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人工智能辅助内镜诊断食管鳞状细胞癌的研究进展

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摘　要

食管鳞状细胞癌(ESCC)是食管癌的主要类型。由于早期缺乏特异性症状，预后较差，而早诊早治可显著改善生存结局。内镜是ESCC诊断的常用方式，但传统白光内镜及窄带成像(NBI)在浅表病变识别和浸润深度判断中受操作者经验限制。近年来，人工智能(AI)，尤其是深度学习技术，在内镜图像与视频分析中发展迅速，可用于病灶检测、边界分割、IPCL分型及浸润深度预测，在多种成像模式及多模态融合中显著提升诊断准确性与一致性，并有助于缩小不同经验医师间的差距。尽管部分系统已实现实时辅助并进入临床验证阶段，但其推广仍面临可解释性、泛化能力、数据标注及伦理等挑战。未来，通过多中心数据整合与可解释AI的发展，人工智能有望实现从研究工具向临床常规辅助诊断的转化。

关键词

食管鳞状细胞癌，深度学习，内镜，早期诊断

Advances in Artificial Intelligence-Assisted Endoscopic Diagnosis of Esophageal Squamous Cell Carcinoma

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Abstract

Esophageal squamous cell carcinoma (ESCC) is the predominant type of esophageal cancer. Due to the lack of specific symptoms in the early stage, its prognosis remains poor; however, early diagnosis and timely treatment can significantly improve survival outcomes. Endoscopy is a commonly used approach for ESCC diagnosis, yet traditional white-light endoscopy (WLE) and narrow-band imaging (NBI) are highly dependent on operator expertise in identifying superficial lesions and assessing depth of invasion. In recent years, artificial intelligence (AI), particularly deep learning, has advanced rapidly in the analysis of endoscopic images and videos. AI models have been successfully applied to lesion detection, boundary segmentation, intrapapillary capillary loop (IPCL) pattern classification, and prediction of tumor invasion depth. By integrating multiple imaging modalities and multimodal data, these systems significantly enhance diagnostic accuracy and inter-observer consistency, thereby reducing performance gaps among endoscopists with varying experience levels. Although several AI systems have achieved real-time assistance and entered clinical validation phases, their widespread clinical adoption still faces challenges related to model interpretability, generalizability, the need for high-quality annotated datasets, and ethical considerations. In the future, through multicenter data integration and advances in explainable AI, AI is expected to transition from a research tool to a routine clinical decision-support system for ESCC diagnosis.

Keywords

Esophageal Squamous Cell Carcinoma, Deep Learning, Endoscopy, Early Diagnosis

1. 引言

根据国际癌症研究机构 IARC GLOBOCAN 2022 统计，食管癌(esophageal cancer, EC)是全球第十一位常见癌症，也是第七大癌症相关死亡原因，分别约占所有新发癌症病例的 2.6%和癌症死亡的 4.6% [1] [2]。EC 主要包括食管腺癌(esophageal adenocarcinoma, EAC)和食管鳞状细胞癌(esophageal squamous cell carcinoma, ESCC)两种组织学类型，其中 ESCC 占病例的 90%，构成主要疾病负担[3]。由于 ESCC 早期缺乏特异性临床症状，多数患者确诊时已处于中晚期，导致整体预后差，其五年总体生存率约为 20% [4]；然而，通过早期诊断与及时治疗，早期 EC 的预后显著改善，5 年生存率超过 90% [5]。因此，实现早诊断早治疗对于改善 ESCC 患者的生存结局至关重要。

大多数 ESCC 患者缺乏特异性临床症状，其诊断高度依赖内镜检查。然而，在临床实践中，使用标准食管胃十二指肠镜识别浅表病变仍具有挑战性。早期 ESCC 在常规成像下常表现隐匿，研究表明，传统白光内镜(white-light imaging, WLI)的敏感性仅为 62%，特异性为 79%，漏诊率高达 10%~40% [6] [7]。相比之下，窄带成像(narrow-band imaging, NBI)通过选择性增强 415 nm 和 540 nm 波长的光，提高黏膜毛细血管与周围组织的光学对比度，使微血管结构和肿瘤表面特征可视化，从而在早期 ESCC 诊断中展现更高的敏感性和准确性[8]。准确识别上皮内乳头样毛细血管袢(intrapapillary capillary loops, IPCLs)的形态异常是关键，因为其结构变化与肿瘤浸润深度密切相关，是评估病变性质和临床分期的重要标志物[9]。当 NBI 与放大内镜(magnifying endoscopy, ME)联合应用时，可清晰呈现 IPCLs 的细微形态，大幅提高早

