Advances in Clinical Medicine 临床医学进展, 2026, 16(4), 2740-2746
Published Online April 2026 in Hans. https://www.hanspub.org/journal/acm
https://doi.org/10.12677/acm.2026.1641528

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基于AI赋能的低剂量造影剂对冠脉病变的诊断进展

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收稿日期：2026年3月13日；录用日期：2026年4月6日；发布日期：2026年4月14日

摘　要

冠状动脉CT血管成像(CCTA)是冠心病无创评估的重要工具，但常规检查依赖较高碘负荷和较快注射流速，限制了其在肾功能边缘受损、静脉条件较差及需重复随访患者中的应用。近年来，低剂量造影剂冠脉成像已从单纯依赖扫描参数优化，逐步发展为“采集端增益－重建端补偿－分析端定量”的协同模式。现有研究表明，低keV虚拟单能图像可提高碘信号利用效率，在部分研究中实现约50%的碘剂量下降而仍保持可诊断图像质量；深度学习重建(DLR/DLIR)可在低体积、低浓度甚至低流速方案下明显降低噪声、提升信噪比和主观评分；超分辨率重建、CE-boost及光子计数CT (PCD-CT)进一步推动“多低”方案走向临床可行。与此同时，AI-QCT、自动斑块定量、高危斑块识别及CT-FFR相关模型，正在使低剂量成像从“可读”走向“可量化、可分层、可支持决策”。总体看，AI显著拓展了低剂量造影剂CCTA的应用边界，但其稳定推广仍需依赖多中心外部验证、复杂病变亚组研究及临床终点证据。

关键词

人工智能，低剂量造影剂，冠状动脉CT血管成像，冠脉病变，深度学习重建

Progress in AI-Enabled Low-Dose Contrast Agent for the Diagnosis of Coronary Artery Lesions

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Received: March 13, 2026; accepted: April 6, 2026; published: April 14, 2026

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文章引用: 罗浩文, 杨源, 杨攀. 基于 AI 赋能的低剂量造影剂对冠脉病变的诊断进展[J]. 临床医学进展, 2026, 16(4): 2740-2746. DOI: 10.12677/acm.2026.1641528

Abstract

Coronary computed tomography angiography (CCTA) is an important noninvasive tool for the evaluation of coronary artery disease. However, conventional CCTA generally relies on a relatively high iodine load and rapid injection rates, which limit its use in patients with borderline renal impairment, poor venous access, or the need for repeated follow-up examinations. In recent years, low-contrast-dose coronary imaging has evolved from a strategy that primarily depended on scan-parameter optimization to a collaborative paradigm integrating acquisition-side enhancement, reconstruction-side compensation, and analysis-side quantification. Existing studies have shown that low-keV virtual monoenergetic imaging can improve the efficiency of iodine signal utilization, enabling approximately a 50% reduction in iodine dose in some studies while still maintaining diagnostic image quality. Deep learning reconstruction (DLR/DLIR) can substantially reduce image noise and improve signal-to-noise ratio as well as subjective image quality scores under low-volume, low-concentration, and even low-injection-rate protocols. In addition, super-resolution reconstruction, contrast enhancement boost (CE-boost), and photon-counting CT (PCD-CT) have further advanced the clinical feasibility of "multi-low" protocols. Meanwhile, AI-based quantitative CT (AI-QCT), automated plaque quantification, high-risk plaque identification, and CT-derived fractional flow reserve (CT-FFR)-related models are driving low-contrast-dose imaging beyond mere interpretability toward quantification, risk stratification, and decision support. Overall, AI has markedly expanded the application boundaries of low-contrast-dose CCTA; however, its stable and widespread implementation still depends on multicenter external validation, subgroup studies of complex lesions, and evidence from clinical endpoints.

