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基于人工智能的医学影像学检查在动脉粥样硬化性狭窄定量评估的研究进展

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摘　要

动脉狭窄是动脉粥样硬化疾病的主要结局之一，其进展和稳定性对动脉粥样硬化疾病的预后和治疗产生重大影响。现有的影像学方法对于动脉粥样硬化性狭窄(Atherosclerotic stenosis, AS)的准确评估存在局限性，而人工智能(Artificial intelligence, AI)在医学影像分析中发挥重要作用，可以实现对病变严重程度和进展速度的定量评估及风险预测。目前，基于AI的医学影像学在动脉狭窄定量评估方面取得了显著进展，尤其是基于深度学习(Deep learning, DL)的算法在血管狭窄预测、斑块分类和识别中表现出良好的性能。本文对基于AI的医学影像学检查在AS定量评估中的研究进展进行综述，并对未来基于AI技术在动脉狭窄定量评估中可能存在的挑战和机遇进行展望。

关键词

动脉粥样硬化性狭窄，人工智能，医学影像学，定量评估

Research Progress of AI-Based Medical Imaging Examination in Quantitative Evaluation of Atherosclerotic Stenosis

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Abstract

Arterial stenosis is one of the main outcomes of atherosclerotic diseases, and its progression and

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stability have a significant impact on the prognosis and treatment of atherosclerotic diseases. Existing imaging methods have limitations for accurate assessment of atherosclerotic stenosis (AS), and artificial intelligence (AI) plays an important role in medical image analysis. The quantitative evaluation and risk prediction of the severity and progression of the disease can be realized. At present, AI-based medical imaging has made remarkable progress in the quantitative assessment of arterial stenosis, especially the algorithm based on deep learning (DL) has shown good performance in the prediction of arterial stenosis, plaque classification and recognition. This article reviews the research progress of AI-based medical imaging in quantitative assessment of AS, and looks forward to the possible challenges and opportunities of AI-based quantitative assessment of arterial stenosis in the future.

Keywords

Atherosclerotic Stenosis, Artificial Intelligence, Medical Imaging, Quantitative Assessment

1. 引言

动脉粥样硬化性狭窄(Atherosclerotic stenosis, AS)影响冠状动脉、脑动脉及外周动脉从而造成的缺血性心脏病和缺血性脑卒中仍是全球死亡和残疾的主要原因[1] [2]。AS 的严重程度能够指导临床医生评估病因，估计风险，并确定适当的干预措施，因此，作为动脉狭窄程度的诊断基础，动脉狭窄的准确量化对于建立最佳的临床管理至关重要[3] [4] [5]。

传统医学影像学检查在 AS 定量评估中发挥了重要作用，已发展到表征病变的各个方面，包括程度狭窄(%)、最小管腔面积(mm^2)、斑块体积(mm^3)、斑块负荷(%)、重塑比(%)、偏心指数和与组织炎症相关的增强率(%) [6] [7] [8]，临床上目前主要依靠超声成像、CTA、MRI 的无创方法进行诊断[8] [9] [10] [11]，然而传统的影像学判读由于大量的图像和广泛的成像范围会导致诊治被延误从而造成不可逆转的损伤[12]。另外目前常用的 AS 定量评估的目测法及手动测量法则存在主观性及耗时、耗力的缺点[13] [14]。相比之下，基于人工智能(Artificial intelligence, AI)的医学影像学检查擅长识别图像数据中复杂的表现形式，能够对图像进行自动分割与自动定量诊断，从而缩短图像后处理及诊断时间，缩小放射科诊断医师之间的差异，避免医生在超负荷工作后由于注意力不集中或视觉感知疲劳而造成的诊断错误，在 AS 的诊断、治疗及预后评估等方面发挥重要作用[15] [16] [17] [18]。本文就基于 AI 的医学影像学检查在 AS 定量评估中的相关研究进行综述。

2. 人工智能的概述

AI 于 1956 年美国达特茅斯会议上首次被提出，因其能够分析复杂数据、自动关联和预测的能力，优于传统的统计方法，在现实世界中显示出巨大的应用前景[19]。AI 的核心是机器学习(Machine learning, ML)，随着计算机设备的不断更新，深度学习(Deep learning, DL)作为 ML 的一个子领域问世[20]，DL 可在没有明确标识的情况下接收输入的数据并学习其特征，形成端－端机器学习模式，广泛应用于众多学科领域中，尤其在临床医疗解决实际疑难问题时有较强的表现，例如基于图像的卷积神经网络(Convolutional neural networks, CNN)融合了学习卷积滤波器进行特征学习的思想，利用隐含层之间简单的

局部非线性连接，创建每个深层的抽象表示，降低了模型的计算代价，还可以跨层共享权重，提取独立于其位置的图像特征，并使用尽可能多的隐藏层进行学习，是医疗领域的热点[19] [21] [22] [23]。目前在血管成像领域，AI 已被开发应用于心血管疾病的定量诊断和预测等方面[24] [25] [26]。

