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· 综述 ·

深度学习在牙发育异常及牙发育相关诊疗中的应用研究进展

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【摘要】 牙发育异常及牙发育相关诊疗是口腔临床工作中的难点,涉及牙发育异常诊治、牙发育评估等多方面,涵盖从疾病诊断到治疗方案制定各环节,诊治难度大,需要医生具有扎实的理论基础和丰富的临床经验。近年来,得益于丰富的口腔临床图像资源,人工智能中以卷积神经网络为代表的深度学习技术不断发展,为口腔疾病诊疗提供了有利支持,显著提高了诊治效率。深度学习在牙发育异常及牙发育相关诊疗方面具有多方面的应用,首先其可以识别影像片和口内照中的牙发育异常疾病,以辅助医生诊断。其次,深度学习可以进行牙发育评估和牙萌出预测,为个性化治疗方案的制定提供参考。此外,其还能够识别牙根及根管形态、定位疑难根管,帮助医生了解根管解剖,提高牙髓治疗成功率。尽管深度学习在牙发育异常及牙发育相关诊疗方面具有重要应用价值,但整体研究仍处于初级阶段,存在无法进行疾病系统化诊治、多为单中心研究等不足。未来应尽可能设计多中心研究,构建集疾病诊断、发育评估等为一体的深度学习模型,综合分析多因素,进一步提高模型应用价值。

【关键词】 深度学习; 人工智能; 卷积神经网络; 牙发育; 牙发育异常; 牙发育评估; 根管形态; 牙萌出

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【Abstract】 Dental developmental abnormalities and dental development-related diagnosis and treatment represents a critical and challenging area of clinical practice. This process spans multiple stages, from diagnosis to the creation of treatment plans, requiring substantial theoretical knowledge and rich clinical experience. In recent years, the development of artificial intelligence (AI), particularly deep learning technologies exemplified by convolutional neural networks, has been facilitated by the abundance of dental clinical image resources. Advancements in AI have provided substantial support for the diagnosis and treatment of oral diseases, significantly enhancing clinical efficiency. Deep learning has numerous applications in developmental abnormalities and dental development-related diagnosis and treatment. First, deep learning can assist in the identification of developmental abnormalities in radiographs and intraoral images, helping dentists make accurate diagnoses. Second, this technology can be used to assess dental development and predict tooth eruption, providing valuable reference for the formulation of personalized treatment plans. Furthermore, deep



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learning can identify root and root canal morphology, as well as locate challenging root canals, thereby enhancing the dentists' understanding of root canal anatomy and improving the success rate of endodontic treatments. Despite its significant potential in these areas, research in this field remains in the early stage. There are several limitations in the literature, including the inability to implement systematic disease diagnosis and treatment and a lack of multi-center studies. Future research should aim to design multi-center studies and develop deep learning models that integrate disease diagnosis, developmental assessment, and other factors, conducting a comprehensive analysis of multiple variables to further enhance the practical value of these models.

【Key words】 deep learning; artificial intelligence; convolutional neural networks; dental development; dental developmental abnormalities; dental development assessment; root canal morphology; tooth eruption

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牙发育是胚胎早期发育过程中,上皮和间充质组织通过各种信号通路相互作用的结果^[1],微观层面器官发生的复杂性一定程度上决定了宏观层面口腔表现的复杂性,不同个体间牙齿数目、牙冠及根管形态、牙齿发育速度、萌出方向等都存在一定差异,因此牙发育异常及牙发育相关诊疗难度大,涵盖广,涉及牙发育异常诊治、牙发育评估、牙根及根管形态评估、牙萌出预测等多方面,对于口腔医生挑战较高。如何降低诊治难度,提高诊治效率,避免医生临床水平差距引起的诊疗效果差异,拉平诊疗基线,是当前临床中的重难点。