Keywords

Artificial Intelligence, Low-Dose Contrast Agent, Coronary Computed Tomography Angiography, Coronary Artery Lesions, Deep Learning Reconstruction

1. 引言

冠状动脉 CT 血管成像具有较高阴性预测价值，能够直接显示冠脉解剖、斑块组成和狭窄程度，已成为疑似慢性冠脉综合征和胸痛患者的重要无创检查手段[1]-[3]。但 CCTA 依赖含碘造影剂获得充分腔内强化，因此在肾功能受损、老年、静脉条件较差及需反复检查人群中常受限制。传统低剂量策略主要依靠低管电压、个体化注射和缩短采集时间，但单纯降低碘输送率往往带来强化不足、远端分支显示下降及图像噪声增高，进而影响病变识别和定量分析。随着能谱 CT、PCD-CT 及 AI 重建与分析技术发展，低剂量冠脉成像的目标已不再只是“勉强显影”，而是尽量在降低碘负荷的同时维持稳定的诊断与分层能力。

2. 低剂量造影剂冠脉成像的临床需求与技术基础

低剂量造影剂策略的核心不是单纯减少注射毫升数，而是在尽量不牺牲冠脉病变识别能力的前提下，降低总碘负荷、注射流速和潜在不良反应风险[1] [2]。对于肾功能边缘状态患者，减少碘暴露可降低临床顾虑；对于静脉通路条件较差患者，降低流速和压力有助于提高检查完成率；对长期随访患者，则有助

于减轻整体检查负担。因此，低剂量方案的评价不能只看血管 CT 值，还应同时关注图像噪声、狭窄分级一致性、斑块定量稳定性和下游功能学分析可行性。其主要挑战在于：低强化会同时降低信噪比和对比噪声比，对远端小分支、重钙化病变、支架内病变及高心率患者影响更明显[4]-[6]。这意味着低剂量成像真正需要解决的问题，并不是“能不能看到血管”，而是“在低强化条件下能否持续、可靠地看清病变并完成后续定量”。

3. AI 赋能下的关键技术进展

在采集端，双能/能谱 CT 的低 keV 虚拟单能图像可提升碘衰减信号利用效率，是降低造影剂剂量的重要路径。Huang 等[4]证实，50 keV 图像可在明显降低碘负荷的同时维持与常规组相当的图像质量；Raju 等[5]也显示 35 mL 方案虽主观质量略降，但诊断可解释率仍接近常规方案。这提示低 keV 图像的临床价值不在于机械追求更低能级，而在于围绕不同任务平衡信号增强与噪声控制[6]。DLR/DLIR 则主要解决低剂量条件下“噪声过高、纹理变差”的问题。Yuan 等[7]显示，在 DLIR 支持下 0.5 mL/kg 方案仍具良好可诊断性；Otgonbaatar 等[8]发现，DLR 联合低浓度对比剂时可获得更低噪声和更高 SNR/CNR；Caruso 等[9]进一步证明，在低辐射、低造影剂“双低”方案中，DLIR 仍可维持甚至改善图像质量。

在 70/80 kVp 甚至儿童 CCTA 场景中，DLIR 同样能明显改善主客观图像质量[10]-[12]。从这一点看，AI 重建已不再只是改善观感的后处理手段，而是低剂量方案能否稳定落地的关键支撑。此外，低剂量方案能否真正进入常规流程，还取决于其对检查一致性和工作流的影响。若某一技术只能在理想心率、简单病变或单一厂商平台上取得良好效果，其临床推广价值仍然有限，因此评价标准应从单次图像“能否诊断”，进一步转向“在不同设备、不同患者条件下能否稳定诊断”。随着算法升级，AI 重建又从“降噪”扩展到“提升空间分辨率”和“强化血管显影”。

