·综　述·

# 超声人工智能在前列腺癌诊断中的应用进展

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［摘要］　前列腺癌（prostate cancer，PCa）的早期诊断和及时干预对改善PCa患者预后意义重大。超声技术具有经济、方便、可术中实时成像等优点，成为PCa诊疗的重要工具，近年来人工智能（artificial intelligence，AI）技术在超声PCa诊疗中得到快速发展。本文从传统机器学习、深度学习和强化学习3个方面综述了超声AI在PCa领域的应用进展。机器学习借助特征工程与模型训练，优化了超声图像的分割精度；同时，通过整合超声多模态影像、临床及蛋白组学特征，机器学习模型提高了PCa的诊断准确度，并增强了对转移性PCa的鉴别能力。深度学习凭借其端到端的学习能力，不仅能有效地识别PCa病灶，还能对其进行精确分级；另外，在PCa近距离放射治疗中，深度学习可从超声图像中准确识别前列腺临床目标体积，并能高效精准地自动重建导管和治疗针，减少人工操作误差和操作时间。强化学习通过交互试错与累积奖励机制，实现了对超声图像质量的自动评估，从而筛选出高质量图像用于AI模型训练，有效地减轻了医师图像标注的工作量；此外，强化学习通过自适应术中规划，降低了术中采样误差，提高了PCa活检的准确度和可靠性。最后，本文分析了目前超声AI技术在PCa临床应用中仍面临的挑战。未来需建立多中心高质量共享数据集，开发可解释性强、安全性好、临床实用性高的超声AI模型，确立标准化的监管策略，以实现超声AI系统切实服务于PCa患者的精准个性化诊疗。

［关键词］　前列腺癌；超声；人工智能；机器学习；深度学习；强化学习
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**Advances in the application of ultrasound artificial intelligence in prostate cancer**　JIANG Wanjun[1], WANG Zhen[2], ZHAO Yunxin[1]　(1. Department of Ultrasound, Shanghai Punan Hospital of Pudong New District, Shanghai 200125, China; 2. College of Medical Instrumentation, Shanghai University of Medicine & Health Sciences, Shanghai 201318, China)

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［**Abstract**］ The early diagnosis and timely intervention of prostate cancer (PCa) are critical for improving patient prognosis. Ultrasound technology, with its economic affordability, convenience, and real-time intraoperative imaging capabilities, has emerged as a vital tool in the diagnosis and treatment of PCa. In recent years, the application of artificial intelligence (AI) in ultrasound-based PCa diagnosis and treatment has demonstrated remarkable progress. This review examined the advancements of ultrasound AI in the field of PCa from three perspectives: traditional machine learning, deep learning, and reinforcement learning. Machine learning, through feature engineering and model training, has optimized the segmentation accuracy of ultrasound images. Furthermore, by integrating multimodal ultrasound imaging, clinical and proteomic features, machine learning models have enhanced diagnostic accuracy for PCa and improved the ability to differentiate metastatic PCa. Deep learning, leveraging its end-to-end learning capability, not only effectively identifies PCa lesions but also enables precise grading of these lesions. Additionally, in brachytherapy for PCa, deep learning has accurately delineated the clinical target volume of the prostate from ultrasound images and efficiently automated the reconstruction of catheters and treatment needles, thereby reducing human operational errors and procedure time. Reinforcement learning, through its trial-and-error interaction and cumulative reward mechanism, has enabled automated quality assessment of ultrasound images to select high-quality images for AI model training and thereby alleviating the workload of manual image annotation by clinicians. Moreover, reinforcement learning has improved the accuracy and reliability of PCa biopsies by reducing intraoperative sampling errors through adaptive intraoperative planning. Finally, this review analyzed the current challenges faced in the clinical application of ultrasound AI for PCa. Future efforts should focus on establishing multi-center, high-quality shared datasets, developing ultrasound AI models with strong interpretability, safety, and clinical practicality, and formulating standardized regulatory strategies. These steps are essential to ensure that ultrasound AI systems can effectively serve the precise and personalized diagnosis and treatment of PCa patients.

