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# 深度学习在上气道三维分析与正颌术后上气道预测中的应用进展

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## 摘　要

**上气道形态评估对牙颌面畸形诊疗及正颌外科预后至关重要。锥形束计算机断层扫描(Cone Beam Computed Tomography, CBCT)结合三维重建技术可实现精确的气道分析。然而，手动分割方法存在耗时且主观性强的问题。近年来，深度学习(Deep Learning, DL)尤其是卷积神经网络(Convolutional Neural Network, CNN)的引入，显著提升了CBCT上气道自动化分析的效率与准确性。本文综述了DL在气道辅助诊断、自动分割及参数测量中的应用，在辅助诊断分级、高精度气道分割、自动测量气道参数等方面DL均展现出优于传统方法的性能。在正颌术后气道预测方面，DL模型初步实现了术后气道容积与流体力学特征的精准预测，为个性化手术方案设计提供支持。然而，当前研究仍面临数据集规模有限、模型可解释性不足、多模态融合欠缺及计算资源依赖等挑战。未来需构建大规模多中心数据库，发展可解释性轻量级模型，并加强临床验证，以推动智能气道分析工具在临床的转化应用。**

## 关键词

**深度学习，锥形束计算机断层扫描，上气道，正颌外科**

# Advances in Deep Learning for Three-Dimensional Analysis of the Upper Airway and Prediction of Upper Airway Changes after Orthognathic Surgery

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## Abstract

**Assessment of upper airway morphology is crucial for the diagnosis and treatment of dentofacial deformities and for predicting the prognosis of orthognathic surgery. Cone-beam computed tomography (CBCT) combined with 3D reconstruction technology enables precise airway analysis. However, manual segmentation methods are time-consuming and highly subjective. In recent years, the introduction of deep learning (DL), particularly convolutional neural networks (CNNs), has significantly improved the efficiency and accuracy of automated upper airway analysis using CBCT. This review summarizes the applications of DL in airway-assisted diagnosis, automatic segmentation, and parameter measurement. DL has demonstrated superior performance compared to traditional methods in areas such as assisted diagnostic grading, high-precision airway segmentation, and automatic measurement of airway parameters. Regarding post-orthognathic surgery airway prediction, DL models have preliminarily achieved accurate prediction of postoperative airway volume and hemodynamic characteristics, providing support for the design of personalized surgical plans. However, current research still faces challenges such as limited dataset size, insufficient model interpretability, lack of multimodal fusion, and dependence on computational resources. Future efforts should focus on establishing large-scale, multicenter databases, developing lightweight, interpretable models, and strengthening clinical validation to advance the clinical translation of intelligent airway analysis tools.**

## Keywords

**Deep Learning (DL), Cone Beam Computed Tomography (CBCT), Upper Airway, Orthognathic Surgery**



## 1. 引言

上气道是由鼻、咽、喉区域组成的空腔结构，其解剖形态受到颅颌面骨组织及周围软组织的共同影响。正畸正颌治疗是通过移动牙齿、调整上下颌骨位置等方式治疗牙颌面畸形的方法。作为颅面复合体的重要组成部分，上气道形态结构、空间容积与通气功能直接影响正畸正颌治疗的疗效及远期预后。因此，准确评估上气道形态对牙颌面畸形的诊断和治疗至关重要[1]。传统气道评估方法依赖头颅侧位片等二维影像资料。然而，多项研究指出，传统头影测量法存在一些局限，其测量结果易出现偏差。这主要源于两个技术难点：其一，由于三维结构被压缩到二维平面，导致解剖细节失真，颅面部结构在影像上相互重叠，导致关键标志点难以精确定位；其二，气道阻塞区域的定位和严重程度分级需要高精度三维数据支持，难以在二维资料中实现[2] [3]。

锥形束计算机断层扫描(Cone Beam Computed Tomography, CBCT)技术使得对颅颌面结构进行立体、可视化的评估成为可能，成为牙科与颌面外科的临床首选工具。CBCT 影像可在矢状面、冠状面及横断面上对上气道边界进行识别，对上气道周围解剖结构进行清晰地界定。CBCT 三维重建技术实现了精确分割上气道，用于测量三维解剖特征并结合计算流体动力学(CFD)评估通气状态。手动分割方式被视为金标准，Mimics 21.0、3D slicer、Dolphin Imaging 等图像处理软件提供了基于 Hounsfield Unit (HU)值、seeds

grow 等方式的半自动分割。然而以上人工处理方法仍存在技术敏感性较高且耗时的问题，导致临床工作流程繁琐且易受人为因素干扰，难以在日常诊疗中常规应用[4]。

数字化技术的进步带来了社会生活和生产方式的变革，也对生物医学领域产生了深远的影响。人工智能是现代计算机科学的一个重要分支，它试图赋予机器模仿人类认知行为的能力[5]。深度学习(Deep learning, DL)算法是机器学习的一个重要分支，被认为是最接近人工智能的方法，已逐渐影响到疾病诊断、方案制定与患者管理等各个医疗环节。在口腔医学领域，深度学习的应用得到了广泛的研究，AI 算法在病变范围检测、危险因素分析、牙齿及下牙槽神经管等解剖结构分割等方面显示出巨大潜力[6]。本综述旨在总结基于深度学习的 CBCT 上气道自动化分析与正颌术后气道变化预测中的临床应用进展。