SR-DLR 可减少钙化 blooming 伪影、改善支架边缘显示[13] [14]，在“quadruple-low”研究中，CE-boost 联合 DLR 获得最高 SNR、CNR 和主观评分，对侵入性冠脉造影的诊断准确率达 96.7%，灵敏度为 100% [15]。另一个值得注意的问题是，低剂量图像的诊断价值并非只受噪声影响，还与边缘锐利度、钙化 blooming 控制及血管–斑块界面保真度密切相关，这也是 SR-DLR、CE-boost 受到关注的重要原因。PCD-CT 则为低流速、低剂量方案提供了新的硬件平台。Lin 等[16]的随机研究显示，在 0.3 mL/kg、1.5~1.8 mL/s 超低流速条件下，近端冠脉客观图像质量仍可与常规方案相当，主要在远端部分指标略有下降。需要指出的是，SR-DLR 对钙化 blooming 伪影的改善，现阶段更应理解为空间分辨率提升与边缘过渡优化带来的表观减轻，而非对钙化伪影的“真实去除”。冠脉钙化所致管腔高估狭窄，既与高密度结构本身有关，也与有限空间分辨率、点扩散函数及部分容积效应共同相关。SR-DLR 通过学习超高分辨率图像特征，可在一定程度上提高边缘陡峭度、改善支架及钙化边界显示，从而减少钙化外扩的视觉表现；但现有证据尚不足以证明其能够在病理或物理层面消除钙化对邻近管腔的全部干扰。相应地，SR-DLR 对于狭窄程度评估的价值，更可能体现在降低假阳性高估、改善可判读性，而不是简单理解为“去钙化”[13] [17]。

这一点也使 SR-DLR 与双能 CT 或 PCD-CT 的虚拟去钙化技术存在本质差异。前者主要依赖 AI 重建改善空间分辨率与噪声特性，本质上属于图像重建层面的边界优化；后者则利用能谱信息进行物质分解或钙化成分减除，更接近材料分离层面的钙化抑制/去除。已有研究显示，基于 PCD-CT 的虚拟去钙化在多数重钙化狭窄中具有可行性，但并非所有病变均能成功处理，且其稳定性仍受病变形态、钙化范围及算法设定影响。相比之下，SR-DLR 优势在于流程简便、无须额外能谱分解，适用于常规重建流程；不足则是其对钙化影响的改善更多体现在显示层面，缺少对钙化成分本身进行分离的能力。因此，两者并非替代关系，而更可能分别适用于“边缘优化”与“材料去钙化”两类不同任务[18]。

结合不同 VMI 能级选择和高分辨率成像优化[19] [20]，PCD-CT 有望把低剂量策略进一步推进到“总量更少、流速更低而任务性能仍可接受”的阶段。综合现有证据，低剂量冠脉成像的技术演进已经形成较清晰路径：先通过能谱或 PCD-CT 提高信号利用效率，再通过 AI 重建补偿噪声与分辨率损失，最终向更低体积、更低浓度和更低流速方案扩展。

4. 低剂量条件下冠脉病变的诊断效果与下游分析

低剂量造影剂并不必然削弱冠脉狭窄识别能力，关键在于是否同步获得足够的信号增益与算法补偿。现有研究提示，在低 keV 图像、DLR/DLIR 及 SR-DLR 支持下，即使造影剂剂量、浓度或流速下降，主要冠脉的主客观图像质量仍可维持在临床可接受范围[4]-[16] [21]。系统综述和 Meta 分析进一步显示，AI 在识别≥50%冠脉狭窄方面具有较高敏感度和特异度，整体表现可优于传统人工读片[22] [23]。这表明低剂量 + AI 的组合，正在使冠脉成像从“图像尚可接受”迈向“关键病变仍可可靠识别”。更重要的是，低剂量冠脉成像的临床价值不应停留于“有无狭窄”，还取决于其是否能稳定支持斑块定量、高危斑块识别和风险分层。

多中心研究显示，深度学习斑块分析系统在总斑块体积、狭窄程度及最小管腔面积等指标上与专家或 IVUS 具有较高一致性[24]；全自动模型对低衰减斑块、点状钙化和正向重构等高危表型也表现出较好识别能力[25] [26]。从研究趋势看，该领域已由单纯“降碘”转向“降碘 + 定量 + 风险预测”并行推进，也就是说，真正有临床意义的低剂量方案，不仅要让影像医师能够完成读片，还要保证 AI 输出的斑块负荷、狭窄分级和缺血判断具有可重复性。在功能学层面，AI-QCT 和 ML-FFR_CT 正推动低剂量成像向临床决策支持延伸。Nurmohamed 等[27]建立的 AI-QCT_ISCHEMIA 模型可较好识别血管特异性缺血，且阳性结果与 MACE 独立相关；van Noort 等[28]的 Meta 分析显示，ML-FFR_CT 在患者和血管水平均具有良好诊断性能。