［**Key words**］ Prostate cancer; Ultrasound; Artificial intelligence; Machine learning; Deep learning; Reinforcement learning

前列腺癌（prostate cancer，PCa）在全球男性癌症发病率中高居第2位，据最新数据统计，中国PCa年发病患者数达13.42万例，死亡患者数约为4.75万例[1]。PCa通常早期无症状，晚期发现患者预后较差，早期诊断和治疗至关重要。

磁共振成像（magnetic resonance imaging，MRI）在PCa早期诊断和精确分期中发挥着重要作用，但存在高成本、低获得性和患者接受度差等局限性，同时16%~35%的临床显著PCa（clinical significant PCa，csPCa）仍可能被遗漏[2]。传统经直肠超声（transrectal ultrasound，TRUS）因其成本低、操作灵活、便携性强等优势至今仍被广泛使用，且随着剪切波弹性成像、超声造影和高分辨率超声等先进超声技术的应用，PCa检出率得到了较大的提高[3]，但仍存在微小病变识别准确度低、多模态数据整合困难、主观性强等问题。近年来人工智能（artificial intelligence，AI）在医学领域的应用得到快速发展，通过高效的数据分析及持续学习、自适应多模态融合、诊疗性能的客观化评估，超声AI技术在PCa的诊断和治疗中也得到了广泛、深入的应用[4]。

AI技术通常分为传统机器学习、深度学习和强化学习，传统机器学习分特征工程与模型训练两个阶段实现给定任务；深度学习能自动学习和提取特征，可做到从输入到输出的端到端映射；强化学习通过与环境的交互试错来学习行动策略，实现最大化累积奖励。无论是机器学习、深度学习，还是强化学习在基于PCa超声数据的多个任务上均得到了有效应用，如PCa图像分割、病灶识别、配准融合等。AI技术通过对超声数据的有效表示及算法模型的持续更新、多维度的模态融合方法、可量化的客观评价指标，可较好地提升识别PCa微小病变的准确度，实现对病变特征的多角度分析，并避免人为主观因素导致的诊疗差异[4]。本文概述超声AI技术在PCa应用中的研究进展，旨在为临床实践及未来研究提供参考。

## 1　传统机器学习技术在PCa中的应用

超声图像分割在PCa诊断治疗中具有非常重要的作用，国内外较多研究将传统机器学习应用于图像分割。为解决超声图像中因阴影伪影导致的前列腺分割性能下降问题，Peng等[5]建立了名为H-SegMed的混合机器学习模型。在此基础上，该团队进一步开发了一种基于主曲线的自适应多边形跟踪模型，以增强前列腺分割的鲁棒性，并提升分割精度[6]。

由于传统TRUS对前列腺低回声和等回声病灶识别困难，德国基尔大学Loch教授团队[7]将人工神经网络用于TRUS图像分析，通过提取PCa图像中的亚视觉特征，可较好地区分前列腺组织的良恶性。进一步，Lorusso等[8]在法国马赛Paoli-Calmettes癌症中心采集的PCa超声图像上进行了外部验证。人工神经网络在机器人扫描得到的前列腺超声图像中也具有较好的csPCa检测性能[9]。

超声射频信号拥有丰富的组织声学信息，可提供较细致的前列腺微观病变特征。有研究[10]从超声射频信号中提取了放射组学特征及频谱特征，通过支持向量机较好地区分出癌区和非癌区。

近年来，机器学习在PCa多模态分析中也得到了较好的应用。Chen等[11]通过整合超声造影和剪切波弹性成像，利用机器学习构建了超声多模态诊断模型，csPCa的诊断性能优于单超声模态。Ou等[12]和Sun等[13]建立了集成临床与超声影像的机器学习诊断模型，相比仅使用临床因素，诊断性能得到提高。Fu等[14]从超声影像中提取了17个特征，通过与蛋白质组学数据进行关联，发现4个影像学特征与PCa转移性生物标志物显著相关，基于这4个特征的机器学习模型可较好地诊断出转移性PCa。