## 2. 深度学习在 CBCT 气道分析中的应用

深度学习算法已成为 CBCT 上气道自动分析的核心技术。典型的深度学习模型包括卷积神经网络(Convolutional Neural Network, CNN)、深度神经网络(Deep Neural Networks, DNN)和循环神经网络(Recurrent Neural Networks, RNN)等，有许多开源 CNN 算法在研究中得到应用[7]。卷积神经网络可视为结构化网格(图像)信息自动化特征提取的处理器，其核心组成包括卷积层、池化层、激活函数和全连接层。卷积层通过滤波器对输入图像执行卷积运算，用于检测特征、边缘、纹理及复杂特征，同时保持像素间的空间关系。池化层通过降低输入的空间维度实现下采样，从而减少网络内部的计算复杂度和参数量。激活函数为模型引入非线性特性，使其能够学习数据中的复杂关系。最终，全连接层基于前一层学习的高级特征进行预测，通过层与层之间的所有神经元结构的连接实现预测功能[8]。

### 2.1. 基于深度学习的辅助诊断与疾病分级

基于 CNN 的分类模型可精准定位气道梗阻区域并量化其严重程度。Dong 等人的研究[9]表明 3D-ResNet 在儿童腺样体肥大诊断中均表现出良好的性能，在分类任务中的曲线下面积(AUC)达 99.41%，腺样体肥大检出准确率达 0.912，敏感性 0.976，特异性 0.867，与 HMSAU-Net 集成可快速完成气道分割与疾病诊断任务。值得注意的是，3D-ResNet10 相较于 3D-ResNet18、30 表现出更优的性能，可能的原因是 3D-ResNet10 网络结构相对更浅、参数量更小，因而在小样本量任务中不易过度拟合，具有更好的泛化性。另一项研究中，研究者构建了一个可解释性 AI 模型(SaxiMHAFB)将腺样体肥大患者 CBCT 影像根据鼻咽气道阻塞比率划分为四个等级，该模型并联 EfficientNet-B0 与 K-NN 算法输出多视图及点阵云表达三维气道分析结果，在分类任务中 AUC 达 0.77~0.94，在量化任务中，回归模型成功预测了鼻咽气道阻塞比率，相关系数 R2 值为 0.728。模型通过表面梯度加权类激活映射(SurfGradCAM)生成的热图，直观揭示 AI 决策依赖的关键影像特征(如腺样体占位区域)，辅助医生理解阻塞发生机制[10]。Lucie Dole 等人[11]同样利用 SaxiMHAFB 开发了识别 CBCT 图像中腺样体肥大影像的二元分类模型，其分类准确率达 81.88%。

此外，为评估并诊断 OSA，Susie Ryu 等人[12]在通过 3D U-Net 实现 CBCT 影像中上气道自动分割的基础上，结合多变量高斯过程回归(MVGPR)模型训练并预测气道内包括气道阻力、流体速度、涡流强度等在内的 12 项计算流体力学特征，进而通过机器学习算法(支持向量机)构建了 OSA 诊断分级程序，其诊断准确率达 81.5%，敏感性 89.3%，特异性 86.2%。以上研究为气道疾病提供快速、客观、精准的辅助诊断工具，具有重要临床转化价值。

### 2.2. 基于深度学习的自动分割算法

3D U-Net 模型在上气道分割中表现出色。Sohaib Shujaat 等人[13]构建的模型对正颌患者上气道进行分割，其精确度(Precision)达 0.97 ± 0.01，召回率(Recall) 0.96 ± 0.03，Dice 相似性系数(Dice similarity

coefficient, DSC) 0.97 ± 0.02，交并比(IoU) 0.93 ± 0.03，且模型在 CBCT 图像上的性能高于计算机断层扫描(Computed Tomography, CT)图像。Sin 等人[14]的模型则对上气道整体进行分割，其 DSC 值约为 0.919，IoU 为 0.993。Fernanda Nogueira-Reis 及其团队[15]构建了一个集成六个 3D U-Net 的自动分割框架，用于分割包括咽气道在内的颅面结构。该模型性能超越半自动分割方法，且处理速度大幅提升。Dong 等人[9]采用的 HMSAU-Net 模型则表现出高于 3D U-Net 与 SAU-Net 的性能，上气道分割 DSC 值达到 0.960。