不过，当前多数研究终点仍以图像噪声、SNR/CNR 和主观评分为主，以侵入性冠脉造影、IVUS 或临床事件为硬终点的研究仍相对有限。对于重钙化、支架内再狭窄、远端小血管以及心率较高患者，低剂量成像更容易暴露信号不足和边界失真问题，因此这些亚组可能是未来验证低剂量 + AI 方案真实上限的关键。因此，低剂量 + AI 真正的临床转化重点，已不再是证明“图像更好看”，而是证实其在不同设备、不同人群和复杂病变中的定量稳定性与结局相关性。

与此同时，DLR/DLIR 在低剂量造影剂 CCTA 中的价值也不应仅以降噪幅度来判断。尽管现有研究普遍显示其可降低噪声、提高 SNR/CNR 并改善主观图像质量，但图像重建本质上仍是一个受训练数据、算法强度和厂商实现影响的先验约束过程。理论上，过强的降噪或边缘优化可能带来局部纹理改变、低对比细节弱化，甚至使运动伪影或复杂边界呈现出“看似更规则”的视觉外观。对于非钙化斑块表面细小溃疡、远端小血管病变及低对比病灶，若仅依据主观评分判断图像“更清晰”，仍不足以证明其诊断真实性同步提升[29]。

5. 总结与展望

AI 正在重塑低剂量造影剂冠脉成像的技术边界和临床价值。现阶段较为成熟的路径，是在采集端借助能谱 CT 或 PCD-CT 提高碘信号利用效率，在重建端通过 DLR/DLIR 或 SR-DLR 补偿噪声与分辨率损失，在分析端结合 AI-QCT、自动斑块定量及 CT-FFR 模型，实现结构化评估与风险分层[1]-[3] [22]-[28] [30]-[33]。从临床应用角度看，低剂量造影剂 CCTA 最具吸引力的场景，是那些既需要保留冠脉评估价值、又希望尽量降低检查负担的人群，例如肾功能轻中度异常者、外周静脉条件欠佳者、老年患者以及需要阶段性复查的慢性冠脉疾病患者。若 AI 能够在这些场景中持续提供稳定的图像重建和定量输出，其

意义将不仅是技术优化，更可能改变检查适应证的边界。同时，CAD-RADS 2.0 等标准化报告体系也为低剂量图像与 AI 结果整合提供了接口。

未来若能把结构化狭窄评估、斑块表型、高危特征及功能学信息统一纳入报告框架，低剂量冠脉成像的临床可解释性和可推广性将进一步增强。但目前仍需警惕两类关键问题。其一，SR-DLR、CE-boost 及其他增强类算法对钙化 blooming、支架边缘及管腔显示的改善，未必等同于真实病变边界的还原；部分“伪影减轻”可能更多体现为边缘锐化和显示优化，而非物理意义上的伪影消除。因此，这类方法是否会改变狭窄程度分级、是否可能低估或高估钙化相关狭窄，仍需依赖以 ICA、IVUS、OCT 或临床结局为参照的进一步验证。其二，DLR/DLIR 虽在多数研究中优于传统 IR 的噪声纹理表现，但在极低剂量、复杂病变和低对比任务中，仍可能出现细节平滑、纹理特征迁移及局部结构真实性不足的问题。特别是对非钙化微小病变、高危斑块表面特征及运动伪影修复后的真实解剖一致性，目前证据仍不充分。未来研究应从“图像质量更好”进一步转向“诊断是否更准、定量是否更稳、结局相关性是否更强”的验证框架。

基金项目

重庆市教委科学技术研究项目青年项目(KJQN202400484)；重庆市中青年医学高端人才项目(yxgdrc20210101)；重庆市科卫联合项目(2025GDRC010)。

参考文献

[1] Vrints, C., Andreotti, F., Koskinas, K.C., Rossello, X., Adamo, M., Ainslie, J., *et al*. (2024) 2024 ESC Guidelines for the Management of Chronic Coronary Syndromes. *European Heart Journal*, **45**, 3415-3537. https://doi.org/10.1093/eurheartj/ehae177