3. 基于人工智能的医学影像学检查在动脉粥样硬化性狭窄定量评估中的应用

3.1. 人工智能在 CTA 中的应用

CT 血管造影(CT angiography, CTA)是一种快速、准确、无创的评估 AS 的工具，特别是在急性情况下其应用更加有必要[27] [28]，疑似心血管疾病的患者通常会行冠状动脉 CT 血管造影(Coronary CT angiography, CCTA)或头颈部 CTA 检查，是当下基于 AI 定量分析中最流行的成像方式[13] [14] [22]。

Fan 等[29]建立了一个基于三维 CNN 模型的用于头颈部 CTA 图像的自动成像重建系统，并对该模型的算法性能、图像重建质量是否满足诊断需求、模型增强后的临床应用效率三个方面进行了全面的定量评估，结果发现该算法对各种增强 CTA 扫描(包括主动脉、颈动脉和颅内动脉)中骨和血管的分割性能好(训练集和验证集的骰子相似系数分别为 0.979 和 0.960、0.975 和 0.944，分割的总体准确率为 93.1%)，且图像质量的合格率为 92%；该研究团队在后来的研究中[14]，又建立了一个结合二维和三维 ResU-Net 的 CNN 模型进行准确的狭窄检测和斑块分类，该模型对狭窄检测($\kappa = 0.84$)、斑块分类($\kappa = 0.78$)及狭窄定量诊断($R = 0.87$, $P < 0.001$) 的一致性好，并能显著减少放射科医生诊断和报告书写的时间。即使在早期，一些半自动化人工智能软件对动脉狭窄程度的定量诊断也有较好的一致性(组内相关系数(Interclass correlation coefficient, ICC > 80%))，但由于 AI 算法的不成熟，对于斑块的分割与识别错误是造成诊断错误的主要原因之一[9] [30] [31]。

基于 AI 的 CCTA 分析也取得了先进成果。Griffin 等[13] [32]评估基于 ML 的 CCTA 狭窄程度量化的性能，分别得到良好和极好的一致性(ICC 分别为 0.73、0.88)。对斑块钙化积分、斑块的体积[26] [32]的定量分析中均表现出极好的一致性(ICC 分别为 0.96、0.96)。除了对管径和管壁的量化，AI 还能应用于血流的定量诊断。侵入性血流储备分数(Fractional flow reserve, FFR)是评估冠状动脉生理功能的“金标准”，但该方法为有创检查且费用昂贵，FFR_{CT} 是基于 CCTA 三维数据模型运用计算流体力学模拟真实冠状动脉血流而获取的冠状动脉血流动力学信息，现有基于 ML 的 FFR_{CT} 能够实现在数分钟内快速分析冠状动脉解剖结构与血流动力学变化[33]，Schuessler 等[34]研究结果表明，基于 ML 的 FFR_{CT} 与 FFR_{CT} 具有良好的相关性，基于量化评估的分层分析显示其诊断性能优于单纯 CCTA (曲线下面积(Area under the curve, AUC)分别为 0.84、0.69)。

3.2. 人工智能在 MRI 中的应用

高分辨率 MRI 血管壁成像作为一种新兴的非侵入性成像方式，因其优越的软组织对比度，已被证明是直接观察颅内和颈动脉血管壁和分类各种斑块特征的首选诊断方法[35]，近年来，3D 涡轮自旋回波被引入颅内及颈动脉血管壁的成像更显示出优越的分辨能力，在对管壁及管腔参数的评估中，ICC 可达 0.988 [36] [37] [38]，。研究者将 CNN 应用于颅内或颅外颈动脉血管壁分析，包括血管壁分割和分类。Shi 等[39] [40]利用重建的 2D 图像切片进行了血管分析，在对管壁面积、管腔面积、最小壁厚、最大壁厚和斑块范围等参数进行定量评估发现一致性极好(ICC 范围 0.77~0.93)。Wan 等[41]开发了一种自动分析颅内外动脉血管壁 3D 图像的方法，对血管中心线跟踪、血管矫直、血管壁分割和形态学量化评估同样发现极好的一致性(骰子系数为 0.88~0.90)，与前期 Gao 等[42]基于 3D 模型的方法结果一致，该研究发现从双序列 MRI 中分割颈动脉壁在所有颈动脉切片人工和自动识别诊断轮廓的一致性也极好(骰子系数均大于 0.87)。在最新的研究中，Wu 等[43]利用多任务学习技术对黑血 MRI 上进行建模并在神经网络中完成颈动脉管

腔分割、外壁分割和颈动脉粥样硬化诊断，该方法在“CAREII 测试”数据集中获得了目前最好的分割性能(管腔分割骰子系数为 0.97，外壁分割骰子系数为 0.97)，对颈动脉粥样硬化诊断的准确性也较好(AUC 为 0.95，准确度为 0.90)。