针对特定解剖部位的气道分割，包括鼻咽、腭咽、口咽、喉咽等，学者们正开展更精细化的探索。Süküt 等人[16]借助 Monai label 开源框架开发的模型对腭咽和口咽区域气道分段的 DSC 值达到与手动分割及半自动分割方法相当的水平，然而其 95% HD (95% Hausdorff distance)高于半自动分割组。在一项聚焦于骨性 III 类患者正颌术后气道变化的研究中[17]，3D U-Net 对鼻咽–喉咽区域气道分割平均 DSC 值为 0.889~0.895，研究者认为模型性能主要受到鼻咽部复杂解剖结构的影响。Suhan Jin 等人[18]结合 Swin Transformer 与 U-Net 开发的轻量级多任务网络实现了鼻腔及上气道子区域的精确分割，整体 DSC 值约为 90.95%~96.29%，IoU 达到 83.68%~92.85%。深度学习模型可有效承担临床诊疗中大量重复性、高耗时的工作环节，显著提升诊疗流程的自动化水平。

### 2.3. 上气道参数自动化测量

基于 AI 的自动化参数测量大幅提升了临床效率与结果的一致性。基于 CNN 的模型，包括 U-Net18、U-Net36、DeepLab50 和 DeepLab101，可实现上气道最小横截面积(minimum cross-section area, CSAmin)的自动定位，其定位精确度均高于 90.0%，与人类医生对照组的定位一致性达到 94.4% [19]。一项研究比较了 AI 软件(Diagnocat)与放射科医生使用 InVivo 软件测量 OSA 与非 OSA 患者上气道参数的结果，研究显示两者在上气道容积和最小横截面面积的测量上无统计学差异($p > 0.05$)，Diagnocat 与 InVivo 软件提供的自动检测功能之间组内相关系数(ICC)为 0.956，与手动检测对照组之间 ICC 达到 0.972，然而，模型可能误将会厌及部分后鼻孔区域纳入上气道范围，从而导致气道总容积的高估[20]。Steven Dorris 等人[21]的研究进一步支持该结论，在 100 例锥形束 CT 数据集中 Diagnocat 与经验丰富的颌面部放射科医生的测量结果具有优异的一致性(ICC > 0.94)。

## 3. 深度学习在正颌术后上气道变化预测中的应用

正颌手术通过调整颌骨位置显著影响上气道三维结构，并与气道结局紧密关联。临床研究证实，不同术式对气道参数的影响存在明确规律。既往文献报道，下颌前移术后上气道容积平均增加 34.3%，软腭及舌水平最小横截面积分别增加 56.8%和 44.9%，同时观察到舌骨位置前移[22]。下颌后退术则导致相反的变化，下牙槽座点每后退 1 mm 可使腭咽区域和舌咽区域容积分别减少 314.6 $mm^3$ 和 656.6 $mm^3$。上颌骨前移手术则显示后鼻棘点每前移 1 mm 可增加鼻咽部容积 626.90 $mm^3$ [23]。此外，骨性III类患者行双颌手术后 6 个月，上气道容积、矢状面面积及最小横截面积均显著减小[24]。

人工智能模型通过整合骨骼位移参数与气道形态数据，实现术后变化的精准预测。Tarek Elshebiny 等人[25]利用 Dolphin 3D 软件的虚拟规划功能预测了 20 例接受双颌手术患者的上气道容积变化，研究显示预测值与术后实测值无统计学差异。Humphries 等人[26]使用 Vitrea Enterprise Suite 软件预测了 Pierre Robin 综合征患者接受下颌牵张成骨术后气道容积变化，并发现预测值与实测值之间存在显著相关性($R^2 = 0.99$)。

尽管目前基于 AI 的气道结局直接预测研究相对较少，且普遍存在样本量较少等局限性，AI 对正颌手术后面部形态变化预测中的高准确率仍表明其具有相当的潜力。ACMT-Net 深度学习模型通过点对点注意力机制关联骨性移动与软组织变化，其预测准确性与基于三维有限元分析的传统生物力学模型相当，

但计算效率大幅提升[27]。P2P-ConvGC 双向三维深度学习框架在预测手术后面部及骨骼形态时，面部标志点平均误差仅 0.895 ± 0.175 mm，骨骼标志点平均误差为 0.906 ± 0.082 mm，其精度显著优于 P2P-Net、P2P-ASNL 和 P2P-Conv [28]。尽管 AI 算法的预测结果并非在任何情况下均优于传统回归模型，然而其准确度仍能达到临床可接受范围，且在处理速度上具有压倒性优势[29]。