[2] Narula, J., Chandrashekhar, Y., Ahmadi, A., Abbara, S., Berman, D.S., Blankstein, R., *et al*. (2021) SCCT 2021 Expert Consensus Document on Coronary Computed Tomographic Angiography: A Report of the Society of Cardiovascular Computed Tomography. *Journal of Cardiovascular Computed Tomography*, **15**, 192-217. https://doi.org/10.1016/j.jcct.2020.11.001

[3] Cury, R.C., Leipsic, J., Abbara, S., Achenbach, S., Berman, D., Bittencourt, M., *et al*. (2022) CAD-RADS™ 2.0-2022 Coronary Artery Disease-Reporting and Data System. *Journal of Cardiovascular Computed Tomography*, **16**, 536-557. https://doi.org/10.1016/j.jcct.2022.07.002

[4] Huang, X., Gao, S., Ma, Y., Lu, X., Jia, Z. and Hou, Y. (2020) The Optimal Monoenergetic Spectral Image Level of Coronary Computed Tomography (CT) Angiography on a Dual-Layer Spectral Detector CT with Half-Dose Contrast Media. *Quantitative Imaging in Medicine and Surgery*, **10**, 592-603. https://doi.org/10.21037/qims.2020.02.17

[5] Raju, R., Thompson, A.G., Lee, K., Precious, B., Yang, T., Berger, A., *et al*. (2014) Reduced Iodine Load with CT Coronary Angiography Using Dual-Energy Imaging: A Prospective Randomized Trial Compared with Standard Coronary CT Angiography. *Journal of Cardiovascular Computed Tomography*, **8**, 282-288. https://doi.org/10.1016/j.jcct.2014.06.003

[6] Albrecht, M.H., Vogl, T.J., Martin, S.S., Nance, J.W., Duguay, T.M., Wichmann, J.L., *et al*. (2019) Review of Clinical Applications for Virtual Monoenergetic Dual-Energy CT. *Radiology*, **293**, 260-271. https://doi.org/10.1148/radiol.2019182297

[7] Yuan, D., Wang, L., Lyu, P., Zhang, Y., Gao, J. and Liu, J. (2024) Evaluation of Image Quality on Low Contrast Media with Deep Learning Image Reconstruction Algorithm in Prospective ECG-Triggering Coronary CT Angiography. *The International Journal of Cardiovascular Imaging*, **40**, 1377-1388. https://doi.org/10.1007/s10554-024-03113-y

[8] Otgonbaatar, C., Ryu, J., Shin, J., Kim, H.M., Seo, J.W., Shim, H., *et al*. (2023) Deep Learning Reconstruction Allows for Usage of Contrast Agent of Lower Concentration for Coronary CTA than Filtered Back Projection and Hybrid Iterative Reconstruction. *Acta Radiologica*, **64**, 1007-1017. https://doi.org/10.1177/02841851221118476

[9] Caruso, D., De Santis, D., Tremamunno, G., Santangeli, C., Polidori, T., Bona, G.G., *et al*. (2024) Deep Learning Reconstruction Algorithm and High-Concentration Contrast Medium: Feasibility of a Double-Low Protocol in Coronary Computed Tomography Angiography. *European Radiology*, **35**, 2213-2221. https://doi.org/10.1007/s00330-024-11059-x

[10] De Santis, D., Polidori, T., Tremamunno, G., Rucci, C., Piccinni, G., Zerunian, M., *et al*. (2023) Deep Learning Image

Reconstruction Algorithm: Impact on Image Quality in Coronary Computed Tomography Angiography. *La Radiologia Medica*, **128**, 434-444. https://doi.org/10.1007/s11547-023-01607-8

[11] Wang, M., Fan, J., Shi, X., Qin, L., Yan, F. and Yang, W. (2022) A Deep-Learning Reconstruction Algorithm That Improves the Image Quality of Low-Tube-Voltage Coronary CT Angiography. *European Journal of Radiology*, **146**, Article ID: 110070. https://doi.org/10.1016/j.ejrad.2021.110070

[12] Sun, J., Li, H., Li, J., Cao, Y., Zhou, Z., Li, M., *et al*. (2021) Performance Evaluation of Using Shorter Contrast Injection and 70 kVp with Deep Learning Image Reconstruction for Reduced Contrast Medium Dose and Radiation Dose in Coronary CT Angiography for Children: A Pilot Study. *Quantitative Imaging in Medicine and Surgery*, **11**, 4162-4171. https://doi.org/10.21037/qims-20-1159