## 2 深度学习技术在PCa中应用

深度学习可应用于PCa超声数据的数据增强、标签自校准及降低标签依赖。Lu等[15]提出了一种嵌入空间线性插值增强策略，丰富了样本多样性。To等[16]借助深度学习及病理学信息，校正了因噪声而受到污染的标签。Wilson等[17]利用自监督学习方法从高频超声数据中提取特征，降低了对超声数据标签的依赖。

深度学习技术在前列腺TRUS图像分割中有较多的应用。为解决图像分割中数据标记缺乏及语义信息广泛的问题，Li等[18]提出了双向语义约束的BiSeC模型。针对TRUS图像低信噪比及存在伪影的问题，Vesal等[19]提出了一种结合监督域适应与知识蒸馏的深度神经网络用于图像分割。在微超声图像的前列腺边界分割中，Jiang等[20]提出了一种名为MicroSegNet的深度学习模型。针对3D TRUS图像分割，Liu等[21]提出了一种边缘感知注意力生成对抗网络。

深度学习还可用于PCa病灶识别。Li等[22]使用残差网络和特征金字塔网络，结合TRUS图像和穿刺路径，PCa识别性能-曲线下面积（area under curve，AUC）达0.93，高于资深超声科医师的识别结果。Huang等[23]通过迁移学习，在TRUS图像中较好地区分了PCa与良性前列腺增生。Li等[24]提出了一种基于多模块的深度学习模型，实现了对PCa较准确的分级。在多中心临床研究中，Wilson等[25]和Sun等[26]分别采集了微超声图像和TRUS视频，并建立深度集成模型和3D P-Net模型，识别结果与经验丰富的超声科医师相当。Rusu等[27]基于TRUS图像开发了ProCUSNet深度学习模型，csPCa检测效果与MRI相当。

深度学习在PCa多模态检测中也具有较好的应用价值。Wu等[28]和Chan等[29]结合TRUS、超声弹性成像、定量超声中频拟合、声辐射力脉冲成像，通过深度学习模型提升了PCa检出率。Akatsuka等[30]结合TRUS影像和患者的年龄、前列腺特异性抗原、前列腺体积等临床数据，建立卷积神经网络，其csPCa检测的AUC高于仅使用临床数据。此外，深度学习技术还可应用于超声与MRI的配准及融合，提高了PCa的病灶检出率[31-32]。

近距离放射治疗是低风险和中风险PCa的有效治疗方法，常需要实时超声图像引导，以此辅助医师精确定位并植入放射源。Liu等[33]利用卷积神经网络模型实现了导管的高效精准自动重建；Goulet等[34]借助3D-UNet模型，在3D超声图像中较准确地实现了治疗针的自动重建；深度学习在识别前列腺临床目标体积方面也起到了重要作用[35]。

## 3 强化学习技术在PCa中应用

强化学习相比机器学习和深度学习，在序列决策、动态环境适应、长期目标优化方面具有独特的优势[36]，其通过试错学习最优策略，在基于PCa图像的诊疗中，具有较好的灵活性和泛化能力，可实现医师与AI系统之间的良好交互。

图像的质量直接关系到AI模型的可靠性，进而影响PCa诊疗的性能。强化学习可以做到对图像质量的自动评估，筛选出高质量的图像用于AI模型训练。Saeed等[37]开发了一种元强化学习框架，通过同时训练任务预测器和图像质量评估控制器，来评估图像对于下游临床任务的适用性，提高了AI模型对PCa诊疗的准确度，并减少了AI模型对医师标记数据的依赖。

强化学习在前列腺图像分割中也发挥了较大的作用。Sahba等[38]将强化学习中的Q学习方法用于TRUS图像中的前列腺分割，通过Q矩阵存储离线阶段获得的知识，使得图像的平均分割精度达88.1%。为了提高图像分割系统的并行处理

能力与容错性，Ghajari等[39]提出了一种基于多智能体强化学习的超声图像分割方法，通过多智能体分工协同并优化参数，实现了前列腺的高效全局分割。在3D图像分割方面，Bae等[40]将强化学习与神经架构搜索相结合，通过参数共享及最优搜索空间配置，在保证分割精度的前提下提高了分割效率。为了解决TRUS图像标注成本高、耗时长、一致性差的问题，Yi等[41]提出了一种名为Boundary-RL的弱监督强化学习分割方法，该方法将前列腺分割视为边界检测问题，在保证分割精度的前提下降低了数据标注成本。