## 4. 局限与展望

目前，基于深度学习的模型在正颌相关气道分析方面取得了一定进展，但仍存在一定局限。AI 的性能依赖于训练所用数据集的体量。应用二维影像资料的口腔科领域人工智能相关研究数据集常高于 1000 例[30]。然而，一项系统评价表明基于 AI 的上气道分析所用 CBCT 数据集约为 30~315 例[31]。数据集的有限可能与 CBCT 图像质量有关，患者体位、噪点、伪影等多种因素均可能降低图像质量导致被排除在研究可用的数据集之外[32]。多项研究表明，伪影会显著降低图像质量，影响 AI 模型的分割精度，其中金属伪影的影响尤为突出[33] [34]。有研究指出，金属充填材料的存在会干扰 CNN 对牙齿分割的准确性，提示邻近目标结构的金属修复体等伪影源可能影响 CNN 对分割对象边界的分析[35]。Angelo Genghi 等研究者[32]开发的伪影模拟方法也表明，伪影的空间分布会影响模型的训练效果。研究涉及的正颌术后患者中，上下颌骨均采用钛板钛钉进行坚固内固定。CBCT 图像显示，术后气道前壁位置空间往往更接近坚固内固定装置所产生的金属伪影区域，从而可能对模型的分割性能造成干扰[36] [37]。为提升影像质量，Zhang Y 等人[38]构建了生成对抗网络(GAN)模型，将 CBCT 质量提升至 CT 水平。Zhang YJ 等人[39]通过引入自适应高频优化机制改良了去噪扩散概率模型(CDDPM)，在 CBCT-to-CT 的合成中显著改善了骨纹理等细微结构。Park 等人[40]训练的 GAN 模型则实现了通过解剖参数直接生成包含术后解剖结构的 3D 面部数据，为正颌手术提供了直观的术后 CBCT 级影像模拟。上述深度学习方法，为未来实现术后虚拟 CBCT 影像的高精度重建与术后气道的直观可视化模拟，提供了切实可行的技术路径。

绝大多数研究仅纳入来自同一中心、使用同一型号仪器，并遵循统一成像协议的影像资料[41]。既往文献表明，即使同一品牌的不同 CBCT 扫描仪之间也存在约 16 HU 的灰度值阈值差异，其数值波动可能干扰阈值分割的可重复性。这提示在未来将 CNN 模型应用于多中心研究时需进行扫描仪特异性校准，避免模型泛化性受损[42] [43]。此外，出于患者隐私保护及数据安全问题考虑，医疗领域的数据可用性受到限制。即使运用正则化与 Dropout 算法可降低模型的复杂性并防止过度依赖单一特征，缺乏外部验证、多中心泛化测试及长期随访数据仍导致模型存在过度拟合的问题[44]。建立一个大规模、标准化、多中心的公共影像数据库将有效规范模型泛化能力[45] [46]。

深度学习模型本身具有“黑箱”特性，模型预测过程缺乏语义级可解释性(例如依据某些具体的图像特征来划定气道边界)，临床医生难以理解预测依据，削弱了其临床信任基础[47]。黑箱模型难以有效整合医学领域知识(如解剖学逻辑、病理机制)，限制了人机协同的深度，同时阻碍研究者对模型偏差的及时干预。更深远的影响在于，深度学习模型的黑箱特性模糊了责任归属，在出现临床决策失误时难以追溯原因，从医学法规层面限制了高性能模型的临床转化[48]。注意力机制、反向事实解释、概念归因等深度学习的可解释方法已在脑肿瘤、肝肿瘤、心脏血管影像分割领域中得到广泛应用[49] [50]。在后续自动化气道分析模型的研究中，引入可视化注意力机制等技术将有助于阐明模型的决策依据，增强其临床可信度。

此外，在上气道自动分析任务中，多模态融合任务研究仍处于早期阶段，现有方法在局部特征提取与跨模态交互方面仍存在缺陷[51]。研究表明，吸气末最小横截面积等静态 CBCT 解剖参数与呼吸暂停低通气指数(AHI)呈显著负相关，然而其单独使用预测效能有限。加入 CFD 压力分布或动态磁共振成像(MRI)塌陷指标后，气道预后预测模型区分度显著提升[52]。未来的多模态气道分析模型有望通过将 CBCT

解剖参数、CFD 衍生的气流阻力指数、动态 MRI 的塌陷程度作为特征向量，输入随机森林、XGBoost、深度学习网络等算法，实现术后 AHI 等功能性指标的预测[53]。

最后，计算资源需求亦是现实障碍。如 3D 卷积网络、模型集成等复杂模型架构带来高能源开销与硬件依赖，难以在资源受限的基层医疗机构部署[54]。未来的研究中需要着力开发轻量级多模态融合架构以强化局部–全局特征交互并降低计算负载，通过更多低偏倚风险的高质量证据进行严格临床验证，推动高效的智能分析工具在医疗场景落地应用，为患者提供更加精准和个性化的治疗方案[55]。

## 5. 总结

综上所述，深度学习为上气道分析提供了新的方法，具有提高临床效率、增强诊断能力的优势。此外，深度学习算法提供标准化分析，确保不同患者和临床环境下检测的一致性，在上气道分析领域具有良好的应用前景。当前研究仍面临数据集规模有限等多种挑战。未来需构建大规模多中心数据库，发展可解释性轻量级模型，并加强临床验证，以推动智能气道分析工具在临床的转化应用。