期 ESCC 的检出率和诊断准确性[10] [11]。然而，NBI 在界定病变边界和判断浸润深度方面仍依赖操作者经验，存在主观性强等局限，其诊断一致性和准确性仍有待进一步提升[12]。

为实现对 EC 更高效、精准地检测与表征，人工智能(artificial intelligence, AI)技术已成为该领域的重要研究方向。AI 主要包括机器学习(machine learning, ML)和深度学习(deep learning, DL)两类方法。传统 ML 依赖人工预设特征，例如病灶大小、边缘形态等，并结合统计模型如支持向量机(SVM)、决策树进行分类，在 EC 早期识别中虽可提升性能约 6%~10%，但其性能高度依赖训练数据质量与算法类型[13]-[15]。相比之下，深度学习(尤其是卷积神经网络)可直接从原始内镜图像中自动提取特征，使其在内镜和病理图像处理方面表现尤为突出[16]-[18]。既往研究表明，基于 CNN 的 DL 模型在 EC 检测的准确率、灵敏度、特异性和 AUROC 等指标上均显著优于传统 ML 方法[15]，不仅提高了检测精度，也减轻医生工作负担，为 AI 辅助早期食管癌诊断提供了可靠技术基础[19]。

近年来，深度学习在医学影像分析领域取得显著进展，其应用场景已从离体病理切片的回顾性分类，发展至内镜检查过程中的实时辅助诊断，展现出强大的临床转化潜力。在食管癌的早诊早治中，人工智能(AI)技术正逐渐融入内镜诊疗全流程，有望缓解传统内镜对操作者经验的高度依赖，通过提供客观、可重复的定量分析，提升内镜医师识别病变的准确性与一致性。因此，本文系统综述 AI 辅助内镜技术在食管癌诊疗中的应用进展，涵盖不同模态诊断性能、临床验证现状、核心挑战及未来发展方向。

2. AI 在不同内镜成像模式下的诊断性能

2.1. AI 在白光内镜中的应用

WLI 因设备普及、操作简便，成为筛查早期 ESCC 的首选技术，但其对浅表病变的敏感性与特异性有限，漏诊风险较高。为弥补 WLI 的不足，AI 技术被引入以提升其诊断效能。Cai 等开发并验证了一种基于深度神经网络(DNN)的计算机辅助检测(CAD)系统，常规 WLI 下识别早期 ESCC 的准确率达 91.4%，敏感度高达 97.8%。该系统可辅助内镜医师发现原本遗漏的病灶，并提升其整体诊断水平，但特异度仅为 85.4%，可能增加不必要的活检[20]。为进一步提升诊断效能，该团队于 2021 年构建了基于非放大 NBI 的 CAD 系统，并与 WLI-CAD 进行对比，结果显示 NBI-CAD 在准确率和特异性上均优于 WLI-CAD，提示二者在临床实践中可形成互补，以此提高早期筛查的可靠性[21]。此外，Liu 等基于 1239 名患者的 13,083 张 WLI 图像训练的 AI 模型，在内外部验证中对病灶检出的准确率分别为 85.7%与 84.5%；在病灶边界划定任务中，准确率进一步提升至 93.4%与 95.7%，表现与专家相当，甚至优于高级内镜医师[22]。上述结果表明，AI 辅助不仅增强了 WLI 对早期 ESCC 的检出能力，还在精准界定病变范围方面展现出重要临床价值。

2.2. AI 在窄带成像中的应用

NBI 通过增强黏膜表层与血管结构对比，使内镜医生能够更有效地区分食管肿瘤性与非肿瘤性病变[23]。该技术目前已集成于内镜系统，可在检查过程中一键切换启用。临床实践中通常采用分步应用：非放大内镜用于快速筛查与病变定位，放大内镜则进一步用于精细观察微血管特征并辅助病灶性质判断[24] [25]。然而，NBI 的诊断准确性仍受观察者间差异及操作者经验影响。为提升诊断的客观性与一致性，人工智能与 NBI 的结合成为重要研究方向。多项研究证实，AI 在 NBI 下对 ESCC 的检出灵敏度达 91%~98%，部分模型在良恶性鉴别中准确率超过 88%，优于非专家医师[26]-[28]。ME-NBI 可清晰可视化 IPCLs，为 ESCC 及其癌前病变识别提供关键依据[29]。基于日本食管学会(JES)分类系统[9]，Everson 等首次利用 CNN 实现 A 型(非癌性)与 B 型(癌性) IPCL 的二分类，准确率达 93.7% [30]；Zhao 等开发的双标签全卷积网络(FCN)在 A、B1、B2 三分类中分别达到 92.5%、87.6%和 93.9%的准确率，显著提升非专家医师的

