [36]. According to the guidelines of PI-RADS v. 2.1, it is utilized for multiple purposes including preparing MRI data for leading specimens in fusion-guided examination platforms that incorporate transrectal ultrasonography with magnetic resonance imaging (MRI), assisting in the planning of radiation therapy, and providing a precise measurement of the total volume of the prostate gland for normalizing serum prostate-specific antigen (PSA) density [37]. The process of manually delineating the prostate is characterized by a high degree of labor intensity and a susceptibility to errors [38]. The application of AI in prostate segmentation is a prevalent practice. However, the manual processing of prostate MRI data is a laborious task, and the availability of commercial solutions for this purpose is currently limited [39]. In contemporary discourse, there is a prevailing notion that AI systems based on deep learning techniques exhibit notable efficacy in the task of segmenting the prostate gland and its respective zones.

Wang *et al.* [40] developed a prostate segmentation model for T2-weighted MRI that is fully automated. This model utilizes a 3D fully convolutional network with deep supervision. The researchers observed a mean dice similarity coefficient (DSC) of 0.88 (range, 0.83-0.93) for the entirety of the prostate when comparing the AI model with the hand segmentations. Sanford *et al.* [41] employed a deep learning methodology that integrated both 2D and 3D architectures, along with the inclusion of transfer learning, in order to develop an algorithm capable of accurately segmenting the entire prostate and the transition zone (TZ). According to the study, the mean Dice similarity coefficients (DSCs) for the entire prostate and TZ were 0.931 and 0.89, respectively. The utilization of a distinctive data augmentation technique in this study resulted in notable improvements in the segmentation performances of both the entire prostate and the TZ. Specifically, the segmentation performances were enhanced by 2.2% and 3% for the entire prostate and TZ, respectively. This augmentation technique was specifically designed to address the deformations, intensity variations, and alterations in image quality that are commonly observed in MRI data obtained from five distinct medical centers [41]. Anisotropic hybrid network (AH-Net) architecture is shown in Figure 2 as part of the training, validation, and testing procedures.

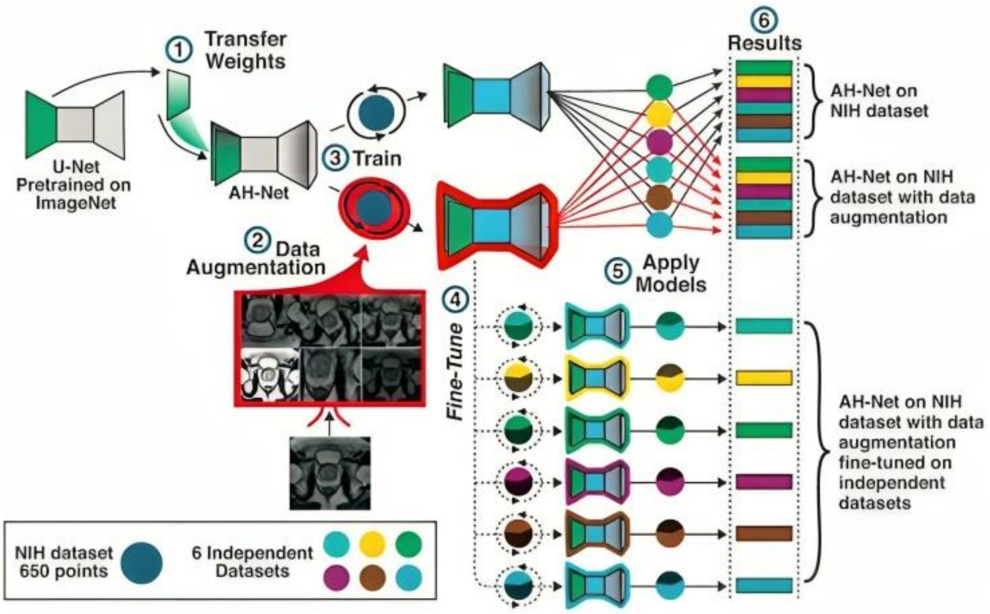

Figure 2. Anisotropic hybrid network (AH-Net) architecture as part of the training, validation, and testing procedure [41]

According to a recent study by Bardis *et al.* [42], the average DSCs for the entire prostate, TZ, and peripheral zone (PZ) were 0.94, 0.91, and 0.774, respectively. The study involved a deep learning model that was constructed using three convolutional networks with a U-Net architecture. The dataset used in the study consisted of 242 patients.