[13] Ryu, J., Kim, K.H., Otgonbaatar, C., Kim, D.S., Shim, H. and Seo, J.W. (2024) Improved Stent Sharpness Evaluation with Super-Resolution Deep Learning Reconstruction in Coronary CT Angiography. *British Journal of Radiology*, **97**, 1286-1294. https://doi.org/10.1093/bjr/tqae094

[14] Nagayama, Y., Emoto, T., Kato, Y., Kidoh, M., Oda, S., Sakabe, D., *et al*. (2023) Improving Image Quality with Super-Resolution Deep-Learning-Based Reconstruction in Coronary CT Angiography. *European Radiology*, **33**, 8488-8500. https://doi.org/10.1007/s00330-023-09888-3

[15] Zhou, H., Tian, H., Chen, W., Hou, H., Shen, D., Zhao, Z., *et al*. (2026) Deep Learning Reconstruction Combined with Contrast-Enhancement Boost Technique in "Quadruple-Low" CCTA Protocol: Evaluation of Image Quality and Diagnostic Accuracy. *Academic Radiology*. https://doi.org/10.1016/j.acra.2026.01.025

[16] Lin, S., Liu, C., Zhou, Y., Chen, Q., Wang, S., Wu, J., *et al*. (2026) Feasibility of Ultra-Low Flow Rate Coronary CT Angiography Using Photon-Counting Detector CT: A Prospective Randomized Trial. *European Radiology Experimental*, **10**, Article No. 19. https://doi.org/10.1186/s41747-026-00677-3

[17] Takafuji, M., Kitagawa, K., Mizutani, S., Hamaguchi, A., Kisou, R., Iio, K., *et al*. (2023) Super-Resolution Deep Learning Reconstruction for Improved Image Quality of Coronary CT Angiography. *Radiology*: *Cardiothoracic Imaging*, **5**, e230085. https://doi.org/10.1148/ryct.230085

[18] Mergen, V., Rusek, S., Civaia, F., Rossi, P., Rajagopal, R., Bättig, E., *et al*. (2024) Virtual Calcium Removal in Calcified Coronary Arteries with Photon-Counting Detector CT—First *In-Vivo* Experience. *Frontiers in Cardiovascular Medicine*, **11**, Article ID: 1367463. https://doi.org/10.3389/fcvm.2024.1367463

[19] Wolf, E.V., Halfmann, M.C., Varga-Szemes, A., Fink, N., Kloeckner, R., Bockius, S., *et al*. (2024) Photon-Counting Detector CT Virtual Monoenergetic Images for Coronary Artery Stenosis Quantification: Phantom and *in Vivo* Evaluation. *American Journal of Roentgenology*, **222**, e2330481. https://doi.org/10.2214/ajr.23.30481

[20] Fahrni, G., Boccalini, S., Lacombe, H., de Oliveira, F., Houmeau, A., Francart, F., *et al*. (2025) Ultra-High-Resolution 40 keV Virtual Monoenergetic Imaging Using Spectral Photon-Counting CT in High-Risk Patients for Coronary Stenoses. *European Radiology*, **35**, 3042-3053. https://doi.org/10.1007/s00330-024-11237-x

[21] Xu, C., Xu, M., Yan, J., Li, Y., Yi, Y., Guo, Y., *et al*. (2022) The Impact of Deep Learning Reconstruction on Image Quality and Coronary CT Angiography-Derived Fractional Flow Reserve Values. *European Radiology*, **32**, 7918-7926. https://doi.org/10.1007/s00330-022-08796-2

[22] Liu, B., Reis, J., Sharma, A. and Wang, W. (2025) Application of Artificial Intelligence in Non-Invasive Cardiovascular Imaging for Coronary Artery Disease: A Systematic Review and Meta-Analysis. *Frontiers in Cardiovascular Medicine*, **12**, Article ID: 1664183. https://doi.org/10.3389/fcvm.2025.1664183

