❖述评

Advances and challenges of artificial intelligence in medical imaging

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[**Abstract**] Medical imaging provides non-invasive visual evidence, but manual analysis suffers from low efficiency, high misdiagnosis rates and challenges in cross-modal integration. The application of artificial intelligence (AI) could significantly enhance diagnostic accuracy and consistency. The application advances and challenges of AI in images obtained with ultrasound, X-ray, CT, MRI, pathology and endoscopy were systematically reviewed in this article.

[**Keywords**] multimodal imaging; artificial intelligence

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人工智能用于医学影像学:进展与挑战

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[**摘　要**] 医学影像可提供非侵入性可视化证据,但人工分析效率低、漏诊率高,跨模态协同困难;利用人工智能(AI)可显著提升诊断效能与一致性。本文针对 AI 在超声、X 线、CT、MRI、病理及内镜影像中的应用与挑战展开述评。

[**关键词**] 多模态成像;人工智能

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医学影像可为诊疗疾病提供非侵入性可视化证据,但传统人工分析面临效率与准确性的双重困境[1],且不同模态影像的物理特性与信息异构性使跨模态协同诊断难以实现。人工智能(artificial intelligence, AI)正在重塑医学影像分析范式[2]。目前部分基于卷积神经网络(convolutional neural network, CNN)、Transformer 等架构[3-4]的深度学习(deep learning, DL)技术在检测及分类任务中的表现可媲美甚至超越高年资医师,显著提升了诊断效率与一致性[5-6]。本文针对 AI 在超声、X 线、CT、MRI、病理及内镜影像中的应用与挑战展开述评。

1　关键技术——DL 算法

1.1　核心算法与技术框架　DL 算法为 AI 用于医学影像的核心技术,其主流架构包括 CNN 及 Transformer。CNN 通过局部感受野与权值共享机制,能有效捕捉局部纹理特征(如 CT 所示结节边缘及病理切片中的细胞形态)且计算效率高,适用数据量有限的场景,如 U-Net 基于编码器-解码器结构与跳跃连接[7]用于分割 CT 中的肝脏的戴斯相似系数(Dice similarity coefficient, DSC)达 88.7%[8];但归纳偏置(局部性假设)限制了其对全局上下文信息的建模能力,使其难以处理长程依赖问题[9]。Transformer 的自注意力机制突破了这一瓶颈,可动态捕捉图像全局关系,尤其在分类高分辨率病理全切片图像中表现突出,如 Vision Transformer 能直接在图像范围内建立像素间关系、同时捕捉局部和全局特征,但其计算复杂度随图像增大而呈平方增长,对显存与数据量的需求显著增加,且缺乏空间先验知识,用于小规模医学数据

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集易出现过拟合[4]。

混合架构(如 CNN-Transformer)有助于平衡模型效率与性能，为当前研究热点。TransUNet 架构在编码器中引入 CNN 提取局部特征、在解码器中引入 Transformer 增强全局上下文感知，其分割 CT 中的胰腺的 DSC 较单一架构提升约 6%[10]。生成对抗网络(generative adversarial network，GAN)利用生成器与判别器进行对抗训练，可用于跨模态合成(如基于 MRI 生成 CT)与数据增强，减少辐射暴露[11]。

1.2　分析流程　AI 用于分析医学影像重点流程：①数据预处理[12]，如针对模态特异性噪声(如超声散斑噪声)可采用非局部均值滤波及 Z-score 等标准化方法消除设备间差异；②优化模型，如迁移学习利用自然图像预训练权重(如 ResNet)加速模型收敛，在基于 CT 的分类肺炎任务中使 F1 分数提升至 99.17%[13]；弱监督学习通过弱标注方式减少模型对标注的依赖，将检出前列腺癌的受试者工作特征曲线下面积(area under the curve，AUC)提升至 0.98[14]；③提高结果可解释性，如基于梯度加权类激活映射(gradient-weighted class activation mapping，Grad-CAM)生成热图能可视化 AI 决策依据(如定位肺结节[15])等。