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本文所有作者均声明不存在任何利益冲突。

## 参考文献

[1] Seifert, L.B., Cleanthous, S.V., Klos, M., Bühling, S., Abazi, S., Berg, B., *et al*. (2025) 3D Volumetric Analysis of Upper Airway Changes Following Orthognathic Surgery. *Head & Face Medicine*, **21**, Article No. 82. https://doi.org/10.1186/s13005-025-00557-y

[2] Yao, K., Xie, Y., Xia, L., Wei, S., Yu, W. and Shen, G. (2023) The Reliability of Three-Dimensional Landmark-Based Craniomaxillofacial and Airway Cephalometric Analysis. *Diagnostics*, **13**, Article 2360. https://doi.org/10.3390/diagnostics13142360

[3] Vassis, S., Glerup, M., Tambjerg, I., Küseler, A., Resnick, C.M., Verna, C., *et al*. (2025) Development of a 3D Cephalometric Index to Grade Severity of Dentofacial Deformity in Patients with Juvenile Idiopathic Arthritis. *Scientific Reports*, **15**, Article No. 2625. https://doi.org/10.1038/s41598-025-86410-3

[4] Valls-Ontañón, A., Arjooca, S., Saavedra, O., Giralt-Hernando, M., Asensio-Salazar, J., Haas, O.L., *et al*. (2024) Does Aesthetic Osseous Genioplasty Impact Upper Airway Volume? *Aesthetic Surgery Journal*, **44**, 354-362. https://doi.org/10.1093/asj/sjad341

[5] Galmarini, C.M. and Lucius, M. (2020) Artificial Intelligence: A Disruptive Tool for a Smarter Medicine. *European Review for Medical and Pharmacological Sciences*, **24**, 7462-7474.

[6] Ahn, S., Kim, M., Kim, J. and Park, W. (2026) Application of Deep Learning in Evaluating the Anatomical Relationship between the Mandibular Third Molar and Inferior Alveolar Nerve: A Scoping Review. *Medicina Oral Patología Oral y Cirugia Bucal*, **31**, e95-e103. https://doi.org/10.4317/medoral.27584

[7] Sohrabniya, F., Hassanzadeh-Samani, S., Ourang, S.A., Jafari, B., Farzinnia, G., Gorjinejad, F., *et al*. (2025) Exploring a Decade of Deep Learning in Dentistry: A Comprehensive Mapping Review. *Clinical Oral Investigations*, **29**, Article No. 143. https://doi.org/10.1007/s00784-025-06216-5

[8] Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., *et al*. (2019) A Guide to Deep Learning in Healthcare. *Nature Medicine*, **25**, 24-29. https://doi.org/10.1038/s41591-018-0316-z

[9] Dong, W., Chen, Y., Li, A., Mei, X. and Yang, Y. (2023) Automatic Detection of Adenoid Hypertrophy on Cone-Beam Computed Tomography Based on Deep Learning. *American Journal of Orthodontics and Dentofacial Orthopedics*, **163**, 553-560.e3. https://doi.org/10.1016/j.ajodo.2022.11.011

[10] Mattos, C.T., Dole, L., Mota-Júnior, S.L., Cury-Saramago, A.d.A., Bianchi, J., Oh, H., *et al*. (2025) Explainable Artificial Intelligence to Quantify Adenoid Hypertrophy-Related Upper Airway Obstruction Using 3D Shape Analysis. *Journal of Dentistry*, **156**, Article ID: 105689. https://doi.org/10.1016/j.jdent.2025.105689

[11] Dole, L., Mattos, C.T., Bianchi, J., Oh, H., Evangelista, K., Valladares Neto, J., *et al*. (2025) Enhancing Airway

Obstruction Diagnosis with Multimodal 3D Shape Analysis. *International Journal of Computer Assisted Radiology and Surgery*, **21**, 529-538. https://doi.org/10.1007/s11548-025-03527-6

[12] Ryu, S., Kim, J.H., Yu, H., Jung, H., Chang, S.W., Park, J.J., *et al*. (2021) Diagnosis of Obstructive Sleep Apnea with Prediction of Flow Characteristics According to Airway Morphology Automatically Extracted from Medical Images: Computational Fluid Dynamics and Artificial Intelligence Approach. *Computer Methods and Programs in Biomedicine*, **208**, Article ID: 106243. https://doi.org/10.1016/j.cmpb.2021.106243

[13] Shujaat, S., Jazil, O., Willems, H., Van Gerven, A., Shaheen, E., Politis, C., *et al*. (2021) Automatic Segmentation of the Pharyngeal Airway Space with Convolutional Neural Network. *Journal of Dentistry*, **111**, Article ID: 103705. https://doi.org/10.1016/j.jdent.2021.103705

[14] Sin, Ç., Akkaya, N., Aksoy, S., Orhan, K. and Öz, U. (2021) A Deep Learning Algorithm Proposal to Automatic Pharyngeal Airway Detection and Segmentation on CBCT Images. *Orthodontics & Craniofacial Research*, **24**, 117-123. https://doi.org/10.1111/ocr.12480