在大数据背景下,随着计算机算力不断提高,机器学习、自然语言处理、语音识别等各类人工智能技术迅速崛起。深度学习是人工智能的重要子领域和技术之一,本质上是多层神经网络架构,主要组成成分为人工神经元^[2]。不同的神经网络架构和算法设计构成了各种深度学习模型。卷积神经网络(convolutional neural networks, CNNs)是深度学习模型中一种具有代表性的神经网络模型,专门用于处理网状数据(如图像),因而广泛应用于分类、分割、检测等计算机视觉任务^[3]。近年来,得益于丰富的口腔临床资源, CNN 模型已经应用于牙菌斑检测^[4]、龋病诊断^[5]、面型分析^[6]等口腔各个领域,具有速度快、自动化、精度高等优点,应用前景广阔^[7]。将深度学习与牙发育异常及牙发育相关诊疗相结合,建立高效、精准的诊疗模式,可以帮助口腔医生作出更加科学合理的临床决策,推动口腔医疗的智能化发展。笔者对深度学习在牙发育异常及牙发育相关诊疗中的研究现状进行综述,以期对深度学习在该领域的深入发展提供思路。

1 牙发育异常

牙发育异常是牙在发育过程中,受到遗传或环境因素的影响,上皮和间充质作用紊乱引起的一类疾病,包括数目异常、形态异常、结构异常、萌出及脱落异常等^[8-9]。牙发育异常疾病不仅会影响美观和咀嚼功能,还可能引起错颌畸形、邻牙牙根吸收、诱发囊肿形成等严重并发症,因此对此类疾病的诊治尤为重要^[10-11]。

1.1 数目异常

牙齿数目异常主要分为数目不足与数目过多两大类,病因不明,均可影响患者的口腔健康^[12]。数目不足包括个别牙或多数牙缺失、先天性无牙症,数目过多包括额外牙和牙瘤。

目前,大部分研究集中于对全景片中多生牙的检测,虽然不同研究使用模型存在差异,但都展现出良好性能,准确率超过 90%,证明了当前 U-Net、Detect-Net 等不同 CNN 模型对多生牙的影像特征的强大分析学习能力^[13-15]。尽管深度学习在多生牙诊断方面的相关研究已较为成熟,但针对其他数目异常疾病的研究却十分有限。在牙瘤诊断上,仅有少量研究提出了识别牙瘤的 CNN 模型,虽然结果显示准确率为 80%,但作者仅使用了 30 张牙瘤图像进行模型训练,20 张进行模型测试,未来仍需要更大数据集的相关研究评估模型的泛化性和鲁棒性^[16]。

此外,虽然许多研究表明深度学习可实现对乳恒牙的精确分割、编号^[17-19],但纳入的数据集均为无数目异常的全景片,无法同时实现编号和数目异常的识别。国内学者首次提出了能同时进行乳恒牙编号和检测多生牙及先天缺牙的深度学习模型。研究人员收集了 800 张全景片按照 6:2:2

分配至训练集、验证集和测试集对以 ResNet-50 为骨干网络的模型进行训练、参数调整和性能测试,并使用额外的 907 张图像作为外部测试集评估模型泛化性和鲁棒性。结果显示,在内部和外部测试集中,模型的敏感性、特异性、阳性预测值、阴性预测值均达到 90% 以上,能够很好地进行数目异常识别^[20]。

1.2 形态异常

牙齿形态异常包括畸形中央尖、牙内陷、牛牙症、双牙畸形等各类疾病。目前,针对此类疾病的深度学习诊断研究较为缺乏,仅有少量研究涉及畸形中央尖和牛牙症,这可能归因于其发病率相对较低,难以收集足够的数据资料。