强化学习在PCa近距离放射治疗中也具有较好的应用价值，Qian等[42]先采用线性规划生成初始治疗计划，再使用基于确定性策略梯度的强化学习对治疗计划进行微调，这种两阶段方法减少了对个人经验的依赖，提高了治疗计划的可重复性，减少了对直肠、膀胱、尿道等器官的损害。在TRUS引导的前列腺活检中，为了减少因图像配准和组织运动导致的采样误差，Gayo等[43]采用基于近端策略优化的强化学习方法，实现了自适应术中规划。与模仿学习相比，该方法降低了术中采样误差，提高了活检的准确性和可靠性。

## 4 挑战和展望

尽管超声AI技术在PCa诊断中的应用取得了较多进展，但在临床实践中还面临数据、技术、监管等多方面挑战。目前PCa超声数据存在有效样本量少、缺乏共享、标签不准确等问题，未来急需建立更大的多中心共享数据集，通过以数据为中心的AI技术降低对标签的依赖，并提高模型的泛化性。目前的超声AI技术在临床应用时通常面临可解释性不足的问题，医师无法理解AI模型的决策依据，未来需要开发可解释性强的AI模型。另一方面，当前超声AI系统尤其是深度学习存在参数大、能耗高的问题，未来需要在保证诊疗性能的同时降低AI系统的复杂性。同时，目前的AI模型较少考虑安全性，未来需借助区块链、同态加密等提高其安全性。目前超声结合多组学如病理组学、基因组学和环境组学等的研究尚不多，不能满足精准医疗背景下的PCa诊断、个性化治疗、预后评估等需求。

未来可在数据、特征、决策3个层面进行PCa超声数据与其他组学的融合，实现多模态信息的互补。另外，目前国内外对超声AI系统的应用缺乏监管，诊疗出错时责任归属不明确，未来需完善法律法规，建立规范合理的标准化监管体系。

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## [参　考　文　献]

[1] HAN B F, ZHENG R S, ZENG H M, et al. Cancer incidence and mortality in China, 2022 [J]. J Natl Cancer Cent, 2024, 4(1): 47-53.
[2] TRECARTEN S, SUNNAPWAR A G, CLARKE G D, et al. Prostate MRI for the detection of clinically significant prostate cancer: update and future directions [J]. Adv Cancer Res, 2024, 161: 71-118.
[3] O'ROURKE K. Can multiparametric ultrasound be used for prostate cancer? [J]. Cancer, 2022, 128(13): 2399.
[4] LARRY GOLDENBERG S, NIR G, SALCUDEAN S E. A new era: artificial intelligence and machine learning in prostate cancer [J]. Nat Rev Urol, 2019, 16(7): 391-403.
[5] PENG T, TANG C Y, WU Y Y, et al. H-SegMed: a hybrid method for prostate segmentation in TRUS images via improved closed principal curve and improved enhanced machine learning [J]. Int J Comput Vis, 2022, 130(8): 1896-1919.
[6] PENG T, WU Y Y, ZHAO J, et al. Organ boundary delineation for automated diagnosis from multi-center using ultrasound images [J]. Expert Syst Appl, 2024, 238: 122128.
[7] LOCH T, LEUSCHNER I, GENBERG C, et al. Artificial neural network analysis (ANNA) of prostatic transrectal ultrasound [J]. Prostate, 1999, 39(3): 198-204.
[8] LORUSSO V, KABRE B, PIGNOT G, et al. External validation of the computerized analysis of TRUS of the prostate with the ANNA/C-TRUS system: a potential role of artificial intelligence for improving prostate cancer detection [J]. World J Urol, 2023, 41(3): 619-625.
[9] HARLAND N, RUSSO G I, KAUFMANN S, et al. Robotic transrectal computed tomographic ultrasound with artificial neural network analysis: first validation and comparison with MRI-guided biopsies and radical prostatectomy [J]. Urol Int, 2022, 106(1): 90-96.