[15] Nogueira-Reis, F., Morgan, N., Suryani, I.R., Tabchoury, C.P.M. and Jacobs, R. (2024) Full Virtual Patient Generated by Artificial Intelligence-Driven Integrated Segmentation of Craniomaxillofacial Structures from CBCT Images. *Journal of Dentistry*, **141**, Article ID: 104829. https://doi.org/10.1016/j.jdent.2023.104829

[16] Süküt, Y., Yurdakurban, E. and Duran, G.S. (2025) Accuracy of Deep Learning-Based Upper Airway Segmentation. *Journal of Stomatology, Oral and Maxillofacial Surgery*, **126**, Article ID: 102048. https://doi.org/10.1016/j.jormas.2024.102048

[17] Kim, D., Woo, S., Roh, J., Choi, J., Kim, K., Cha, J., *et al*. (2023) Subregional Pharyngeal Changes after Orthognathic Surgery in Skeletal Class III Patients Analyzed by Convolutional Neural Networks-Based Segmentation. *Journal of Dentistry*, **135**, Article ID: 104565. https://doi.org/10.1016/j.jdent.2023.104565

[18] Jin, S., Han, H., Huang, Z., Xiang, Y., Du, M., Hua, F., *et al*. (2023) Automatic Three-Dimensional Nasal and Pharyngeal Airway Subregions Identification via Vision Transformer. *Journal of Dentistry*, **136**, Article ID: 104595. https://doi.org/10.1016/j.jdent.2023.104595

[19] Chu, G., Zhang, R., He, Y., Ng, C.H., Gu, M., Leung, Y.Y., *et al*. (2023) Deep Learning Models for Automatic Upper Airway Segmentation and Minimum Cross-Sectional Area Localisation in Two-Dimensional Images. *Bioengineering*, **10**, Article 915. https://doi.org/10.3390/bioengineering10080915

[20] Orhan, K., Shamshiev, M., Ezhov, M., Plaksin, A., Kurbanova, A., Ünsal, G., *et al*. (2022) AI-Based Automatic Segmentation of Craniomaxillofacial Anatomy from CBCT Scans for Automatic Detection of Pharyngeal Airway Evaluations in OSA Patients. *Scientific Reports*, **12**, Article No. 11863. https://doi.org/10.1038/s41598-022-15920-1

[21] Dorris, S., Anamali, S., Castro, J.P., Dabdoub, S.M. and Allareddy, T. (2026) Comparisons of the Reliability of Airway Measurements on Cone Beam Computed Tomography Scans among Human Raters and a Convolutional Neural Network. *Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology*, **141**, 255-264. https://doi.org/10.1016/j.oooo.2025.10.001

[22] Altay, M., Quereshy, F., Williams, J., Quereshy, H., Özalp, Ö. and Baur, D. (2018) Quantification of Volumetric, Surface Area and Linear Airway Changes after Orthognathic Surgery: A Preliminary Study. *European Oral Research*, **52**, 33-38. https://doi.org/10.26650/eor.2018.28870

[23] Li, H., Sun, C., Chen, Y., Sun, Z. and Gao, X. (2022) Quantitative Changes of Upper Airway in Class III Patients Undergoing Bimaxillary Surgery after One-Year Follow-Up: A Retrospective Study. *Head & Face Medicine*, **18**, Article No. 14. https://doi.org/10.1186/s13005-022-00317-2

[24] Li, G., Chen, Z., Li, Y., Cai, G., Ruan, X., Wang, T., *et al*. (2024) Correlation between Oral Cavity Volume and Upper Airway Changes in Skeletal Class III Patients Undergoing Bimaxillary Orthognathic Surgery: A Pilot Cone-Beam Computed Tomography Study. *The Angle Orthodontist*, **94**, 432-440. https://doi.org/10.2319/112223-774.1

[25] Elshebiny, T., Bous, R., Withana, T., Morcos, S. and Valiathan, M. (2020) Accuracy of Three-Dimensional Upper Airway Prediction in Orthognathic Patients Using Dolphin Three-Dimensional Software. *Journal of Craniofacial Surgery*, **31**, 1098-1100. https://doi.org/10.1097/scs.0000000000006566

[26] Humphries, L.S., Yates, E.K., Mhlaba, J.M., Collins, J.M., Baroody, F.M. and Reid, R.R. (2018) Airway Volume Simulation in Virtual Mandibular Distraction: A Cohort Study. *Plastic & Reconstructive Surgery*, **141**, 1003-1009. https://doi.org/10.1097/prs.0000000000004249

[27] Fang, X., Kim, D., Xu, X., Kuang, T., Lampen, N., Lee, J., *et al*. (2024) Correspondence Attention for Facial Appearance Simulation. *Medical Image Analysis*, **93**, Article ID: 103094. https://doi.org/10.1016/j.media.2024.103094

[28] Bao, J., Zhang, X., Xiang, S., Liu, H., Cheng, M., Yang, Y., *et al*. (2024) Deep Learning-Based Facial and Skeletal Transformations for Surgical Planning. *Journal of Dental Research*, **103**, 809-819. https://doi.org/10.1177/00220345241253186