2　应用进展

2.1　超声　超声是筛查多种疾病的首选影像学工具，但诊断一致性受图像噪声(散斑、声影)与操作者依赖性影响。AI 通过识别标准切面、自动分割病变及多模态关联分析，有望实现器官特异性诊疗闭环。

获取标准切面、测量胎儿相应生长参数是产前超声的关键，但高度依赖操作者经验。PU 等[16]开发的可实时从超声视频流中获取时间和空间特征进行切面识别和定位的多任务学习模型可在一定程度上解决效率低、误差率高的问题。ZENG 等[17]将深度分离卷积模型集成至分割模型，再以最小椭圆法拟合获取胎儿头围。LIANG 等[18]以 nnU-Netv2 分割胎儿心脏切面中的关键结构，并通过直线拟合、椭圆拟合等方式计算心脏参数。PEI 等[19]基于 AI 模型识别标准切面并分割其中的最大妊娠囊，以估算妊娠早期孕周。

AI 辅助浅表器官超声诊断主要针对乳腺、甲状腺、浅表淋巴结、皮肤、唾液腺及肌肉骨骼等实施分割/检测病灶、鉴别良或恶性病变并判断其分级，以及实时动态辅助诊断及多任务联合学习[20-22]；AI 结合超声鉴别良、恶性淋巴结尤其具有重要临床价值[23-24]。CZAJKOWSKA 等[25]通过迁移学习及 DeepLabv3+模型分割皮肤表皮层，经 Grad-CAM 可视化后有助于识别皮肤病变。

2.2　X 线　AI 显著提高了诊断骨折效率和准确性，用于急诊及识别复杂骨折表现尤为突出。LINDSEY 等[26]开发的针对急诊骨折的 DL 模型检测 X 线片中腕部和踝关节骨折的敏感度为 92.5%、特异度为 98.7%，并使漏诊率减少 47%。GUERMAZI 等[27]构建的 AI 辅助诊断模型可识别多部位骨折，使诊断敏感度提高 10.4%，且平均阅片时间缩短 6.3 s。AI 用于辅助识别胸片中的感染性病变、肿瘤及慢性肺病等方面同样展现出巨大潜力。WANG 等[28]的 ResNet-50 模型分析胸片并区分 COVID-19 与其他肺炎的敏感度、特异度分别为 94% 和 91%，AUC 达 0.96；LAKHANI 等[29]的 CNN 模型检测胸片中的肺结核的敏感度为 97%、特异度为 100%，AUC 达 0.99。AI 可提高 X 线钼靶摄影筛查乳腺癌的敏感度和特异度，使假阳性率降低 5.7%、假阴性率降低 9.4%[30]；AI 模型分类乳腺密度结果与高年资医师高度一致(Kappa=0.82)[31]，能显著提高致密乳腺癌变检出率。

2.3　CT 及 MRI　AI 可通过 GAN 和 CNN 实现高质量重建低剂量 CT[32]，其识别 CT 中的微小病变的敏感度远超于人工阅片。FU 等[33]开发的 DL 模型能准确评估头颈 CT 血管造影(CT angiography，CTA)中的血管狭窄程度并分类斑块，效能与高年资医师相当。SHANMUGA 等[34]利用 AI 区分 CT 中的肺小结节与周围组织，提升了鉴别良、恶性肺结节能力。此外，AI 用于三维重建 CT 显示脊柱、骨盆等复杂骨折同样表现优异[35]。

AI 可通过结合压缩感知与 DL 显著加速 MR 成像过程、提升图像分辨率[36]。相比传统的压缩感知重建，DL 超分辨率重建技术在弥散加权成像(diffusion weighted imaging，DWI)中可显著提升脑梗死的显示质量，对于检出小病灶表现尤为出色[37]。既往研究[38]以 DL 对 MRI 中的脑肿瘤进行重建，相比传统方法，DSC 提高了 16.9%(0.83 *vs.* 0.71)、假阳性率降低 40%。CHANG 等[39]利用基于多序列 MRI[T1WI、T2WI、液体衰减反转恢复(fluid attenuated inversion recovery，FLAIR)、DWI]开发的 DL 模型于术前预测胶质瘤异柠檬酸脱氢酶(isocitrate dehydrogenase，IDH)突变状态和 1p/19q 共缺失状态，其 AUC 为 0.88～0.91，与术后病理结果的一致性达 89%。