判读水平，但因 B3 型样本稀缺未纳入模型[31]。值得注意的是，B3 型血管通常提示黏膜下深层浸润(≥SM2)，指导内镜医生治疗方式的选择。Uema 等构建包含 B3 的 ResNeXt-101 模型，对 B3 识别准确率达 95.4%，并通过集成学习缓解小样本过拟合，但受限于单中心研究，临床泛化性待验证[32]。鉴于 ME-NBI 下微血管模式与肿瘤浸润深度密切相关[33]。研究进一步聚焦 AI 在深度预测中的应用。Nakagawa 等基于 14,338 张图像训练的深度学习模型在区分黏膜/SM1 与 SM2/3 病变中实现 91.0%准确率，性能媲美资深医师[34]；Tokai 等的 AI 系统可在 10 秒内完成 ESCC 检出与深度预测，整体表现优于多数内镜医生[35]；Shimamoto 等在视频级验证中发现，AI 对深浸润病灶(SM2-3)的敏感度(71%)显著高于专家(42%)，而专家敏感性较低可能导致漏诊[36]。AI 系统所展现的高敏感性有望减少漏诊，同时其高特异度(95%)可减少过度治疗。因此，AI 不仅提升了 NBI 下病变检出与 IPCL 分型的一致性，更在食管癌浸润深度预测中展现出辅助甚至超越人类专家的潜力。

2.3. AI 在共聚焦成像中的应用

基于探针的共聚焦激光内镜(probe-based confocal laser endomicroscopy, pCLE)作为一种新兴的显微成像技术，能够实现体内实时、无创的食管黏膜病变观察，为 ESCC 提供“光学活检”的可能[37]。研究表明，pCLE 在胃肠道恶性肿瘤诊断中的敏感度和特异度优于 WLE [38] [39]，且在食管或胃病变患者中，其诊断准确性与标准活检相当[40]。然而，pCLE 图像解读高度依赖操作者对组织病理学特征的理解，需经过系统培训，限制了其广泛应用。为此，Ma 等开发了一种用于 pCLE 图像的计算机辅助诊断系统(intelligent CLE, iCLE)，专门用于识别食管鳞状上皮内瘤变(esophageal squamous neoplasia, ESN)。结果显示，iCLE 系统在 ESN 诊断中优异性能，不仅显著提升了非专业内镜医师诊断性能，并有望减少不必要的活检[41]。然而，该研究为一项单中心研究，未来仍需多中心前瞻性研究验证其临床效能与泛化能力。

2.4. AI 在多模态中的应用

尽管 WLE 与非放大 NBI 是筛查浅表 ESCC 及癌前病变的常用技术，但因早期病变隐匿及医师经验差异，ESCC 漏诊率在 4.2%~17.0% [42]-[46]。为改善单一成像模态的局限，多模态 AI 系统通过融合不同成像信息显著提升诊断全面性与准确性。Horie 等结合 WLE 与 NBI 的 AI 系统虽实现 98%的高敏感度，但阳性预测值仅 40%，提示存在较高的假阳性率[47]。随后 Meng 等基于改进 YOLOv5 框架构建支持 WLI + NBI 的系统，并通过无失真影像校正模拟临床动态图像干扰，实现了 AUROC 0.982、准确率 92.9%、灵敏度 91.9%、特异度 94.7%，且显著缩小非专家与专家的诊断差距，体现多模态 CAD 在统一不同经验医师表现方面的潜力[48]。进一步的真实临床证据来自 Yuan 等基于 YOLACT 模型开发的实时检测与分割一体化系统，在多中心随机对照试验中将总体病变漏诊率降低 5.0% [49]，Li 等开展的大规模前瞻性 RCT (n = 3400)进一步显示，采用 CAD 优先策略的 NBI 检查显著提高食管肿瘤性病变检出率，且初级内镜医师获益尤为明显，而资深医师无显著差异，表明 CAD 可有效弥合内镜医师经验差距[50]。在更高阶的多模态融合方向上，Yu 等提出的 MUMA-EDx 系统首次融合放大内镜(ME)与内镜超声(EUS)，通过特征级深度学习实现早期 ESCC 识别与浸润深度精准分类，在包含 460 例的回顾性队列和 131 例的前瞻性验证中均表现卓越，在前瞻性验证中，对肿瘤识别 AUC 达 1.00，对浸润深度多类分类 AUC 为 0.80，其性能与专家相当，并优于新手医师[51]。这些研究共同表明，从双模态(WLE/NBI)到高阶多模态(ME/EUS)，AI 不仅能实现实时(最高 135 帧/秒)、高敏感性、高特异性的病灶检测与边界勾画，更在真实临床环境中可显著提升检出率、优化治疗决策，并推动内镜诊断向标准化、均质化发展。

