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·正畸学专栏 综述·

人工智能在正畸源性牙根吸收诊断中的应用进展

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【摘要】 人工智能（AI）技术在口腔影像学领域快速发展，为正畸源性牙根吸收（OIRR）的早期识别和定量评估提供了新的技术手段。本文在梳理OIRR的临床特征及传统影像诊断局限的基础上，综述了近年来卷积神经网络（CNN）、动态图卷积神经网络（DGCNN）、YOLO目标检测和U-Net分割等深度学习算法在牙根吸收自动检测、三维分割、体积测量及严重程度分级中的应用，重点介绍基于锥形束计算机断层扫描（CBCT）的三维定量方法以及CBCT与数字化牙模融合构建复合三维牙模型的相关研究。文献复习结果表明，特定的深度学习模型（包括用于病灶分类的CNN、用于目标检测的YOLO、用于图像分割的U-Net以及用于点云分析的DGCNN）有助于提高OIRR评估效率和测量一致性，实现不同牙位及根段的精细化量化，但整体仍受CBCT图像伪影、数据标准不统一和算法可解释性不足等因素制约。引入Transformer架构以捕捉全局特征、应用联邦学习以解决数据隐私孤岛是未来的研究方向，建议将AI诊断结果与正畸临床流程深度融合，以促进OIRR的早期预警和风险分层管理。

【关键词】 人工智能；　牙根吸收；　正畸学；　医学图像处理；　深度学习；　卷积神经网络；　YOLO目标检测；　计算机辅助诊断；　锥形束计算机断层摄影术；　三维成像
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Advances in the application of artificial intelligence for diagnosing orthodontically induced root resorption

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【Abstract】 Artificial intelligence (AI) technology is developing rapidly in the field of dental imaging, providing new technical means for the early identification and quantitative assessment of orthodontically induced root resorption (OIRR). This article reviews recent advances in deep learning algorithms—such as convolutional neural networks (CNNs), dynamic graph CNNs (DGCNNs), YOLO object detection, and U-Net segmentation—for automatic root resorption detection, three-dimensional (3D) segmentation, volume measurement, and severity grading, with a focus on 3D quantitative methods based on cone-beam computed tomography (CBCT) and the integration of CBCT with digital dental models to construct composite 3D tooth models. The review is based on an analysis of the clinical features of OIRR and the limitations of traditional imaging diagnostics. The literature review indicates that specific deep learning models—including CNNs for lesion classification, YOLO for object detection, U-Net for image segmentation, and DGCNNs for

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point cloud analysis—contribute to improved efficiency and consistency in root resorption assessment, enabling detailed quantification across different tooth positions and root segments. However, overall performance is still constrained by factors such as CBCT imaging artifacts, lack of standardized data, and limited algorithm interpretability. Future research directions include adopting Transformer architectures to capture global features and applying federated learning to address data privacy silos. It is recommended to deeply integrate AI diagnostic results with orthodontic clinical workflows to promote early warning and risk-stratified management of OIRR.

【Key words】 artificial intelligence; root resorption; orthodontics; medical image processing; deep learning; convolutional neural network; YOLO for object detection; computer-aided diagnosis; cone-beam computed tomography; three-dimensional imaging

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人工智能(artificial intelligence,AI)技术在医学影像领域的应用已成为重要趋势,特别是在图像分析、疾病诊断及治疗风险预测方面[1-3]。AI通过机器学习和深度学习模型,特别是卷积神经网络(convolutional neural network,CNN),能高效处理大规模数据并实现自动特征提取与模式识别[4-6],广泛应用于医学影像的分类和检测中[7-8]。相较于传统方法,AI在影像预处理、分割及预测等环节展现出更高的准确性与安全性[9-10]。例如,深度学习模型在口腔医学中通过分析二维X线片、三维锥形束计算机断层扫描(cone-beam computed tomography,CBCT)影像及数字化牙模,显著提高了诊断效率与量化水平[11-12]。