2.4　病理　AI 正在深刻影响病理影像，尤其在检测癌症、分割组织及预测病理结果等领域[40-42]。SCHAUMBERG 等[43]构建 AI 模型预测前列腺癌编

码斑点型痘病毒和锌指蛋白（speckle-type pox virus and zinc finger protein，SPOP）突变状态，仅输入标准 HE 染色后的数字切片对由多个残余网络构成的集成框架进行训练，其区分 SPOP 突变型与野生型的 AUC 为 0.74。JACKSON 等[44]基于 CNN 开发的全切片成像技术（即虚拟免疫组化）可根据 HE 染色结果预测细胞特异性免疫表型并以图形形式呈现，其用于 SOX10 核染色试点研究的敏感度为 91.62%、特异度为 85.66%。LIU 等[45]的深卷积网络模型基于 HE 染色结果预测 Ki-67 阳性细胞，其识别不同类型细胞的平均准确率达 93.71%。

2.5　内镜　AI 用于内镜影像可通过 CNN 和注意力机制精准识别内镜图像中的异常区域，其核心价值在于提升病变检出率、优化操作流程并推动精准医疗。DL 模型基于结肠镜检出结直肠息肉的敏感度达 98.6%、特异度达 94.2%，且漏诊率较传统方法降低 53%[46]。WANG 等[47]以 AI 于结肠镜图像中自动标记息肉，大幅提高了＜5 mm 扁平息肉的检出率。针对早期胃癌，URBAN 等[48]提出白光内镜＋窄带成像双模态模型，其区分癌变与非癌变黏膜的敏感度为 92%、AUC 为 0.96。AI 可实时帧频分析内镜视频，辅助定位病变、优化操作路径；用于经内镜逆行胆胰管造影可实时判断插管位置、方向和距离[49]，有助于提升操作安全性和检查效率。

3　挑战与局限性

受隐私保护、设备成本等因素影响，难以批量获取医学影像数据，罕见病和复杂病数据尤其稀缺。专业医师标注图像、尤其多模态图像耗时且一致性差；半监督学习和合成数据生成等有所助益，但合成数据的生物学合理性尚待验证。且不同医疗机构的设备、扫描协议和重建算法不同，数据分布存在差异，跨中心数据标准化不足可致特征提取偏差。现有 AI 方法如领域自适应和联邦学习可解决部分问题，但异构数据的特征对齐尚缺乏理论支持。此外，AI 模型虽在特定数据集中表现良好，但用于其他人种、设备或罕见情况下其泛化能力有所下降；DL 模型的“黑箱”特性与临床决策的透明性需求存在矛盾；而可视化技术仍无法解释疾病复杂的病理机制，导致临床医师对 AI 决策信任度不足，阻碍其临床转化。

4　小结

AI 将在医学影像分析中扮演越来越重要的角色。其主要发展方向如下：①通过弱或自监督学习技术不断减低对标注数据的依赖[50]，以及通过 GAN 生成合成数据，解决数据稀缺问题；②在多模态数据融合方面实现更多突破，通过影像学、基因组学、病理与临床数据等多模态信息相结合，构建个性化风险模型；③提升时间序列分析能力，通过跟踪随访精准预测疾病复发风险或疗效拐点；④加速边缘计算与便携设备的结合，实现现场快速诊断。未来 AI 将从辅助工具进化为诊疗全流程的“智能伙伴”，推动医疗模式向精准化、智能化、普惠化转型，最终实现“以患者为中心”的全生命周期健康管理。

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