畸形中央尖是牙发育期间,内釉上皮和牙乳头干细胞过度增殖和折叠所致,常表现为中央窝处一突起牙尖,好发于亚洲人种^[21-22]。Choi 等^[23]纳入 402 张根尖片构建了 6 个 CNN 模型用于畸形中央尖诊断,结果表明 Resnet 模型性能最佳,曲线下面积 (area under curve, AUC) 为 0.878,准确率为 80.5%,证明了深度学习应用于诊治该疾病的可行性。鉴于根尖片常用于畸形中央尖患牙的进一步检查,国内学者开发了基于全景片的畸形中央尖检测模型,AUC 为 0.956,不仅可以检测已萌出的畸形中央尖患牙,更重要的是其还能够识别牙胚中的畸形中央尖,从而做到早期发现、早期干预,避免畸形中央尖折断引起严重后果^[24]。

牛牙症是一种少见的牙齿形态异常,主要特征为髓腔增大、髓室垂直高度增加、牙根短小^[25]。Duman 等^[26]利用 U-Net 对全景片中的牛牙症患牙进行分割检测,发现该模型对牛牙症的诊断能力已经接近专家水平,敏感性为 86.5%,精确度为 78.98%。虽然模型展现出不错的性能,但鉴于上颌磨牙影像受到上颌窦等影响,难以分割,作者提出应进一步对上下颌磨牙进行亚组分析,以明确模型在上下颌牛牙症的检测中是否存在差异。

1.3 结构异常

牙齿结构异常包括牙釉质发育不全、牙本质发育不全、氟牙症等,由于牙体硬组织的发育不全,导致对牙髓的保护作用减弱,常引发牙齿敏感甚至牙髓感染等。此外,前牙结构异常容易引起美观和心理方面的问题^[27]。因此,该类疾病的诊治对于患者口腔健康具有重要意义。目前,对于结构异常疾病的检测研究集中于牙釉质发育缺陷型疾病 (developmental defects of enamel, DDE) 方

面,其诊断主要基于口腔医生的临床检查,因此口内摄影照片便成为深度学习相关研究的重要数据资源。

磨牙-切牙釉质矿化不全 (molar-incisor hypomineralization, MIH) 是指多因素引起的至少一颗第一恒磨牙牙釉质矿化不全,常伴切牙受累,目前正成为重要的全球公共卫生问题^[28]。许多研究已经成功构建出能识别口内照中 MIH 的检测模型,Neumayr 等^[29]和 Schönewolf 等^[30]是将 MIH 与正常牙齿进行区别,而 Felsch 等^[31]和 Alevizakos 等^[32]则是对 MIH 和龋病、氟斑牙等进行鉴别诊断,其模型的最佳准确率均达到 90% 以上。值得一提的是,Neumayr 等^[29]的研究是完全基于互联网中公开的 MIH 图像数据进行的模型训练、测试,说明当前深度学习模型已经可以很好地捕获 MIH 的临床特征,如釉质斑块、釉质崩解、非典型性修复体等。

遗传性牙釉质发育不全 (amelogenesis imperfecta, AI) 和氟牙症分别是牙齿发育期间遗传因素和获得性氟摄入过多而导致的牙釉质发育缺陷型疾病^[33]。国外学者构建了 ResNet34、ResNet50、AlexNet、VGG16、DenseNet121 这五种模型用于氟牙症、遗传性牙釉质发育不全、龋齿、MIH 的识别^[32]。结果显示,VGG16 模型虽然对氟牙症的检测准确率最高,达 95% 以上,但对遗传性牙釉质发育不全的检测准确率却仅约 55%。而对氟牙症检测准确率最低的 AlexNet 模型却对遗传性牙釉质发育不全有高达 90% 的检测准确率,这提示模型在区分氟牙症和遗传性牙釉质发育不全方面具有一定限制性。

1.4 萌出及脱落异常

该类疾病主要分为萌出过早、萌出过迟、异位萌出以及脱落异常。牙齿萌出异常一般累及恒牙,目前,深度学习相关研究热点集中于异位萌出诊断。

牙齿异位萌出是指恒牙未在牙列的正常位置萌出,常见于上颌第一恒磨牙及尖牙^[34]。鉴于全景片能够很好地评估牙齿萌出状况,且辐射剂量低,因此异位萌出相关研究所使用的均为全景片影像数据。