在口腔影像领域,AI被广泛运用在龋齿检测[13-15]、根管治疗[16-18]、牙髓病分析[19-20]、牙种植[21-23]及牙周骨缺损评估[24]等诸多方面,取得了不错的成效。CNN在根尖片以及CBCT影像中的运用,可提高疾病的诊断准确率及早期发现率[25-27]。在正畸学方面,AI技术也呈现出极大潜力[28-29]。在牙根吸收的早期诊断以及风险评估中,借助AI自动分析CBCT影像,可更加精准地识别牙根结构以及病变,为正畸治疗当中的个体化诊疗提供数据支撑[30-31]。

随着技术的进一步发展,AI的应用正向着更加智能化、精准化的方向迈进,特别是在牙根吸收的早期诊断和随访管理方面,其优势将更加突出[32-33]。本文将系统综述人工智能技术在正畸源性牙根吸收(orthodontically induced root resorption,OIRR)诊断中的研究进展,重点总结不同深度学习算法在牙根自动检测、三维分割与定量评估中的应用现状与诊断性能,分析其临床价值与局限性,并对未来技术发展方向与临床转化前景进行展望,以期为正畸治疗中牙根吸收的早期识别与精准管理提供参考。

1　正畸源性牙根吸收的临床特征及诊断需求

牙根吸收是正畸治疗过程中常见的副作用之一,表现为牙根硬组织的永久性丧失,具有不可逆性[34]。按发生部位和病因可分为牙根内吸收和牙根外吸收,而OIRR是指由正畸治疗诱发的炎性牙根外吸收,是正畸治疗中较常见的医源性不良后果[35-36]。OIRR可发生于正畸治疗各阶段,显著影响牙齿预后与疗效稳定,早期识别高危个体、规避主要危险因素对降低其发生率具有重要意义[37-38]。

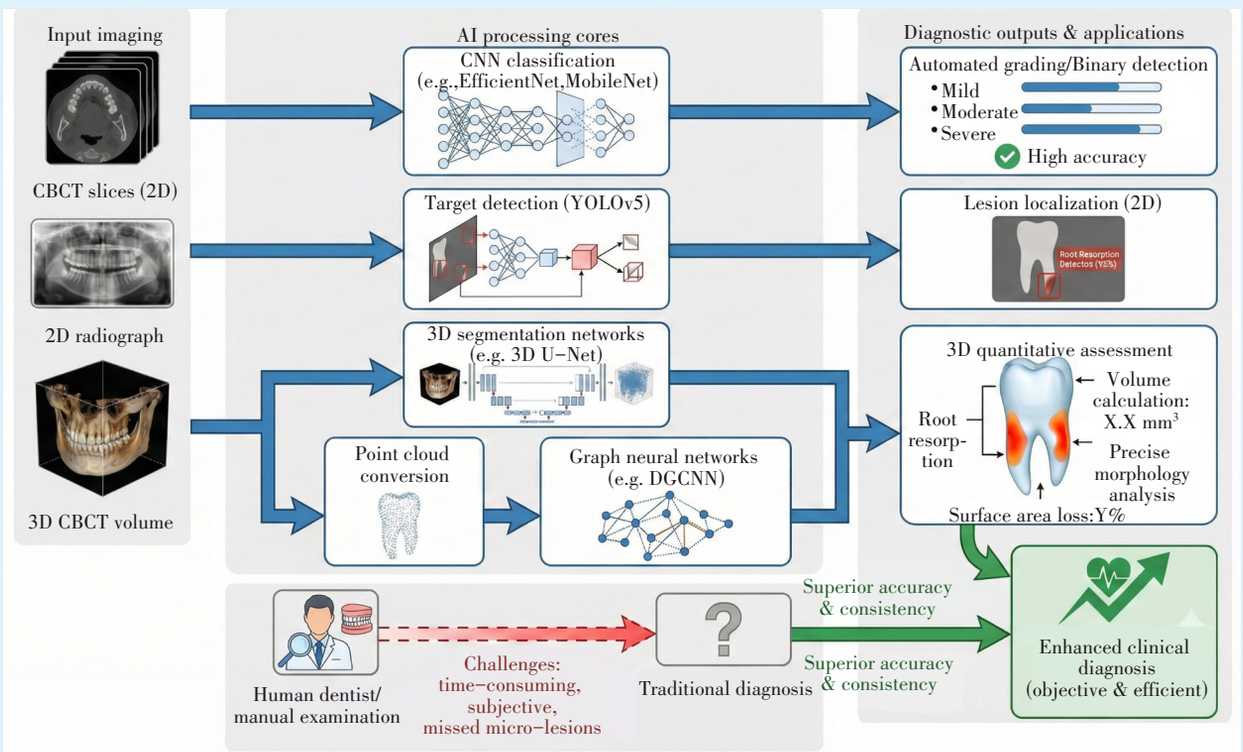
传统OIRR诊断主要依赖X线影像,但受限于操作者经验及影像重叠,难以识别早期微小病变,而鉴于牙根吸收的不可逆性,早期发现对阻断病程进展至关重要[39-40]。CBCT三维成像及自动化影像分析可辅助牙根吸收评估与牙科影像处理[41-42],全景片AI分析在牙科病变检测及诊断记录方面展现出潜力[43-44],但不同牙科结构和病变的识别性能仍存在差异[45],这一临床痛点迫切需要引入智能化手段,通过算法层面的特征提取来弥补传统影像学的不足。近年来,基于CNN的智能诊断系统可自动提取特征,显著提高检测敏感性与特异性,为早期精准诊断提供了新途径[46-47]。