Prostate segmentation has garnered significant attention as one of the primary applications of AI in prostate MRI. Several algorithms for prostate segmentation have been documented in the existing literature. However, it is worth noting that only a limited selection of five algorithms is currently accessible on commercially available platforms designed for user interaction. The Food and Drug Administration (FDA) has granted approval for the utilization of the following devices within the United States: Prostate MR® (manufactured by Siemens), Quantib Prostate® (manufactured by Quantib), OnQ Prostate® (manufactured by Cortechs.ai), PROView® (manufactured by GE Medical Systems), and QP-Prostate® (manufactured by Quibim) [43], [44]. The utilization of AI-powered prostate segmentation algorithms offers two distinct advantages: the ability to obtain precise prostate-specific antigen (PSA) density calculations and a reduction in the amount of time required for MRI data preparation in the context of biopsies. Automated segmentation of the prostate and its zones can provide valuable assistance in the detection and classification of intraprostatic lesions (5).

4. AI IN INTRAPROSTATIC INFLAMMATION SCREENING

The success of finding intraprostatic lesions during prostate MRI scans has a direct effect on how well clinically significant prostate cancer can be found with MRI guidance. As prostate MRI becomes more common in clinical practice, a reliable AI system with a satisfactory true-positive/false-positive rate is in high demand [45], [46]. Ishioka *et al.* [47] in their research of 335 patients, created a DL-based model that made use of U-Net and residual network (ResNet) designs to identify specific lesions indicative of biopsy-confirmed prostate cancer. Area under the curve (AUC) values for prostate cancer detection obtained from testing the model on two different populations were 0.636 and 0.645, respectively [47]. For the purpose of identifying lesions on MRI that may indicate the presence of cancer after a targeted biopsy was performed, Schelb *et al.* [48] constructed and evaluated a U-Net-based DL model that was trained on data from 250 patients. On a per-patient basis, the sensitivity and specificity of the PI-RADS cut-offs 3 and above versus 4 and above were 96% and 88%, respectively, in the test set [48]. Another study involving 292 low-risk prostate cancer patients found that a U-Net-based DL model could detect targeted biopsy-confirmed prostate cancer lesions with volumes of >0.03 to >0.5 cc with an average sensitivity of 82% to 92% and an AUC of 0.65-0.89. Larger data sets are preferable for training AI algorithms, according to experts [49]. Yoo *et al.* [50] trained a ResNet architecture-based neural network on 427 cases using MRI and guided biopsies, and the reported AUCs for prostate cancer identification in a separate 108 sample size test cohort were 0.87 and 0.84 at the slice and patient level, respectively. The AI was a commercial system that has been approved for use in both Europe and the US. The average performance of radiologists using an AI system increased from 0.84 to 0.88 when searching for PI-RADS >3 lesions. The median reading time in the unaided/aided scenario dropped from 103 to 81 s, a reduction of 21%. Inter reader agreement also improved, from = 0.22 to 0.36. This was a multi reader study designed to simulate what a radiologist would see before performing a biopsy; hence, histopathological validation was not included. Despite these caveats, the work provides a useful blueprint for how to evaluate lesion detection AI systems for prostate MRI [51]. Saha *et al.* [52] built a sophisticated AI model consisting of two parallel 3D CNNs (dual-attention U-Net detector and residual classifier) and a decision fusion node. The model was trained on data from 1,950 patients and its purpose is to automate the identification of clinically relevant prostate cancer using biparametric MRI (bpMRI). The experiment was conducted on a sample size of 486 patients. The authors achieved superior results compared to four advanced baseline architectures (U-SEResNet, unit network (UNet)++, U-Net, and Attention U-Net) in diagnosing patients. They obtained an area under the receiver operating characteristic curve of 0.882±0.030 and sensitivity values of 83.69±5.22% and 93.19±2.96% at false positive rates of 0.50 and 1.46 per patient, respectively. Notably, this AI model exhibits a moderate level of agreement with human radiologists (0.51±0.04) and pathologists (0.56±0.06). A recent meta-analysis of 12 trials found that the area under the curve (AUC) for detecting prostate cancer was 0.86, which is considered clinically significant. The 95% confidence interval for this AUC ranged from 0.81 to 0.91 [52].