[10] XIAO T L, SHEN W W, WANG Q M, et al. The detection of prostate cancer based on ultrasound RF signal [J]. Front Oncol, 2022, 12: 946965.
[11] CHEN P R, TURCO S, WANG Y, et al. Can 3D multiparametric ultrasound imaging predict prostate biopsy outcome? [J]. Ultrasound Med Biol, 2024, 50(8): 1194–1202.
[12] OU W, LEI J H, LI M H, et al. Ultrasound-based radiomics score for pre-biopsy prediction of prostate cancer to reduce unnecessary biopsies [J]. Prostate, 2023, 83(1): 109–118.
[13] SUN Y, FANG J Y, SHI Y P, et al. Machine learning based on radiomics features combing B-mode transrectal ultrasound and contrast-enhanced ultrasound to improve peripheral zone prostate cancer detection [J]. Abdom Radiol (NY), 2024, 49(1): 141–150.
[14] FU Q H, LUO L, HONG R X, et al. Radiogenomic analysis of ultrasound phenotypic features coupled to proteomes predicts metastatic risk in primary prostate cancer [J]. BMC Cancer, 2024, 24(1): 290.
[15] LU X, GUO Y Q, ZHANG S L, et al. Deep augmented metric learning network for prostate cancer classification in ultrasound images [J]. IEEE J Biomed Health Inform, 2025, 29(3): 1849–1860.
[16] TO M N N, FOOLADGAR F, JAVADI G, et al. Coarse label refinement for improving prostate cancer detection in ultrasound imaging [J]. Int J Comput Assist Radiol Surg, 2022, 17(5): 841–847.
[17] WILSON P F R, GILANY M, JAMZAD A, et al. Self-supervised learning with limited labeled data for prostate cancer detection in high-frequency ultrasound [J]. IEEE Trans Ultrason Ferroelectr Freq Control, 2023, 70(9): 1073–1083.
[18] LI Z X, DU W, SHI Y T, et al. A bi-directional segmentation method for prostate ultrasound images under semantic constraints [J]. Sci Rep, 2024, 14(1): 11701.
[19] VESAL S, GAYO I, BHATTACHARYA I, et al. Domain generalization for prostate segmentation in transrectal ultrasound images: a multi-center study [J]. Med Image Anal, 2022, 82: 102620.
[20] JIANG H X, IMRAN M, MURALIDHARAN P, et al. MicroSegNet: a deep learning approach for prostate segmentation on micro-ultrasound images [J]. Comput Med Imag Graph, 2024, 112: 102326.
[21] LIU M Q, SHAO X, JIANG L P, et al. 3D EAGAN: 3D edge-aware attention generative adversarial network for prostate segmentation in transrectal ultrasound images [J]. Quant Imaging Med Surg, 2024, 14(6): 4067–4085.
[22] LI S Y, YE X Q, TIAN H T, et al. An artificial intelligence model based on transrectal ultrasound images of biopsy needle tract tissues to differentiate prostate cancer [J]. Postgrad Med J, 2024, 100(1182): 228–236.
[23] HUANG T L, LU N H, HUANG Y H, et al. Transfer learning with CNNs for efficient prostate cancer and BPH detection in transrectal ultrasound images [J]. Sci Rep, 2023, 13(1): 21849.
[24] LI X R, LIU Z Y, YANG L. Image enhancement and deep learning in predicting the gleason score of transcrectal ultrasound images of prostate cancer [C] //2024 Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC). April 12–14, 2024, Dalian, China. IEEE, 2024: 7–12.
[25] WILSON P F R, HARMANANI M, TO M N N, et al. Toward confident prostate cancer detection using ultrasound: a multi-center study [J]. Int J Comput Assist Radiol Surg, 2024, 19(5): 841–849.
[26] SUN Y K, ZHOU B Y, MIAO Y, et al. Three-dimensional convolutional neural network model to identify clinically significant prostate cancer in transrectal ultrasound videos: a prospective, multi-institutional, diagnostic study [J]. EClinicalMedicine, 2023, 60: 102027.
[27] RUSU M, JAHANANDISH H, VESAL S, et al. ProCUSNet: prostate cancer detection on B-mode transrectal ultrasound using artificial intelligence for targeting during prostate biopsies [J]. Eur Urol Oncol, 2025, 8(2): 477–485.
[28] WU H, FU J, YE H S, et al. Towards multi-modality fusion and prototype-based feature refinement for clinically significant prostate cancer classification in transrectal ultrasound [M] // Medical Image Computing and Computer Assisted Intervention–MICCAI 2024. Cham: Springer Nature Switzerland, 2024: 724–733.
[29] CHAN D Y, CODY MORRIS D, MOAVENZADEH S R, et al. Multiparametric ultrasound imaging of prostate cancer using deep neural networks [J]. Ultrasound Med Biol, 2024, 50(11): 1716–1723.
[30] AKATSUKA J, NUMATA Y, MORIKAWA H, et al. A data-driven ultrasound approach discriminates pathological high grade prostate cancer [J]. Sci Rep, 2022, 12(1): 860.
[31] GUO H T, XU X A, SONG X R, et al. Ultrasound frame-to-volume registration via deep learning for interventional guidance [J]. IEEE Trans Ultrason Ferroelectr Freq Control, 2023, 70(9): 1016–1025.
[32] AZAMPOUR M F, MACH K, FATEMIZADEH E, et al. Multitask weakly supervised generative network for MR-US registration [J]. IEEE Trans Med Imaging, 2024, 43(11): 3780–3793.
[33] LIU D, TUPOR S, SINGH J, et al. The challenges facing deep learning-based catheter localization for ultrasound guided high-dose-rate prostate brachytherapy [J]. Med Phys, 2022, 49(4): 2442–2451.
[34] GOULET M, DUGUAY-DROUIN P, MASCOLO-FORTIN J, et al. Clinical application of deep learning-assisted needles reconstruction in prostate ultrasound brachytherapy [J]. Int J Radiat Oncol Biol Phys, 2025, 122(1): 199–207.
[35] HAMPOLE P, HARDING T, GILLIES D, et al. Deep learning-based ultrasound auto-segmentation of the prostate with brachytherapy implanted needles [J]. Med Phys, 2024, 51(4): 2665–2677.