3. AI 的实时辅助与临床验证

近年来，AI 在 ESCC 内镜实时辅助诊断领域取得了显著进展。Guo 等基于 6473 张 NBI 图像开发的

实时 CAD 系统，AUC 达 0.989，视频中对早期 ESCC 及癌前病变的病灶敏感度为 100%，并可生成概率热图辅助诊断[52]。然而，该模型仅限于 NBI，未包含 WLI 等其他模式，其临床应用场景受限。为进一步提升诊断的广泛适用性，Yang 等通过整合多模态数据(包括白光、光学增强/碘染色、放大与非放大图像以及实时视频)构建了一个更为全面的深度学习模型。研究显示，在白光成像中，系统的患者级准确率、敏感性和特异性分别为 99.5%、100%和 99.5%；光学增强/碘染图像的准确率为 97.0%、敏感性为 97.2%、特异性为 96.4%；放大图像的准确率为 88.1%、敏感性为 90.9%、特异性为 85.0%。该模型的总体准确性与专家相当，并且优于新手。此外，AI 辅助系统能够显著提升初级医师的诊断性能，显示出其在培训和标准化诊断中的潜在价值[53]。与此同时，Shiroma 等开发了一个支持 30 帧每秒的视频处理系统，用于在视频中检测表浅 ESCC。该系统具有较高的检出能力，且能在实时辅助下提升内镜医生的敏感性[54]。然而，尽管这些系统对表浅 ESCC 表现良好，但其在识别更早期的癌前病变时存在不足，且多为单中心研究，缺乏多中心外部数据的支持，泛化性仍待进一步确认。尽管 AI 在实时辅助内镜技术上取得了显著进展，但在临床环境中的实际应用效果尚不确定。Tani 等在单中心前瞻性单臂非劣效研究中，虽然 AI 系统与内镜医生的诊断准确率接近，但未能证明其具有非劣效性[55]。Nakao 等在 320 例高危患者的随机对照试验表明，在常规 WLI/NBI 流程下，使用 ESCC 的 AI 诊断支持系统未能显著提高食管癌的检测率[56]。因此，尽管 AI 在诊断早期 ESCC 中展现出巨大的潜力，但其在真实临床环境中的应用仍面临许多挑战。

既往用于实时内镜视频分析的 AI 系统多基于传统卷积神经网络(CNN)架构，视频级决策主要依赖连续帧结果的持续显示或简单时序后处理，从而在保证实时性的同时降低计算复杂度，但其在建模跨帧长程依赖关系方面仍存在局限[57]。作为新兴架构，Vision Transformer (ViT)凭借自注意力机制在捕捉全局上下文和远距离依赖方面展现出潜力，并逐步被探索用于内镜视频流分析，以提升早期 ESCC 在复杂动态场景下病灶识别的稳定性[58]。然而，ViT 对大规模标注数据的需求远高于 CNN，且计算成本更高，限制了其在资源受限临床环境中的实际应用可行性[59]。相比之下，CNN 由于技术成熟且已在多种内镜应用中得到充分验证，在实时性要求较高的临床场景中仍具优势。未来，结合 CNN 的高效局部特征提取能力与 ViT 在跨帧语义建模方面的优势，构建混合架构，有望在精度、计算效率与临床实时应用可行性之间实现更优平衡。