Prostate cancer analysis there is still several caveats despite the fact that the present published results are encouraging for AI applications in prostate cancer detection with MRI. The first is that large-scale, diversified, and well-annotated training and independent testing data sets are essential for DL-based AI algorithms [53]. Current evidence in the literature is largely based on research with sample sizes of 1,000 cases, which is likely to limit the widespread applicability of existing AI systems. Since data governance standards might vary globally, and bureaucracy can frequently be time-consuming and resource-intensive, it can be difficult to construct big, multicenter, and consequently diverse data sets for constructing stronger AI models. In order to speed up the construction of models between institutions and provide higher generalizability in clinical application without actual data exchange, alternatives such as federated learning can be highly effective [54]. The current published performance measures are not reflective of a real-world scenario because they are largely based on cross-validation and do not involve a real-world interaction between a radiologist and AI. The consequences of such a connection and the discrepancies between radiologist interpretations and AI findings are not well understood [55]. The AI will undoubtedly prove useful in prostate cancer detection during MRI in the future.

5. CONCLUSION

In conclusion, there has been a substantial rise in the utilization of MRI over the past decade. The utilization of prostate MRI in the detection of prostate cancer is influenced by several critical procedures, nearly all of which are currently vulnerable to human-induced errors. In recent years, there have been notable advancements in the field of imaging attributed to AI. It has been suggested that AI-based systems possess the ability to undertake tasks traditionally performed by diagnostic radiologists. The tasks encompassed in this study involve the assessment of scan quality, segmentation of the prostate, detection of lesions, and classification of PI-RADS in research environments. Currently, there are commercial AI platforms for prostate MRI. However, the majority of AI solutions developed for this purpose in research settings necessitate training with larger and more diverse datasets. Furthermore, before these AI models can be routinely employed in clinical practice, they must undergo testing in actual situations.

REFERENCES

[1] K. Thakore MD *et al.*, “Prostate cancer incidence and survival by race: A narrative review,” *International Public Health Journal*, vol. 15, no. 1, pp. 69–75, 2023.

[2] S. Belkahla, I. Nahvi, S. Biswas, I. Nahvi, and N. Ben Amor, “Advances and development of prostate cancer, treatment, and strategies: A systemic review,” *Frontiers in Cell and Developmental Biology*, vol. 10, Sep. 2022, doi: 10.3389/fcell.2022.991330.

[3] C. Würnschimmel, T. Chandrasekar, L. Hahn, T. Esen, S. F. Shariat, and D. Tilki, “MRI as a screening tool for prostate cancer: Current evidence and future challenges,” *World Journal of Urology*, vol. 41, no. 4, pp. 921–928, Feb. 2022, doi: 10.1007/s00345-022-03947-y.

