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· 文献综述 ·

## 医学影像人工智能在甲状腺癌诊疗中的应用：现状与展望

刘才广<sup>1</sup>, 莫屈<sup>1</sup>, 肖羿<sup>1</sup>, 赵敏<sup>2</sup>

(1. 中南大学湘雅医院 核医学科, 湖南 长沙 410008; 2. 中南大学湘雅三医院 核医学科, 湖南 长沙 410013)

### 摘要

甲状腺癌是内分泌系统最常见的恶性肿瘤, 近年来, 其发病率正逐年攀升。甲状腺乳头状癌 (PTC) 和甲状腺滤泡状癌 (FTC) 统称为分化型甲状腺癌 (DTC), 约占甲状腺癌 95%。在 DTC 的诊断、分期、危险度分层以及治疗过程中, 影像检查例如超声、电子计算机断层成像 (CT)、磁共振成像 (MRI)、单光子发射计算机断层显像 (SPECT/CT) 及正电子发射计算机断层显像 (PET/CT) 发挥了重要作用。然而, 影像检查图像的分析高度依赖于医师的能力与经验, 医师对图像的判读易受图像的数量、复杂程度以及医师自身主观性的影响, 尤其是在工作量大的情况下, 错误难以避免。另外, 仪器分辨率及肉眼判别能力等客观因素亦影响医师读图的准确性。人工智能 (AI) 是一门模拟、延伸和扩展人类智能的技术科学, 已逐步应用于医学领域。在 DTC 诊疗中涉及的 AI 技术包括机器学习与深度学习, 此外还涉及影像组学技术, 主要应用于 DTC 的诊断与鉴别诊断、DTC 的分期评估、DTC 基因突变的预测以及 DTC 的碘-131 治疗。AI 技术及影像组学技术的应用有望提高 DTC 的诊断准确性, 实现对 DTC 的准确分期及对 DTC 基因突变的准确预测, 优化 DTC 的治疗过程, 从而实现对 DTC 的精准诊断与个体化治疗, 使患者最大程度获益。

### 关键词

甲状腺肿瘤; 人工智能; 肿瘤分期; 综述  
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## Applications of medical imaging artificial intelligence in the diagnosis and treatment of thyroid cancer: current status and future prospects

LIU Caiguang<sup>1</sup>, MO Qu<sup>1</sup>, XIAO Yi<sup>1</sup>, ZHAO Min<sup>2</sup>

(1. Department of Nuclear Medicine, Xiangya Hospital, Central South University, Changsha 410008, China; 2. Department of Nuclear Medicine, the Third Xiangya Hospital, Central South University, Changsha 410013, China)

### Abstract

Thyroid cancer is the most common malignant tumor of the endocrine system, and its incidence has been steadily increasing in recent years. Papillary thyroid carcinoma (PTC) and follicular thyroid carcinoma (FTC), collectively known as differentiated thyroid cancer (DTC), account for approximately 95% of thyroid cancer cases. Imaging examinations such as ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT/CT), and positron

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作者简介: 刘才广, 中南大学湘雅医院住院医师, 主要从事甲状腺核医学方面的研究。

通信作者: 赵敏, Email: mzhao1981@csu.edu.cn

emission tomography (PET/CT) play a critical role in the diagnosis, staging, risk stratification, and treatment of DTC. However, the analysis of imaging results heavily depends on the skills and experience of the physician, making the interpretation prone to errors due to factors such as image volume, complexity, and subjective judgment, particularly under high workloads. Additionally, objective factors like equipment resolution and the limitations of human vision can also affect diagnostic accuracy. Artificial intelligence (AI), a technology that simulates, extends, and enhances human intelligence, has gradually been applied in the medical field. In the diagnosis and treatment of DTC, AI technologies such as machine learning and deep learning, as well as radiomics, have been utilized. These technologies are primarily applied in the diagnosis and differential diagnosis of DTC, staging assessments, prediction of genetic mutations, and iodine-131 therapy for DTC. The application of AI and radiomics holds great promise for improving diagnostic accuracy, enabling precise staging, predicting genetic mutations with higher precision, and optimizing treatment strategies for DTC. This advancement is expected to facilitate accurate diagnosis and personalized treatment, maximizing benefits for patients.