3.3. 人工智能在超声中的应用

超声优异的软组织分辨率和亚毫米空间分辨率非常适合血管细节成像，尤其适用于大的、浅表的、接近颈总动脉分叉处的血管探测[2] [44] [45]。与 CCTA 检查相比，心脏研究相对较少，因为体外超声不适用于冠状动脉检查，识别无症状性颈动脉疾病并提供临床决策支持的 ML 工具的开发是当前超声研究的主要焦点[46]。由于颈动脉内膜厚度(Intimamedia thickness, IMT)在 CTA 检查中的空间分辨率低使得超声检查成为 IMT 的独特诊断方法。IMT 的自动分割基于深度学习单层前馈神经网络使用了几种超声成像参数，如 Hough 转换、频域分析、像素强度分析，与专家手动分割相比，基于定量分析的分层分析得出灵敏度和特异性均大于 97% [47]。Huang 等[48]对单个斑块进行灰度分布分析，将斑块分为回声丰富、中等和回声清晰并建立回声类型和斑块易感性之间的关联，斑块类型的诊断准确率为 77.5%。Roy 等[49] [50]利用多种参数研究回声强度与颈动脉斑块易损性的相关性，AUC 可高达 0.97。

3.4. 基于人工智能的预后预测与风险评估

正确识别具有 AS 高危因素的患者，及时给予干预政策是心脑血管医学面临的一个重大挑战。尽管当前有各式各样的预测模型应用于预测心血管不良事件中，但传统的预测模型是基于对人群的分析而建立的，只能分析部分变量，无法有效地进行个体风险评估，而 AI 模型能够识别并综合分析大量的风险预测，因子及影像学参数，对心脑血管不良事件进行预测，帮助临床医生提前识别出不同风险层的患者，制定个性化治疗计划和随访方案，从而降低心脑血管疾病的发病率和死亡率[51]。

Hilbert 等[52]建立 DL 模型以利用 CTA 图像直接预测血管内治疗后良好的再灌注和良好功能结果，AUC 分别为 0.65、0.71。此外，MRA 可以显示与年龄相关的脑动脉变化，但测量或评估这种变化的工具或方法有限，Nam [53]等开发了一种三维 CNN 模型并在三维 MRA 上量化评估年龄相关的脑动脉变化，可预测年龄差以此定量分析脑血管衰老。Mu 等[26]评估基于 DL 的 CCTA 和非对比 CT 冠状动脉钙化评分的风险分类一致极好(加权 $\kappa = 0.94$)，分类准确率为 93%。Johnson 等[54]利用 ML 算法开发了一个血管特征模型，用来识别未来有无发生心血管不良事件的患者，发现该模型在预测冠状动脉疾病死亡率和全因死亡率时的预测效能均优于传统冠状动脉血管评分。先前 Motwani 等[55]研究的模型预测性能也高于传统 CCTA 指标评分，但其性能低于 Johnson 等开发的模型。这些研究观察到的结果都展现了在预测疑似心脑血管疾病患者的预后风险方面，AI 模型已具备传统模型所没有的优势。

4. 人工智能的限制

近年来，随 AI 技术在医学影像学领域的不断发展，相关研究表明[13] [14] [49] [52]，AI 技术能够通过对图像信息、病变特征和生物标记物进行分析，可从管腔直径、管腔面积、斑块成分等多个参数评估血管并预测 AS 患者的发病风险、疾病转归和临床结局，并为 AS 患者的危险分层提供参考依据。但其研究仍存在一些问题：1) 目前尚无统一的数据库，且 AI 技术应用于 AS 领域是一个跨学科、多领域的交叉学科，如何将多个领域的相关数据进行整合仍是一个需要解决的问题；2) AI 技术对 AS 患者发病风险预测及预后评估仍停留在初步阶段，如何进一步优化模型、提高模型泛化能力、完善预测体系是目前需要解决的问题；3) AI 技术在临床应用中仍存在许多伦理问题，如何平衡好患者的隐私保护和 AI 技术发展之间的关系是未来需要解决的问题。

5. 小结与展望

总之，虽然 AI 技术的发展为 AS 评估带来了新的机遇，但目前仍存在许多不足之处，需要进一步改进和完善。首先，目前的 AI 技术在分类准确性方面仍有待提高，未来研究需进一步完善算法，开发新的分类特征或改进已有特征。其次，对于斑块风险的评估需要更多高质量的前瞻性临床研究来证明其价值。最后，虽然 AI 技术在 AS 风险评估中表现出了一定的优势，但其对斑块的准确识别还存在很多问题，如斑块异质性、图像质量等。随着研究的深入，AI 技术对动脉粥样硬化斑块的分类将更加准确、定量评估将更加精确，为放射科医师及临床医师提供更准确的诊断依据。

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