[4] A. Saha *et al.*, "Artificial intelligence and radiologists at prostate cancer detection in MRI-the PI-CAI challenge," *Medical Imaging with Deep Learning*, 2023.
[5] B. Turkbey and M. A. Haider, "Deep learning-based artificial intelligence applications in prostate MRI: Brief summary," *The British Journal of Radiology*, vol. 95, no. 1131, Mar. 2022, doi: 10.1259/bjr.20210563.
[6] B. Turkbey and A. Oto, "Factors impacting performance and reproducibility of PI-RADS," *Canadian Association of Radiologists Journal*, vol. 72, no. 3, pp. 337–338, Aug. 2021, doi: 10.1177/0846537120943886.
[7] A. Stabile *et al.*, "Factors influencing variability in the performance of multiparametric magnetic resonance imaging in detecting clinically significant prostate cancer: a systematic literature review," *European Urology Oncology*, vol. 3, no. 2, pp. 145–167, Apr. 2020, doi: 10.1016/j.euo.2020.02.005.
[8] A. R. Padhani, I. G. Schoots, B. Turkbey, G. Giannarini, and J. O. Barentsz, "A multifaceted approach to quality in the MRI-directed biopsy pathway for prostate cancer diagnosis," *European Radiology*, vol. 31, no. 6, pp. 4386–4389, Jun. 2021, doi: 10.1007/s00330-020-07527-9.
[9] J. C. Weinreb *et al.*, "PI-RADS prostate imaging–reporting and data system: 2015, version 2," *European Urology*, vol. 69, no. 1, pp. 16–40, Jan. 2016, doi: 10.1016/j.eururo.2015.08.052.
[10] B. Turkbey *et al.*, "Prostate imaging reporting and data system version 2.1: 2019 update of prostate imaging reporting and data system version 2," *European Urology*, vol. 76, no. 3, pp. 340–351, Sep. 2019, doi: 10.1016/j.eururo.2019.02.033.
[11] S. A. Harmon, S. Tuncer, T. Sanford, P. L. Choyke, and B. Türkbey, "Artificial intelligence at the intersection of pathology and radiology in prostate cancer," *Diagnostic and Interventional Radiology*, vol. 25, no. 3, 2019.
[12] S. Masoudi *et al.*, "Quick guide on radiology image pre-processing for deep learning applications in prostate cancer research," *Journal of Medical Imaging*, vol. 8, no. 01, Jan. 2021, doi: 10.1117/1.JMI.8.1.010901.
[13] Z. H. Zhou, "Machine learning," *Springer Nature*, 2021.
[14] M. Shehab *et al.*, "Machine learning in medical applications: A review of state-of-the-art methods," *Computers in Biology and Medicine*, vol. 145, Jun. 2022, doi: 10.1016/j.compbiomed.2022.105458.
[15] T. Oladipupo, "Types of machine learning algorithms," in *New Advances in Machine Learning*, InTech, 2010.
[16] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *SN Computer Science*, vol. 2, no. 3, May 2021, doi: 10.1007/s42979-021-00592-x.
[17] L. Lo Vercio *et al.*, "Supervised machine learning tools: a tutorial for clinicians," *Journal of Neural Engineering*, vol. 17, no. 6, Dec. 2020, doi: 10.1088/1741-2552/abbff2.
[18] M. Usama *et al.*, "Unsupervised machine learning for networking: Techniques, applications and research challenges," *IEEE Access*, vol. 7, pp. 65579–65615, 2019, doi: 10.1109/ACCESS.2019.2916648.
[19] Z. Obermeyer and E. J. Emanuel, "Predicting the future — big data, machine learning, and clinical medicine," *New England Journal of Medicine*, vol. 375, no. 13, pp. 1216–1219, Sep. 2016, doi: 10.1056/NEJMp1606181.
[20] A. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," *New England Journal of Medicine*, vol. 380, no. 14, pp. 1347–1358, Apr. 2019, doi: 10.1056/NEJMra1814259.
[21] J. P. Bharadiya, "Convolutional neural networks for image classification," *International Journal of Innovative Science and Research Technology*, vol. 8, no. 5, pp. 673–677, 2023, doi: 10.5281/zenodo.7952031.
[22] N. Sharma, V. Jain, and A. Mishra, "An analysis of convolutional neural networks for image classification," *Procedia Computer Science*, vol. 132, pp. 377–384, 2018, doi: 10.1016/j.procs.2018.05.198.