**Key words**

Thyroid Neoplasms; Artificial Intelligence; Neoplasm Staging; Review

**CLC number:** R736.1

近年来,甲状腺癌的发病率逐年攀升,位居所有癌症第九位<sup>[1]</sup>。甲状腺癌主要包括乳头状癌(papillary thyroid cancer, PTC)、滤泡状癌(follicular thyroid cancer, FTC)、髓样癌(medullary thyroid cancer, MTC)和未分化癌(anaplastic thyroid cancer, ATC)四种类型。其中,PTC与FTC统称为分化型甲状腺癌(DTC),约占甲状腺癌95%。在DTC的诊疗中,常用的影像检查包括超声、电子计算机断层成像(computed tomography, CT)、磁共振成像(magnetic resonance imaging, MRI)、单光子发射计算机断层显像(single-photon emission computed tomography/computed tomography, SPECT/CT)及正电子发射计算机断层显像(positron emission tomography/computed tomography, PET/CT)等。然而,由于影像医师的经验水平参差不齐,其对检查图像的判读准确性存在差异,因此,提高诊断准确性成为亟待解决的问题。针对这一问题,人工智能(artificial intelligence, AI)提供了新的解决方案。AI作为计算机科学的一个重要分支,最初于1956年的达特茅斯会议被提出,旨在构建能够模仿人类思维和行为的系统<sup>[2]</sup>。自此以后,其应用领域不断扩展,包括医学影像诊断等重要领域。在DTC的诊断与分期、DTC基因突变的预测以及DTC碘-131(<sup>131</sup>I)治疗等诸多方面,AI发挥着重要作用。本文旨在综述AI在DTC诊疗领域的研究方法取得的成果,并进一步探讨其

在该领域的应用前景及潜在价值。

## 1 AI概述

### 1.1 机器学习

机器学习为AI的核心技术,它使计算机通过分析示例数据来学习执行任务并作出预测。机器学习主要分为监督学习和无监督学习两种类型。监督学习依赖于有标签的数据集,算法从中学习并将输入数据映射到特定输出<sup>[3]</sup>;而无监督学习则处理无标签数据,旨在发现数据中的潜在模式与结构,从而将数据进行分类。在机器学习算法的开发中,通常涉及训练、验证和测试三个阶段。训练集用于构建和调整模型,验证集用于优化模型参数,而测试集则用于评估模型的最终性能与泛化能力<sup>[4]</sup>,此过程对于确保算法的准确性和可靠性至关重要。

影像组学作为机器学习在医学图像分析中的应用,通过结合图像采集、分割、预处理、特征提取与选择以及预测模型的开发<sup>[5]</sup>,旨在提高诊断的自动化程度与准确性。在处理医学图像时,影像医师首先选取感兴趣区,并在计算机辅助下进行分割与轮廓勾画,随后通过特征提取技术获取定量的像素特征,并执行特征选择以确定与预测最相关的特征,防止过拟合。最终,选定的特征被用于开发分类模型,此类模型可单独使用,亦

可结合人口统计学、临床或基因数据等信息来提高预测准确性<sup>[6]</sup>。

## 1.2 深度学习

深度学习为机器学习的子集之一，其使用多层神经网络来模拟人脑处理信息的方式，擅长处理图像和语音等复杂数据，能自动提取特征并进行复杂的非线性映射<sup>[7]</sup>。在医学领域，深度学习被广泛用于病变检测和疾病进展分析，通过减少人为干预来提高自动化诊断水平。

简而言之，AI领域广泛，机器学习是AI中使机器从数据中学习的技术，而深度学习是机器学习中使用复杂神经网络处理高维度数据的子集。

## 2 AI在DTC诊断中的应用

在甲状腺结节中，恶性结节约占5%<sup>[8]</sup>，由于性质不同的甲状腺结节，其后续诊疗方式存在差异，故判断甲状腺结节良恶性至关重要。此类AI模型的构建主要基于影像检查图像，部分研究涉及超声视频。AI模型性能的评估主要通过不同级别的影像科医师，尤其是经验丰富的医师阅片结果进行比较，比较不同AI模型的表现。同时，在AI辅助前后，对比不同级别影像医师的阅片结果，能否减少不必要的有创操作。