2　人工智能在正畸源性牙根吸收诊断中的应用研究

2.1　AI诊断正畸源性牙根吸收的算法与技术方法

本文将从3个核心技术维度探讨深度学习在OIRR诊断中的应用体系:首先分析基于CNN的病灶分类与目标检测性能;其次阐述利用分割算法实现三维重建与体积量化的进展;最后探讨针对

影像伪影及模型“黑箱”问题，提升算法鲁棒性与可解释性的优化策略。在此框架下，EfficientNet、YOLO、U-Net及DGCNN等模型各司其职：基于CNN的模型（如EfficientNet系列）被用于CBCT影像的牙根吸收分类检测，能自动识别病变区域[47-48]。目标检测网络如YOLO也应用于此，通过边界框定位牙根吸收区域，实现快速检测[49-50]。与此同时，U-Net等分割网络被用于从全景片中提取牙齿和根部的二维结构，为后续病变分析提供基础[51-52]；更先进的三维模型如DGCNN将CBCT数据点云化，实现牙冠-牙根的自动分割[53]。这些方法共同构建了自动化的牙根吸收诊断体系（图1）。



AI: artificial intelligence

Figure 1　The core process of AI application in the diagnosis of orthodontically induced root resorption

图1　AI在正畸源性牙根吸收诊断中应用的核心流程

2.1.1　基于CNN的病灶分类与目标检测性能　在分类与检测任务中，深度学习模型展现出优异的诊断效能。多个经过预训练的CNN模型，在OIRR的诊断方面，准确率都超出了90%[47-48]。有研究显示，基于CNN的EfficientNet-B1模型对于CBCT切片的识别准确率达到了0.97，F1值约为0.98，明显优于正畸医生肉眼0.86的诊断率[47]。另一项研究里的基于CNN的EfficientNet-B4分级模型，在判别牙根吸收严重程度的时候，准确率可达到94%[48]。

2.1.2　利用分割算法实现三维重建与体积量化的进展　在分割以及三维重建方面，深度学习可开展对牙根吸收的三维定量分析的处理工作。有研究利用深度学习结合特征选择识别离体牙CBCT切片中的人工牙根外吸收缺损，最高分类准确率为81.9%[54]。特别指出的是，U-Net及其三维衍生架构（如3D U-Net）依托其经典的编码器-解码器设计与跳跃连接机制，能够高效跨层融合高分辨率的空间细节与深层语义特征，从而有望用于牙根吸收边缘的分割探索，将为病灶的三维可视化与精准量化提供坚实的算法基础[51-52]。借助把CBCT数据转换为点云，并且运用DGCNN来分割牙冠与牙根，研究者实现了全自动的牙根体积测量：所测得的牙根体积和人工方法高度一致（各牙位测量ICC > 0.95）[53]。这种方法还可对牙根吸收严重程度进行自动分类，准确率超过80%，给临床提供了可靠的三维评估工具[53]。此外，最新的验证研究进一步证实，AI辅助的三维定量方法在正畸-正颌联合治疗后的牙根吸收评估中也表现出极高的可