[23] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-Net: fully convolutional neural networks for volumetric medical image segmentation," in *2016 Fourth International Conference on 3D Vision (3DV)*, Oct. 2016, pp. 565–571, doi: 10.1109/3DV.2016.79.
[24] H. Yu, L. T. Yang, Q. Zhang, D. Armstrong, and M. J. Deen, "Convolutional neural networks for medical image analysis: State-of-the-art, comparisons, improvement and perspectives," *Neurocomputing*, vol. 444, pp. 92–110, Jul. 2021, doi: 10.1016/j.neucom.2020.04.157.
[25] G. Zaharchuk, E. Gong, M. Wintermark, D. Rubin, and C. P. Langlotz, "Deep learning in neuroradiology," *American Journal of Neuroradiology*, vol. 39, no. 10, pp. 1776–1784, Oct. 2018, doi: 10.3174/ajnr.A5543.
[26] A. B. Rosenkrantz *et al.*, "Prostate magnetic resonance imaging and magnetic resonance imaging targeted biopsy in patients with a prior negative biopsy: A consensus statement by AUA and SAR," *Journal of Urology*, vol. 196, no. 6, pp. 1613–1618, Dec. 2016, doi: 10.1016/j.juro.2016.06.079.
[27] G. A. Sonn *et al.*, "Prostate magnetic resonance imaging interpretation varies substantially across radiologists," *European Urology Focus*, vol. 5, no. 4, pp. 592–599, Jul. 2019, doi: 10.1016/j.euf.2017.11.010.
[28] M. Coskun, A. F. Sarp, S. Karasu, M. F. Gelal, and B. Turkbey, "Assessment of the compliance with minimum acceptable technical parameters proposed by PI-RADS v2 guidelines in multiparametric prostate MRI acquisition in tertiary referral hospitals in the Republic of Turkey," *Diagnostic and Interventional Radiology*, vol. 25, no. 6, pp. 421–427, Feb. 2020, doi: 10.5152/dir.2019.18537.
[29] S. J. Esses, S. S. Taneja, and A. B. Rosenkrantz, "Imaging facilities' adherence to PI-RADS v2 minimum technical standards for the performance of prostate MRI," *Academic Radiology*, vol. 25, no. 2, pp. 188–195, Feb. 2018, doi: 10.1016/j.acra.2017.08.013.
[30] J. Sackett *et al.*, "Quality of prostate MRI: is the PI-RADS standard sufficient?," *Academic Radiology*, vol. 28, no. 2, pp. 199–207, Feb. 2021, doi: 10.1016/j.acra.2020.01.031.
[31] M. Wagner *et al.*, "Effect of butylscopolamine on image quality in MRI of the prostate," *Clinical Radiology*, vol. 65, no. 6, pp. 460–464, Jun. 2010, doi: 10.1016/j.crad.2010.02.007.
[32] T. Ullrich *et al.*, "Hyoscine butylbromide significantly decreases motion artefacts and allows better delineation of anatomic structures in mp-MRI of the prostate," *European Radiology*, vol. 28, no. 1, pp. 17–23, Jan. 2018, doi: 10.1007/s00330-017-4940-7.
[33] F. Giganti, C. Allen, M. Emberton, C. M. Moore, and V. Kasivisvanathan, "Prostate imaging quality (PI-QUAL): a new quality control scoring system for multiparametric magnetic resonance imaging of the prostate from the PRECISION trial," *European Urology Oncology*, vol. 3, no. 5, pp. 615–619, Oct. 2020, doi: 10.1016/j.euo.2020.06.007.
[34] F. Giganti *et al.*, "Inter-reader agreement of the PI-QUAL score for prostate MRI quality in the NeuroSAFE PROOF trial," *European Radiology*, vol. 32, no. 2, pp. 879–889, Feb. 2022, doi: 10.1007/s00330-021-08169-1.
[35] S. Gassenmaier, S. Afat, D. Nickel, M. Mostapha, J. Herrmann, and A. E. Othman, "Deep learning–accelerated T2-weighted imaging of the prostate: Reduction of acquisition time and improvement of image quality," *European Journal of Radiology*, vol. 137, Apr. 2021, doi: 10.1016/j.ejrad.2021.109600.
[36] Z. Khan, N. Yahya, K. Alsaih, M. I. Al-Hiyali, and F. Meriaudeau, "Recent automatic segmentation algorithms of MRI prostate regions: a review," *IEEE Access*, vol. 9, pp. 97878–97905, 2021, doi: 10.1109/ACCESS.2021.3090825.
[37] A. M. Brown *et al.*, "Recent advances in image-guided targeted prostate biopsy," *Abdominal Imaging*, vol. 40, no. 6, pp. 1788–1799, Aug. 2015, doi: 10.1007/s00261-015-0353-8.