Zhu 等^[35]首次提出基于 nnU-Net 的第一恒磨牙异位萌出检测模型,其纳入 285 张全景片进行研究,结果表明,模型识别第一恒磨牙的准确率达 99%,精确度达 84.5%,显著优于医生水平。Liu 等^[36]进一步指出在 CNN 模型辅助下,医生对于上

颌第一恒磨牙异位萌出的诊断能力得到提高,能够较好地提高临床工作效率。Yu等^[37]则构建了针对全口牙异位萌出检测的CNN模型,结果显示其能够精确分割及识别全部异位萌出患牙,证明了深度学习在此类疾病诊治中的有效性。

2 牙发育评估

牙发育评估在儿童口腔临床工作中具有重要作用,其能够为乳恒牙牙髓疾病治疗、错颌畸形治疗方案制定等提供参考^[38]。此外,牙发育评估还可帮助医生判断牙龄,更加准确地掌握儿童生长发育趋势。目前,针对恒牙钙化阶段的分类方法包括Nolla法、Demirjian法、Willems法、Moorrees法等,虽然各类方法存在一定差异,适用人群有所不同,但本质上均是基于恒牙牙冠和牙根钙化程度进行发育阶段分期^[39-40]。

此前,大多数基于深度学习的牙发育评估研究集中于单颗牙,尤其是第三磨牙^[41-42],尽管也有少量研究针对左下颌前磨牙^[43],且这些研究已经达到了一定的分类准确性,但仅对单颗牙或两颗牙分类意义有限,极大限制了其临床应用。近年来,众多学者开始尝试对全景片中的更多牙齿进行发育评估,以期建立更加完善的分类模型。

Matthijs等^[44]和Kurt等^[45]分别提出了使用改良Demirjian法和Demirjian法对左下颌牙齿进行发育评估的深度学习模型,结果均表明模型在切牙分类任务中表现最差,在磨牙分类任务中表现最好。在进一步对全牙列进行发育评估的相关研究中,大部分研究基于Demirjian法^[46-48],仅一项研究涉及Moorrees法和Nolla法^[37]。虽然这些研究使用不同模型,准确率、召回率、精确度等指标存在较大差异,但均发现模型分类错误集中在相邻阶段,说明现阶段模型难以准确捕捉相邻分类阶段的细小特征差异。

此外,也有大量研究在牙发育评估分级的基础上,利用深度学习进行牙龄估算以期更加精确地掌握儿童及青少年所处的生长发育阶段。与牙发育评估分级类似,先前研究大多使用第三磨牙^[49-50]进行牙龄估算,但现在越来越多的研究开始纳入全景片中的所有牙齿进行牙龄估算^[47,51],力求更加接近真实年龄。

Shi等^[47]利用深度学习自动计算牙龄与真实年龄的差异,平均绝对误差为0.72岁,Kokomoto等^[51]研究的平均绝对误差更是缩小至0.261岁,十

分接近真实年龄。将深度学习这种端到端的方法应用到牙龄估算中,可以直接输入图像并生成所需输出,从而省去了传统方法中分割、特征提取、回归等易出错的中间步骤,因此结果更加准确、重复性好^[52]。

3 牙根及根管发育

了解牙根及根管的数目与形态对于根管治疗具有重要意义,准确掌握根管系统的解剖特征能够有效指导临床操作,减少并发症的发生,是成功治疗的前提^[53]。

Hiraiwa等^[54]构建了能在全景片中识别下颌第一磨牙远中双牙根的CNN模型,准确率达86.9%。国内学者利用CNN模型对下颌第二磨牙根管形态进行分类,结果发现模型能够以高于医生的水平将根尖片中的根管形态分为融合型、对称型和不对称型^[55]。Jeon等^[56]则首次提出能预测全景片中下颌第二磨牙为C形根管的CNN模型,准确率为95.1%,梯度加权类激活映射(gradient-weighted class activation maps, Grad-CAM)显示其是通过牙根走形和根分叉形状区分C形与非C形根管。Yang等^[57]研究则发现,当把根尖片和全景片结合使用,且单独截取出牙根部分进行识别时,模型对于C形根管的预测性能最佳,AUC为0.99。随后,该团队又进行多中心研究进一步说明了模型具有优异的泛化性能^[58]。而对髓腔和根管进行3D分割则可进一步帮助口腔医生熟悉侧支根管等复杂的根管系统解剖结构^[59]。由于U-Net模型具备优异的分割性能,因此大部分研究均将采用该模型的基本架构^[60-61]。