重复性，这拓展了该技术在复杂正畸病例中的应用范围[41, 55]。

2.1.3　提升算法鲁棒性与可解释性的优化策略　在提高模型的鲁棒性以及解释性方面，可运用多种影像预处理和解释策略，在模型开展训练之前，增强CBCT影像，比如把高斯锐化作为工具运用，突出牙根边缘的细节，同时把图像统一进行重采样，让其达到固定分辨率，以提高模型对牙根吸收的识别表现[47]。CBCT中的明显束硬化伪影会增加模型对种植支持冠、牙冠及桥体等结构的识别难度[45]。为了提高模型决策的可解释性，选用Grad-CAM等可视化方法来生成热图，将模型关注的关键区域高亮显示，验证模型依据与临床知识的契合性，这些策略一起保证了人工智能诊断OIRR的可靠性以及可解释性[47-48]。

2.2　正畸源性牙根吸收AI诊断的研究现状与应用评估

现有研究表明，AI在OIRR诊断和评估中已取得甚至优于传统人工方法的效果，并展现出独特的优势。对于体积定量评估的一致性，AI模型在牙根体积定量评估中与人工测量结果高度一致[35, 37]。一项研究报告显示牙根体积损失测量的检查者间ICC为0.870，这表明相关测量具有较好的可重复性[35]。但不同分割及测量方法在局部体积变化特别是在牙根根中及根尖三分之一区域的测量上存在差异[35, 53]。这种差异提示应关注AI与人工评估在不同部位测量上的偏差，并在临床解读时加以考虑[35]。

在定位牙根吸收部位和结果解释方面，深度学习模型可自动开展牙根吸收发生部位的定位工作，并且凭借配准治疗前后的CBCT数据来确定主要吸收区[37]，同时，借助Grad-CAM等技术可以把模型决策以热图的形式可视化，凸显模型关注区域，Grad-CAM显示模型主要是依靠根尖区域去判断吸收情况，其他热图分析也说明CNN聚焦在了牙根的关键特征上[47-48]。这些可解释性的手段可帮助医生理解AI的判别依据，并且可直观呈现出吸收分布情况。