[23] Du, M., He, S., Liu, J. and Yuan, L. (2025) Artificial Intelligence in CT Angiography for the Detection of Coronary Artery Stenosis and Calcified Plaque: A Systematic Review and Meta-Analysis. *Academic Radiology*, **32**, 3776-3787. https://doi.org/10.1016/j.acra.2025.03.054

[24] Lin, A., Manral, N., McElhinney, P., Killekar, A., Matsumoto, H., Kwiecinski, J., *et al*. (2022) Deep Learning-Enabled Coronary CT Angiography for Plaque and Stenosis Quantification and Cardiac Risk Prediction: An International Multicentre Study. *The Lancet Digital Health*, **4**, e256-e265. https://doi.org/10.1016/s2589-7500(22)00022-x

[25] Ihdayhid, A.R., Sehly, A., He, A., Joyner, J., Flack, J., Konstantopoulos, J., *et al*. (2024) Coronary Artery Stenosis and High-Risk Plaque Assessed with an Unsupervised Fully Automated Deep Learning Technique. *JACC*: *Advances*, **3**, Article ID: 100861. https://doi.org/10.1016/j.jacadv.2024.100861

[26] Nannini, G., Saitta, S., Baggiano, A., Maragna, R., Mushtaq, S., Pontone, G., *et al*. (2024) A Fully Automated Deep Learning Approach for Coronary Artery Segmentation and Comprehensive Characterization. *APL Bioengineering*, **8**, Article ID: 016103. https://doi.org/10.1063/5.0181281

[27] Nurmohamed, N.S., Danad, I., Jukema, R.A., de Winter, R.W., de Groot, R.J., Driessen, R.S., *et al*. (2024) Development and Validation of a Quantitative Coronary CT Angiography Model for Diagnosis of Vessel-Specific Coronary Ischemia. *JACC*: *Cardiovascular Imaging*, **17**, 894-906. https://doi.org/10.1016/j.jcmg.2024.01.007

[28] van Noort, D., Guo, L., Leng, S., Shi, L., Tan, R., Teo, L., *et al*. (2024) Evaluating Machine Learning Accuracy in

Detecting Significant Coronary Stenosis Using CCTA-Derived Fractional Flow Reserve: Meta-Analysis and Systematic Review. *IJC Heart & Vasculature*, **55**, Article ID: 101528. https://doi.org/10.1016/j.ijcha.2024.101528

[29] Koetzier, L.R., Mastrodicasa, D., Szczykutowicz, T.P., van der Werf, N.R., Wang, A.S., Sandfort, V., *et al*. (2023) Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects. *Radiology*, **306**, e221257. https://doi.org/10.1148/radiol.221257

[30] Shrivastava, P., Kashikar, S., Parihar, P.H., Kasat, P., Bhangale, P. and Shrivastava, P. (2025) A Systematic Review on Deep Learning-Enabled Coronary CT Angiography for Plaque and Stenosis Quantification and Cardiac Risk Prediction. *European Journal of Radiology Open*, **14**, Article ID: 100652. https://doi.org/10.1016/j.ejro.2025.100652

[31] Liao, J., Huang, L., Qu, M., Chen, B. and Wang, G. (2022) Artificial Intelligence in Coronary CT Angiography: Current Status and Future Prospects. *Frontiers in Cardiovascular Medicine*, **9**, Article ID: 896366. https://doi.org/10.3389/fcvm.2022.896366

[32] Kobayashi, T., Nishii, T., Umehara, K., Ota, J., Ohta, Y., Fukuda, T., *et al*. (2022) Deep Learning-Based Noise Reduction for Coronary CT Angiography: Using Four-Dimensional Noise-Reduction Images as the Ground Truth. *Acta Radiologica*, **64**, 1831-1840. https://doi.org/10.1177/02841851221141656

[33] Bernardo, R., Nurmohamed, N.S., Bom, M.J., Jukema, R., de Winter, R.W., Sprengers, R., *et al*. (2025) Diagnostic Accuracy in Coronary CT Angiography Analysis: Artificial Intelligence versus Human Assessment. *Open Heart*, **12**, e003115. https://doi.org/10.1136/openhrt-2024-003115