Sherwood等^[62]提出了3种能在CBCT中对C形根管分割和分类的深度学习模型,模型敏感性均超过70%,而Santos-Junior等^[63]则不仅开发出了一种能在CBCT中对单根牙进行根管系统分割的CNN模型,研究结果还证明了其分割精度和效率都明显优于人工手动分割,能够生成更加精细的3D模型,证明了人工智能在三维数据的分析处理上具有巨大潜力。

上颌磨牙多为三根牙,近颊根常会有1个以上的根管,MB2的遗漏是导致根管治疗失败的重要原因^[64-65]。由于MB2具有较大的解剖变异,难以寻找,因此国外学者利用CBCT影像数据开发出了能检测MB2的深度学习模型^[66-67]。Albitar等^[66]使用的是已接受根管治疗的牙齿影像,而Duman

等^[67]使用的是未接受根管治疗的牙齿影像,虽然数据类型存在差异,但模型均展现出来良好性能,说明了深度学习在MB2识别方面的广阔临床应用前景,能够帮助医生在CBCT图像中定位MB2。

4 萌出预测

4.1 第三磨牙萌出预测

目前,牙齿萌出预测的人工智能相关研究主要集中于第三磨牙,预测第三磨牙的萌出对于正畸、拔牙治疗方案的制定等具有重大参考价值,并促进临床决策精准化^[68]。

大部分研究是通过构建深度学习模型测量第三磨牙长轴与邻近第二磨牙长轴的夹角,来预测第三磨牙是否阻生^[69-70]。但考虑到第三磨牙的萌出受到磨牙后间隙宽度、磨牙发育状态等多种因素的影响^[71],仅使用长轴夹角的预测方法效果有限。

Chopra等^[72]纳入了771例患者的两个不同时间点共1542张右下第三磨牙图像,通过纵向对比分析了磨牙发育阶段、第三磨牙与第二磨牙的长轴夹角、磨牙后间隙宽度等因素并构建CNN模型预测萌出,结果发现,当使用长轴夹角与磨牙后间隙宽度综合分析时,模型显示出最佳性能,敏感性和特异性均超过70%。

预测第三磨牙萌出对于第三磨牙的全周期健康管理具有重要意义,人工智能的应用不仅可以提高评估效率,还可辅助医师进行临床决策。虽然当前研究已经初步证明了其可行性,但仍需进一步研究综合萌出高度、发育状态等多种因素建立更为全面的CNN模型。

4.2 尖牙萌出预测

尖牙是全口牙列中除第三磨牙外阻生率最高的牙齿,其正常萌出对于口腔面部美观及建立健康的咬合关系具有重要作用^[73]。

虽然许多研究发现尖牙与侧切牙长轴夹角等因素能够预测其萌出^[74-75],且已有研究使用监督式机器学习的方法成功构建出了尖牙阻生预测模型^[76],但目前尚无预测尖牙萌出的CNN模型,仅有识别尖牙阻生的CNN模型以及诊断尖牙阻生造成邻牙牙根吸收的CNN模型^[77-78]。