[38] B. Garvey, B. Turkbey, H. Truong, M. Bernardo, S. Periaswamy, and P. L. Choyke, "Clinical value of prostate segmentation and volume determination on MRI in benign prostatic hyperplasia," *Diagnostic and Interventional Radiology*, vol. 20, no. 3, pp. 229–233, May 2014, doi: 10.5152/dir.2014.13322.

[39] K. G. van Leeuwen, S. Schalekamp, M. J. C. M. Rutten, B. van Ginneken, and M. de Rooij, "Artificial intelligence in radiology: 100 commercially available products and their scientific evidence," *European Radiology*, vol. 31, no. 6, pp. 3797–3804, Jun. 2021, doi: 10.1007/s00330-021-07892-z.

[40] B. Wang *et al.*, "Deeply supervised 3D fully convolutional networks with group dilated convolution for automatic MRI prostate segmentation," *Medical Physics*, vol. 46, no. 4, pp. 1707–1718, Apr. 2019, doi: 10.1002/mp.13416.

[41] T. H. Sanford *et al.*, "Data augmentation and transfer learning to improve generalizability of an automated prostate segmentation model," *American Journal of Roentgenology*, vol. 215, no. 6, pp. 1403–1410, Dec. 2020, doi: 10.2214/AJR.19.22347.

[42] M. Bardis *et al.*, "Segmentation of the prostate transition zone and peripheral zone on MR images with deep learning," *Radiology: Imaging Cancer*, vol. 3, no. 3, May 2021, doi: 10.1148/rycan.2021200024.

[43] "OnQ prostate," *Cortechs AI*. https://www.cortechs.ai/products/onq-prostate/ (accessed Jul. 10, 2023).

[44] J. J. Twilt, K. G. van Leeuwen, H. J. Huisman, J. J. Fütterer, and M. de Rooij, "Artificial intelligence based algorithms for prostate cancer classification and detection on magnetic resonance imaging: A narrative review," *Diagnostics*, vol. 11, no. 6, May 2021, doi: 10.3390/diagnostics11060959.

[45] G. De Meerleer *et al.*, "The magnetic resonance detected intraprostatic lesion in prostate cancer: Planning and delivery of intensity-modulated radiotherapy," *Radiotherapy and Oncology*, vol. 75, no. 3, pp. 325–333, Jun. 2005, doi: 10.1016/j.radonc.2005.04.014.

[46] M. J. Belue and B. Turkbey, "Tasks for artificial intelligence in prostate MRI," *European Radiology Experimental*, vol. 6, no. 1, Dec. 2022, doi: 10.1186/s41747-022-00287-9.

[47] J. Ishioka *et al.*, "Computer-aided diagnosis of prostate cancer on magnetic resonance imaging using a convolutional neural network algorithm," *BJU International*, vol. 122, no. 3, pp. 411–417, Sep. 2018, doi: 10.1111/bju.14397.

[48] P. Schelb *et al.*, "Classification of cancer at prostate MRI: Deep learning versus clinical PI-RADS assessment," *Radiology*, vol. 293, no. 3, pp. 607–617, Dec. 2019, doi: 10.1148/radiol.2019190938.

[49] M. P. Wilson *et al.*, "Diagnostic accuracy of dual-energy CT for the detection of bone marrow edema in the appendicular skeleton: a systematic review and meta-analysis," *European Radiology*, vol. 31, no. 3, pp. 1558–1568, Mar. 2021, doi: 10.1007/s00330-020-07236-3.

[50] S. Yoo, I. Gujrathi, M. A. Haider, and F. Khalvati, "Prostate cancer detection using deep convolutional neural networks," *Scientific Reports*, vol. 9, no. 1, Dec. 2019, doi: 10.1038/s41598-019-55972-4.

[51] D. J. Winkel *et al.*, "A novel deep learning based computer-aided diagnosis system improves the accuracy and efficiency of radiologists in reading biparametric magnetic resonance images of the prostate: Results of a multireader, multicase study," *Investigative Radiology*, vol. 56, no. 10, pp. 605–613, Oct. 2021, doi: 10.1097/RLI.0000000000000780.

[52] A. Saha, M. Hosseinzadeh, and H. Huisman, "End-to-end prostate cancer detection in bpMRI via 3D CNNs: Effects of attention mechanisms, clinical priori and decoupled false positive reduction," *Medical Image Analysis*, vol. 73, Oct. 2021, doi: 10.1016/j.media.2021.102155.

[53] R. Cuocolo *et al.*, "Machine learning for the identification of clinically significant prostate cancer on MRI: A meta-analysis," *European Radiology*, vol. 30, no. 12, pp. 6877–6887, Dec. 2020, doi: 10.1007/s00330-020-07027-w.

[54] K. V Sarma *et al.*, "Federated learning improves site performance in multicenter deep learning without data sharing," *Journal of the American Medical Informatics Association*, vol. 28, no. 6, pp. 1259–1264, Jun. 2021, doi: 10.1093/jamia/ocaa341.

[55] A. S. Panayides *et al.*, "AI in medical imaging informatics: current challenges and future directions," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 7, pp. 1837–1857, Jul. 2020, doi: 10.1109/JBHI.2020.2991043.

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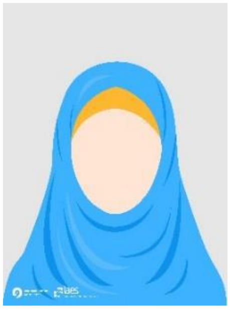

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