4. AI 面临的挑战

4.1. “黑箱”问题与可解释性不足

人工智能模型在食管癌早期诊断中展现出显著潜力，但其决策过程的“黑箱”特性，即深度学习模型复杂的内部机制难以被直观理解，这种不透明性可能削弱医生对 AI 诊断建议的信心，从而影响其实际临床应用价值[60] [61]。目前，主流的可解释性方法多为事后分析、模型特定和局部性的视觉型解释，虽然在透明度上有所进展，但未能完全满足临床对推理逻辑的需求。早期的 AI 系统主要提供粗略的定位，如 Li 等开发的模型虽达到 91.0%的灵敏度和 96.7%的特异性，但仅输出方形边界框，无法有效指导精准活检[21]；Waki 等人的多边形标注虽在精度上有所提升，但缺乏临床验证[62]。近年来，可视化技术逐步向精细化发展，Yuan 等基于 YOLACT 实现了像素级实时分割，显著提高了病变边界的精度，超越了初级医师并达到高级专家水平[63]；Everson 等开发的 CNN 系统能够以视频速率实时分析 ME-NBI 图像，在达到 91.7%分类准确率的同时，通过类激活图技术直观展示影响决策的关键特征区域。这种将可解释性从病变定位深化至决策依据层面的创新，使医生能够理解算法为何做出特定判断[30]。近期，Kang 等提出的可解释半监督模型，通过 Xception 骨干网络生成 Grad-CAM 热力图实现视觉定位，同时结合特征重要性、偏依赖图(PDP)与局部分解图量化“环形成”和“不规则性”等特征对预测贡献，构建了“视觉定位 + 数值归因”的双通道解释框架，显著提高了初级医师的诊断准确率[64]。然而，尽管这些方法提

升了透明度，它们依然存在挑战性，解释模块多为事后附加，无法揭示内在推理机制，且高度依赖特定架构，难以实现跨平台迁移。在此基础上，为进一步突破传统热图解释的局限，近年来研究逐渐引入基于案例推理(Case-Based Reasoning, CBR)和概念瓶颈模型(Concept Bottleneck Models, CBM)等更具临床可读性的可解释框架。CBR 可通过检索与当前内镜图像或视频片段最相似的已标注病例，并展示其对应的病理结果、IPCL 分型及临床结局，为 AI 预测提供可追溯的相似病例证据，其决策逻辑与医生基于既往经验进行类比判断的诊断过程具有高度一致性[65]。相比之下，CBM 通过将医学先验知识(如 IPCL 形态、AVA 结构)作为中间概念层嵌入模型，使模型预测过程能够在概念层面被拆解和解释，例如，Zhang 等提出的 AI-IDPS 系统已尝试将 IPCL 分型、AVA 形态等病理特征量化为变量输入，并以可视化权重形式展示其对浸润深度预测的贡献，显著提升了人机协作的可信度[66]。该模式在 ESCC 场景中具有较大应用潜力，但其临床转化仍受限于对高质量参考病例库和标准化概念标注的依赖，并面临模型复杂度增加及跨中心泛化能力不足等挑战。

4.2. 泛化能力与鲁棒性不足

尽管 AI 在理想数据集上表现优异，其在真实临床环境中的泛化能力与鲁棒性仍面临显著挑战。现有模型多基于单中心、单一设备(如 Olympus)数据训练，因而对不同厂商设备、光源设置与噪声水平的适应性不足，数据分布偏倚易削弱其跨场景泛化能力。Tang 等虽在外部数据集上验证了稳定性，但仍局限于同品牌设备[67]；Feng 等整合多中心多设备数据，却主要在合作机构内完成验证，难以代表基层或资源受限地区的真实分布[68]。与此同时，真实内镜检查常伴随运动模糊、黏液遮挡、光照不均与非标准视角等干扰，导致模型对复杂临床场景的适应能力不足。近期一项基于单中心 WLI 数据的系统性基准研究表明，在包含 4 类病理与 7 类伪影的 11 标签检测任务中，即便采用统一训练协议，主流检测器(如 YOLOv5/v8)对异型增生的召回率仍不足 45%，且约 20%阳性预测无对应病变，导致假阳性[69]。这提示模型在低对比度、形态模糊的早期病变区域仍缺乏足够敏感性与判别力。当前泛化验证多聚焦常见病变与相对理想条件，对罕见亚型、不同设备及极端成像场景的测试仍明显不足。