当前对于尖牙阻生的人工智能研究有限,未来需进一步加强人工智能在该疾病中的研究,以帮助医生进行早期诊断尖牙阻生,从而早期干预,降低治疗难度。

5 当前局限和未来展望

当前,深度学习在牙发育诊疗相关研究的局限性及展望有以下几点:①在牙发育异常方面,研究多集中于多生牙的识别,其他疾病相关研究十分缺乏,这可能归因于疾病患病率低,难以获得足够的数据资源。鉴于单中心研究数据的有限性,未来应尽量设计多中心研究,既可解决数据缺乏的问题,又可评估模型的泛化性及稳健性。②由于部分疾病如牙釉质发育缺陷型疾病彼此之间、牙釉质发育缺陷型疾病与龋病等存在相似的临床和影像学表现,而当前研究大多是将正常图像与疾病图像进行区分,导致模型可能难以对此类疾病进行鉴别诊断,从而限制其临床应用。③当前研究多是针对单一病种进行诊治,未来应形成更加全面的智能化诊疗系统,例如将发育评估和发育异常诊断相结合,进而可辅助医生制定更科学的治疗方案。④遗传性牙釉质发育不全、MIH、先天缺牙、萌出延迟等发育异常可能是某些遗传罕见病如外胚层发育不全综合征、颅骨锁骨发育不良的口腔表现,今后应考虑在对牙发育疾病诊治的基础上,纳入全身因素等进行评估,从而帮助口腔医生提高对遗传罕见病的诊治率。⑤在牙发育评估上,国内外学者多基于Demirjian法建立深度学习模型,然而由于该分类方法无法完全满足临床需求,应加强对其他分类方法的相关研究以用于不同的临床场景。⑥在牙根及根管发育方面,当前研究均为单中心研究,因此研究结果的外推性受到一定限制,此外大部分研究将含有高密度充填物的影像数据排除在外,导致模型可能难以对再治疗的根管进行识别。⑦当前研究大多仅基于单一图像数据,今后应尝试构建多模态模型,如将影像学 and 口内照联合应用或将时间序列数据、文本数据与图像数据联合应用等,使诊断更加精确,具有解释性和预测性^[79]。

6 小结

牙发育异常及牙发育相关诊疗是口腔临床工作中十分具有挑战性,也是十分重要的一环,人工智能尤其是深度学习的出现为提高临床工作效率、降低诊治难度提供了很好的解决思路(图1)。虽然已有研究涉及该领域,但整体而言仍处于初期阶段,需要更多高质量研究进一步阐明深度学习模型应用于牙发育相关临床诊治的可行性,从而推动临床诊疗的智能化发展。

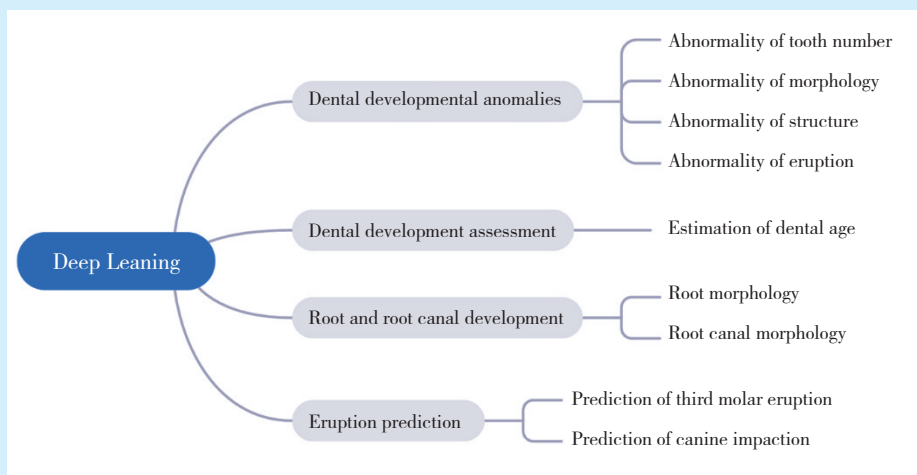


Figure 1 Application of deep learning in dental developmental abnormalities and dental development-related diagnosis and treatment

图 1 深度学习在牙发育异常及牙发育相关诊疗中的应用

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