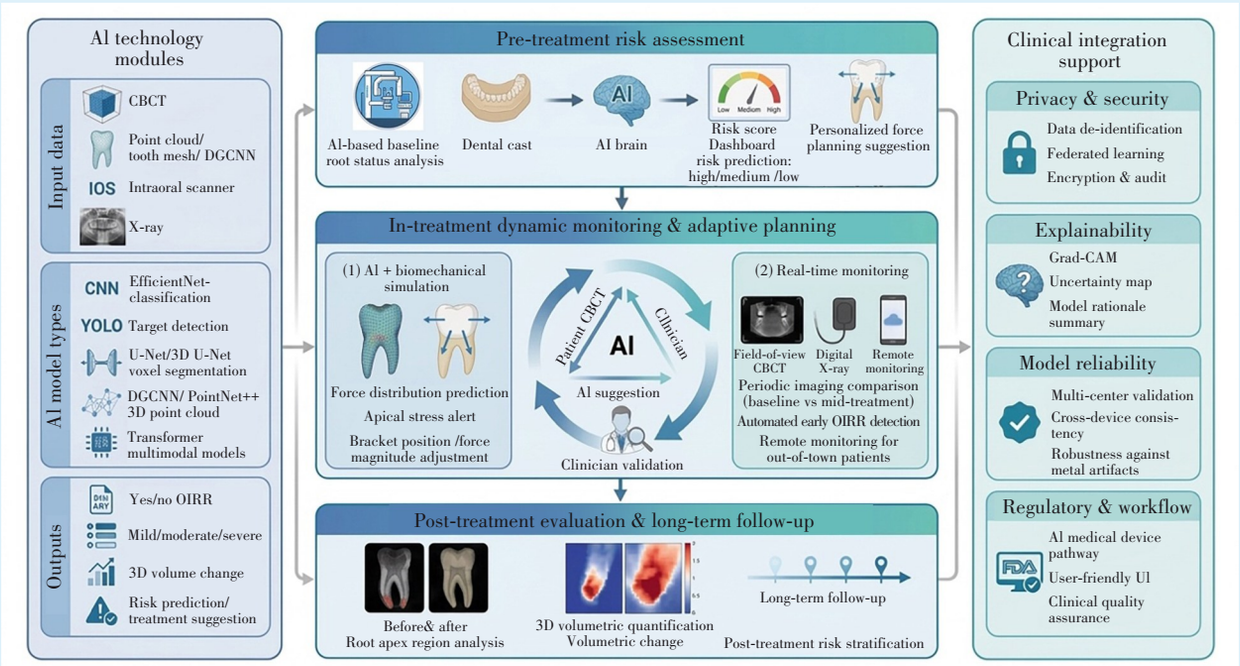
综合不同算法的诊断性能，传统CNN及YOLO网络在病情自动分级与二维病灶定位上高度成熟（准确率达0.94~0.97，分割F1值约0.98），显著超越了传统人工评估水平[47-48, 50]。相比之下，U-Net与DGCNN等网络在图像分割与全牙列体积定量中专长显著（ICC > 0.95），提供了更具临床直观性的病灶辅助定位[51-54]。具体而言，U-Net系列模型生成的精细三维分割结果结合表面配准，可弥补二维影像在牙根形态评估中的局限，通过呈现牙根表面的三维变化并量化其长度和体积变化，有助于减少人工手动勾画的耗时，且具有较好的测量重复性，为牙根吸收的评估提供三维形态学与定量依据[41]。

然而，多数三维深度网络面临较高的算力部署需求，且模型固有的“黑箱”特性导致其临床可解释性依然受限，同时整体性能仍受CBCT金属伪影干扰与缺乏统一评估标准的制约[45, 56]。尽管现有研究的牙位和样本来源不同[37, 54]，但最新的研究利用基于点云的DGCNN，通过捕捉精细的三维几何特征，已在包括后牙在内的全牙列中实现了高度一致的体积测量（ICC＞0.95）[53]。未来在改进影像预处理与建立标准化多中心数据的基础上，积极引入擅长全局模式捕捉的Transformer架构或多模态混合模型，将是突破现阶段单一模型性能瓶颈的核心方向[57]。

2.3　临床应用

AI正一步步融入正畸临床，从治疗之前的风险评估到监测及决策支持，在治疗之前，AI会对初始CBCT进行分析，来量化牙根长度并且检测隐匿吸收的迹象，识别出牙根吸收高风险的患者，提示医生去降低加力、加强随访以预防根吸收[54, 58-59]。

在治疗过程当中，AI未来有望运用生物力学模拟以及反馈控制来开展动态优化加力的工作，如果预测到某一个牙根尖应力过大的情况，那就会提示去调整托槽或者是把力量减小，以实现避免因为过度用力而致使根吸收[33, 60]。这样在临床AI可结合影像数据监测牙根变化，检测早期吸收的征象，及时预警并且辅助医生做出决策，让医生可以尽早干预[61-62]。如图2所示，AI在正畸临床流程中的集成应用主要涵盖三大核心阶段：治疗前基于多模态数据的风险评估与个性化加力规划；治疗中结合生物力学模拟的根尖应力预警及动态监测；治疗后基于三维体积量化的长期随访与风险分层。同时，该闭环流程需依托数据隐私保护与模型可解释性等底层支持。值得注意的是，一项采用AI辅助体积评估的随机对照试验未显示个性化力值方案较传统方案显著降低总体牙根体积损失，且个性化力值组的部分根尖指标提示吸收稍高[58]。因此，实时反馈及个性化加力仍应作为待验证的研究方向，同时AI融入临床也面临数据隐私、算法可解释性以及伦理等挑战[63-64]。



AI: artificial intelligence

Figure 2　Integrated application framework of AI in an orthodontic clinical workflow