4.3. 高质量标注数据稀缺

ESCC 内镜 AI 研究高度依赖专家标注，而早期病变形态细微，IPCL/AVA 等微血管模式判读主观性强，且需病理金标准配对，导致高质量标注数据稀缺。Zhao 等开发了双标签全卷积网络(FCN)，在仅 1383 例病变的有限标注下实现 IPCL 自动分类，其病灶与像素级准确率分别达 89.2%与 93.0%，对 B1/B2 型恶性病变及炎症的识别性能显著优于初级和中级内镜医师[31]。然而，该方法仍需专家密集参与定义语义与区域双标签，本质上未摆脱对高质量标注的依赖。在浸润深度预测中，Kang 等进一步通过自监督对比学习在海量无标签 ME-NBI 图像上进行预训练，再以小批量标注数据微调，并集成可解释模块，使辅助后初级与高级医师的诊断准确率分别提升至 0.833 与 0.917 [65]。尽管弱监督方法提升了标注效率，模型性能仍受限于高质量标注数据的规模与代表性，制约其临床推广。

4.4. 人机协作中的信心与伦理困境

AI 辅助诊断的核心价值不仅在于提升诊断准确性，更在于优化人机协作效率，但检查者的信心波动、信任边界模糊与决策冲突成为临床转化的挑战。Roser 等的多中心随机对照串联视频试验数据显示，AI 辅助可显著提高检查者的诊断信心与准确性($p < 0.001$)，而撤除 AI 辅助后，检查者信心明显下降($p < 0.001$)，但准确性未受影响，提示 AI 对心理状态的影响可能超出技术本身[70]。值得注意的是，在 16%的病例中，检查者忽视了正确的 AI 建议；而在 9%的病例中，原本正确的临床判断被错误地更改为 AI 预测结果。这些偏差源于过度依赖、算法厌恶或对 AI 不确定性缺乏理解，反映出人机信任边界的模糊性。

更为深层的挑战在于临床决策权与信任边界的重新界定。当 AI 的“黑箱式”建议与医生的专业判断发生冲突时，最终决策权威的归属不仅涉及法律责任的划分，更触及医学伦理的核心问题。正如 Grote 等指出，不透明的 AI 系统因无法提供 “尊重的认知支持”，难以真正增强医生的临床能力，反而可能迫使医生陷入“防御性医学”困境，即教条式遵从机器输出以规避责任[71]。这种信任危机不仅削弱诊疗质量，还可能影响医患关系的稳定性。

5. 未来发展方向

未来食管癌 AI 辅助诊断的发展需从多方面协同推进。在可解释性方面，应提升算法透明度，整合内镜影像、病理结果、患者病史及基因组数据，构建临床适配的可解释模型，并进一步从以事后可视化为主的解释方式，发展为基于概念层证据的可追溯决策推理框架。在此过程中，可借助大型语言模型将复杂诊断结果转化为患者易懂的个性化报告，促进人机协同与诊疗依从性[72] [73]。在泛化能力方面，需建立覆盖多厂商设备、多种组织学类型及真实干扰因素的多中心大规模数据集，结合迁移学习、自监督预训练与图像增强等技术，增强模型在真实场景中的鲁棒性[74]。同时，应制定统一临床标注标准(如 IPCL 分型、浸润深度)，并通过半监督或联邦学习等弱监督方法缓解高质量标注数据稀缺问题，Ziegler 等利用联邦学习框架实现六家医院隐私保护下的联合建模，为打破医疗数据孤岛提供可行参考[75] [76]。在模型架构层面，未来可进一步探索面向临床实时应用需求的 CNN 与 ViT 的融合设计，以在保证实时性的同时增强对复杂内镜视频中跨帧语义关系的建模能力，并通过多中心前瞻性研究验证其在真实临床流程中的实际增益。最后，需完善伦理与监管体系，明确人机协作中的法律责任，将 AI 系统纳入医疗器械审批流程，强化数据安全与隐私保护，并通过国际协作形成兼具普适性与本土适应性的医疗 AI 伦理治理范式[77] [78]。

6. 总结

食管癌早期诊断的主要挑战在于病变隐匿性与内镜医师经验差异。AI 已从单一白光成像发展至多模态融合，从静态识别转向实时视频辅助，并实现从病灶检测到 IPCL 分型及浸润深度预测，在提升灵敏度、降低漏诊率方面优势显著，尤其有助于缩小不同年资医师间的诊疗差距。尽管 AI 可增强检查者信心，但过度依赖与决策冲突等问题仍需通过可解释性提升与伦理规范加以应对。当前，“黑箱”特性、泛化能力不足、标注数据稀缺及人机协作中的伦理困境仍是临床转化的挑战。未来，结合可解释算法、多模态融合、联邦学习与建立标准化数据体系，AI 有望深度融入食管癌诊疗全流程，成为早筛、精准诊断与个体化治疗的有用工具，最终改善患者生存结局。

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