[29] Park, J., Moon, J., Lee, J., Cho, S.J., Seo, B., Donatelli, R.E., *et al*. (2024) Does Artificial Intelligence Predict

Orthognathic Surgical Outcomes Better than Conventional Linear Regression Methods? *The Angle Orthodontist*, **94**, 549-556. https://doi.org/10.2319/111423-756.1

[30] Ismail, I.N., Subramaniam, P.K., Chi Adam, K.B. and Ghazali, A.B. (2024) Application of Artificial Intelligence in Cone-Beam Computed Tomography for Airway Analysis: A Narrative Review. *Diagnostics*, **14**, Article 1917. https://doi.org/10.3390/diagnostics14171917

[31] Tsolakis, I.A., Kolokitha, O., Papadopoulou, E., Tsolakis, A.I., Kilipiris, E.G. and Palomo, J.M. (2022) Artificial Intelligence as an Aid in CBCT Airway Analysis: A Systematic Review. *Life*, **12**, Article 1894. https://doi.org/10.3390/life12111894

[32] Genghi, A., Fartaria, M.J., Siroki-Galambos, A., Flückiger, S., Franco, F., Strzelecki, A., *et al*. (2025) Augmenting Motion Artifacts to Enhance Auto-Contouring of Complex Structures in Cone-Beam Computed Tomography Imaging. *Physics in Medicine & Biology*, **70**, Article ID: 035016. https://doi.org/10.1088/1361-6560/ada0a0

[33] Luo, F., Ma, C., Shi, J. and Xu, K. (2025) CBCT-To-CT Synthesis with a Hybrid of Cyclegan and Latent Diffusion. *Neuroradiology*, **67**, 2083-2096. https://doi.org/10.1007/s00234-025-03634-w

[34] Can, E., Böning, G., Lüdemann, W.M., Hosse, C., Kolck, J., Paparoditis, S., *et al*. (2024) Evaluation of a Prototype Metal Artifact Reduction Algorithm for Cone Beam CT in Patients Undergoing Radioembolization. *Scientific Reports*, **14**, Article No. 16399. https://doi.org/10.1038/s41598-024-66978-y

[35] Fontenele, R.C., Gerhardt, M.d.N., Pinto, J.C., Van Gerven, A., Willems, H., Jacobs, R., *et al*. (2022) Influence of Dental Fillings and Tooth Type on the Performance of a Novel Artificial Intelligence-Driven Tool for Automatic Tooth Segmentation on CBCT Images—A Validation Study. *Journal of Dentistry*, **119**, Article ID: 104069. https://doi.org/10.1016/j.jdent.2022.104069

[36] Yey Özkeskin, S.Z., Ersan, N., Öztürk Muhtar, M., Cansiz, E. and Ramazanoğlu, M. (2024) Evaluation of Minimum Axial Airway Area and Airway Volume in Orthognathic Surgery Patients. *Journal of Craniofacial Surgery*, **35**, 1938-1946. https://doi.org/10.1097/scs.0000000000010533

[37] Park, S.B., Kim, Y.I., Son, W.S., Hwang, D.S. and Cho, B.H. (2012) Cone-beam Computed Tomography Evaluation of Short- and Long-Term Airway Change and Stability after Orthognathic Surgery in Patients with Class III Skeletal Deformities: Bimaxillary Surgery and Mandibular Setback Surgery. *International Journal of Oral and Maxillofacial Surgery*, **41**, 87-93. https://doi.org/10.1016/j.ijom.2011.09.008

[38] Zhang, Y., Yue, N., Su, M., Liu, B., Ding, Y., Zhou, Y., *et al*. (2021) Improving CBCT Quality to CT Level Using Deep Learning with Generative Adversarial Network. *Medical Physics*, **48**, 2816-2826. https://doi.org/10.1002/mp.14624

[39] Zhang, Y., Li, L., Wang, J., Yang, X., Zhou, H., He, J., *et al*. (2025) Texture-Preserving Diffusion Model for CBCT-To-CT Synthesis. *Medical Image Analysis*, **99**, Article ID: 103362. https://doi.org/10.1016/j.media.2024.103362

[40] Park, Y.S., Choi, J.H., Kim, Y., Choi, S.H., Lee, J.H., Kim, K.H., *et al*. (2022) Deep Learning-Based Prediction of the 3D Postorthodontic Facial Changes. *Journal of Dental Research*, **101**, 1372-1379. https://doi.org/10.1177/00220345221106676

[41] Choi, Y., Yu, W., Nagarajan, M.B., Teng, P., Goldin, J.G., Raman, S.S., *et al*. (2023) Translating AI to Clinical Practice: Overcoming Data Shift with Explainability. *RadioGraphics*, **43**, e220105. https://doi.org/10.1148/rg.220105