[36] TADESSE D M, KEBEDE S R, DEBELE T G, et al. Application of deep reinforcement learning in various image processing tasks: a survey [J]. Evol Syst, 2024, 16(1): 13.
[37] SAEED S U, FU Y G, STAVRINIDES V, et al. Image quality assessment for machine learning tasks using meta-reinforcement learning [J]. Med Image Anal, 2022, 78: 102427.
[38] SAHBA F, TIZHOOSH H R, SALAMA M M A. Application of reinforcement learning for segmentation of transrectal ultrasound images [J]. BMC Med Imaging, 2008, 8: 8.
[39] GHAJARI S, NAGHIBI SISTANI M B. Improving the quality of image segmentation in ultrasound images using reinforcement learning [J]. Commun Adv Comput Sci Appl, 2017, 2017(1): 33-40.
[40] BAE W, LEE S, LEE Y H, et al. Resource optimized neural architecture search for 3D medical image segmentation [M] // Medical Image Computing and Computer Assisted Intervention-MICCAI 2019. Cham: Springer International Publishing, 2019: 228-236.
[41] YI W X, STAVRINIDES V, BAUM Z M C, et al. Boundary-RL: reinforcement learning for weakly-supervised prostate segmentation in TRUS images [M] //Machine Learning in Medical Imaging. Cham: Springer Nature Switzerland, 2023: 277-288.
[42] QIAN Y, WASHINGTON P, PODDER T K, et al. A linear programming and deep reinforcement learning framework to choose dwell positions and dwell time in high-dose-rate prostate brachytherapy using curvilinear catheters [C] //Volume 4: Biomedical and Biotechnology Engineering. November 17-21, 2024. Portland, Oregon, USA. American Society of Mechanical Engineers, 2024: V004T06A030.
[43] GAYO I J M B, SAEED S U, BONMATI E, et al. The distinct roles of reinforcement learning between pre-procedure and intra-procedure planning for prostate biopsy [J]. Int J Comput Assist Radiol Surg, 2024, 19(6): 1003-1012.

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