图2　AI在正畸临床流程中的集成应用框架

3　未来展望与发展方向

3.1　新兴技术与研究方向

目前，相关牙科及OIRR影像诊断的AI研究主要涉及EfficientNet等CNN分类模型[47-48]、YOLO系列模型[49-50]、U-Net分割模型[51-52]及DGCNN图网络[53]，用于病变分类、牙齿分割或三维定量分析，这些方法在X线片及CBCT影像分析中已取得一定进展。尽管现有方法仍具临床价值，但其性能提升日趋缓慢，还需引入更具潜力的前沿技术以寻求突破。

Transformer架构如Vit等凭借全局自注意力有希望提高病灶检测及分割的精度[65-66]，点云网络如PointNet++等可直接处理牙齿点云实现精细三维分析，属于下一代高潜力工具[8, 67]。除此之外，自监督学习可借助海量未标注数据预训练模型，在标注有限的情况下提升模型的鲁棒性和敏感度[68-69]。模型轻量化如MobileNetV3等能让AI更便于部署在临床终端并且保持足够的精度[48]。多模态融合如CLIP将影像与文本信息结合有希望为正畸诊断引入跨域信息，实现低标注条件下的病变识别[70-71]。把上述新兴的方法有机结合起来，预期可在牙根吸收的自动诊断中极大程度提升分割精度、定位准确性、模型鲁棒性以及解释性；相比较而言，仅依靠传统CNN在小数据集上面的迭代改进可能很快就会碰到瓶颈。

3.2　临床集成、伦理与法律挑战

在临床落实AI辅助诊断工作，仍需克服不少现实挑战。数据隐私是首要问题：鉴于法规的限制，医疗机构很难把患者的影像汇集起来给模型训练。联邦学习（federated learning）提供了一种“数据不动模型动”的解决方案，在本地保存数据的前提下，开展跨机构联合建模[72-74]。系统的综述显示，联邦学习已在多中心医学影像分析中展现出与集中式训练相当的性能，且隐私保护能力显著增强[75-76]。

模型的解释性跟可信度也需重视：深度模型一般都是“黑箱”，医生很难理解它的判别依据，这对取得信任来说是不利的[77-78]。针对这个情况，可以依靠可视化模型的关注区域、提高决策透明度等方式来提升解释性，提高临床的接纳度，比如在OIRR检测中引入Grad-CAM热图来辅助呈现模型关注的根尖区域，这就是一种增加可解释性的尝试[47-48]。

AI用于影像辅助诊断的法律责任边界尚存争议[79-80]，在没有明确的法规来进行指导的情况下，容易让医生对AI有顾虑甚至拒绝使用[81-82]。最新的法律伦理研究指出，AI在医疗中的应用引发了关于责任归属和决策透明度的广泛讨论，尤其是

在AI出现误诊时，医生与软件开发商的责任边界尚不明确。因此，应制定明确的专业指南以界定AI的诊疗定位，并且借助立法以澄清AI决策的责任划分。为促进规范应用，建议制定“人机协同”的行业指南，明确AI仅作为初筛辅助工具，最终诊断责任归属临床医生[83-84]；此外，立法层面需进一步界定软件开发商在算法系统性错误中的责任边界[85]。借助联邦学习、可解释AI等以及制度如指南、法规两个方面的完善，才可在保证数据合规、模型可靠的前提下，把AI融入到正畸临床工作中，真正成为医师可以信赖的辅助决策工具[83, 85]。

4　小　结

人工智能显著提升了OIRR诊断效能，其检测与定位能力已匹敌甚至超越人工水准，增强了量化评估的可靠性[47-49]。尽管目前仍受CBCT伪影、数据标准及伦理法律等挑战限制[86-88]，但未来Transformer、图神经网络及自监督学习等技术的引入有望进一步突破精度瓶颈[89-90]。结合多模态融合、联邦学习及可解释性技术，并完善相关应用规范，将有效提升模型可信度并推动其在正畸临床的安全落地。总而言之，AI在OIRR诊断中的应用前景非常广阔，将持续赋能正畸诊疗，促进其向精准化与个体化方向发展。

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