[42] Schröder, L., Stankovic, U. and Sonke, J. (2020) Technical Note: Long-Term Stability of Hounsfield Unit Calibration for Cone Beam Computed Tomography. *Medical Physics*, **47**, 1640-1644. https://doi.org/10.1002/mp.14015

[43] Taxis, J., Platz Batista da Silva, N., Grau, E., Spanier, G., Nieberle, F., Maurer, M., *et al*. (2023) Novel Three-Dimensional and Non-Invasive Diagnostic Approach for Distinction between Odontogenic Keratocysts and Ameloblastomas. *Dentistry Journal*, **11**, Article 193. https://doi.org/10.3390/dj11080193

[44] Jensen, M.P., Qiang, Z., Khan, D.Z., Stoyanov, D., Baldeweg, S.E., Jaunmuktane, Z., *et al*. (2024) Artificial Intelligence in Histopathological Image Analysis of Central Nervous System Tumours: A Systematic Review. *Neuropathology and Applied Neurobiology*, **50**, e12981. https://doi.org/10.1111/nan.12981

[45] Zhang, X., Xiong, Z., Zhou, Y. and Zeng, X. (2026) Artificial Intelligence in Imaging for Obstructive Sleep Apnea: A Comprehensive Review. *Sleep Medicine*, **137**, Article ID: 108662. https://doi.org/10.1016/j.sleep.2025.108662

[46] Eche, T., Schwartz, L.H., Mokrane, F. and Dercle, L. (2021) Toward Generalizability in the Deployment of Artificial Intelligence in Radiology: Role of Computation Stress Testing to Overcome Underspecification. *Radiology*: *Artificial Intelligence*, **3**, e210097. https://doi.org/10.1148/ryai.2021210097

[47] Ding, W., Geng, Y., Huang, J., Ju, H., Wang, H. and Lin, C. (2025) MGRW-Transformer: Multigranularity Random Walk Transformer Model for Interpretable Learning. *IEEE Transactions on Neural Networks and Learning Systems*, **36**, 1104-1118. https://doi.org/10.1109/tnnls.2023.3326283

[48] Salahuddin, Z., Woodruff, H.C., Chatterjee, A. and Lambin, P. (2022) Transparency of Deep Neural Networks for Medical Image Analysis: A Review of Interpretability Methods. *Computers in Biology and Medicine*, **140**, Article ID: 105111. https://doi.org/10.1016/j.compbiomed.2021.105111

[49] Saleem, H., Shahid, A.R. and Raza, B. (2021) Visual Interpretability in 3D Brain Tumor Segmentation Network. *Computers in Biology and Medicine*, **133**, Article ID: 104410. https://doi.org/10.1016/j.compbiomed.2021.104410

[50] Yang, J., Dvornek, N.C., Zhang, F., Zhuang, J., Chapiro, J., Lin, M., *et al*. (2019) Domain-Agnostic Learning with Anatomy-Consistent Embedding for Cross-Modality Liver Segmentation. 2019 *IEEE/CVF International Conference on Computer Vision Workshop* (*ICCVW*), Seoul, 27-28 October 2019, 323-331. https://doi.org/10.1109/iccvw.2019.00043

[51] Xie, X., Zhang, X., Tang, X., Zhao, J., Xiong, D., Ouyang, L., *et al*. (2025) MACTFusion: Lightweight Cross Transformer for Adaptive Multimodal Medical Image Fusion. *IEEE Journal of Biomedical and Health Informatics*, **29**, 3317-3328. https://doi.org/10.1109/jbhi.2024.3391620

[52] Isaac, M., ElBeshlawy, D.M., Elsobki, A., Ahmed, D.F. and Kenawy, S.M. (2024) Correlation between Cone-Beam Computed Tomographic Findings and the Apnea-Hypopnea Index in Obstructive Sleep Apnea Patients: A Cross-Sectional Study. *Imaging Science in Dentistry*, **54**, 147-157. https://doi.org/10.5624/isd.20230249

[53] Thai, K.H., Chen, Y., Yao, C., Chen, N., Liao, Y. and Chen, Y. (2025) Comparison of Phenotypic Characteristics between Responders and Non-Responders to Treatment for Obstructive Sleep Apnea with Maxillomandibular Advancement in Adults. *Sleep Medicine*, **129**, 346-353. https://doi.org/10.1016/j.sleep.2025.03.006

[54] Chen, Y., Chen, C., Kuo, C. and Lin, C. (2024) An Efficient Deep Neural Network for Automatic Classification of Acute Intracranial Hemorrhages in Brain CT Scans. *Computers in Biology and Medicine*, **176**, Article ID: 108587. https://doi.org/10.1016/j.compbiomed.2024.108587

[55] Lee, J., Kim, D., Jun, D.W. and Kim, Y. (2024) Multimodal Fusion-Based Lightweight Model for Enhanced Generalization in Drug-Target Interaction Prediction. *Journal of Chemical Information and Modeling*, **64**, 9215-9226. https://doi.org/10.1021/acs.jcim.4c01397