### 2.1 基于超声静态图像的AI模型

超声检查具有经济、无创、无辐射及操作简便等优点，为甲状腺结节的首选影像检查，为提高诊断准确性，新的超声技术如超声弹性成像正逐渐开展。在预测甲状腺结节良恶性时，AI与超声图像的结合最为常见。

**2.1.1 AI与医师诊断性能比较** Kim等<sup>[9]</sup>将卷积神经网络模型与经验丰富的彩超医师进行比较，后者依据美国放射学会甲状腺图像报告及数据系统（American College of Radiology Thyroid Imaging Reporting and Data System, ACR TI-RADS）进行诊断，结果显示二者诊断性能相当。Zhu等<sup>[10]</sup>构建的深度卷积神经网络模型可在超声图像上准确定位并自动诊断甲状腺结节，其诊断准确性优于具有7年以上经验的3名超声医师。此外，Wu等<sup>[11]</sup>对TI-RADS 4类及TI-RADS 5类结节的超声图像进行研究，构建的深度学习模型的表现亦优于超声医师。Yang等<sup>[12]</sup>对FTC术前超声图像进行研究构建了深度学习模型，其对大体侵入性FTC的诊断准

确性明显优于超声医师[二者曲线下面积（area under the curve, AUC）分别为0.903、0.561]。

**2.1.2 医师在AI辅助前后性能对比** Zhang等<sup>[13]</sup>表明，计算机辅助诊断（computer-aided diagnosis, CAD）系统能提高初级（2年经验）医师的诊断敏感度（从75.3%增加到88.2%）。Jin等<sup>[14]</sup>证实，在CAD系统辅助下，初级医师的诊断性能可与中级医师相媲美。He等<sup>[15]</sup>进行一项前瞻性研究，结果显示AI系统可潜在提高初级医师的诊断效率并接近高级医师。Peng等<sup>[16]</sup>亦发现，在深度学习模型辅助下，初级医师的诊断准确性得到显著提高。

**2.1.3 AI辅助减少有创操作** 作为术前确诊DTC的金标准，细针穿刺活检（fine needle aspiration biopsy, FNAB）对操作者的要求相对较高，在医疗资源相对落后地区难以实施，且操作不当可发生出血、神经损伤及气管食管损伤等并发症。Hoang等<sup>[17]</sup>发现，超声医师依据ACR TI-RADS进行诊断可显著降低推荐行FNAB的甲状腺结节数量，并提高诊断特异性，基于此，Buda等<sup>[18]</sup>开发出一种深度学习算法，该算法依据超声图像决定甲状腺结节是否需行FNAB，并与医师的表现进行比较，结果显示其建议行FNAB的敏感性、特异性与依据ACR TI-RADS的超声专家相似。Zhao等<sup>[19]</sup>利用超声图像与剪切波弹性成像图像开发的机器学习模型，在诊断甲状腺结节时性能卓越，并有助于降低需行FNAB的结节比例（从37%降至4.7%）。同样，在Peng等<sup>[16]</sup>构建的深度学习模型的辅助下，医师的诊断能力得到提高，其建议行FNAB的结节比例从61.9%降至35.2%，同时DTC的漏诊率亦从18.9%降至17.0%。

### 2.2 基于超声动态视频的AI模型

动态超声AI辅助诊断系统作为诊断甲状腺结节的新方法，可从多个剖面视图、不同角度对病灶进行实时同步动态分析，进一步提高诊断效率。Zhang等<sup>[20]</sup>通过前瞻性采集超声动态视频和静态图像，提出两种深度学习模型，即视频模型与图像模型，在训练队列与验证队列中，前者的AUC分别为0.947和0.923，高于后者的0.928和0.864，展现出视频模型的优越性能。Wang等<sup>[21]</sup>开发的动态AI模型的诊断敏感度、特异度和准确率分别为92.21%、83.20%和89.97%，与术后病理结果高度吻合。此外，李晓宇等<sup>[22]</sup>联合AI软件与超声造影动态诊断甲状腺结节，展现的AUC、敏感度、特

异度、准确率比单独应用这两种方法时更高。Zhang等<sup>[23]</sup>前瞻性招募4个中心的PTC患者进行研究,结果显示,利用超声视频的AI模型可以准确、可重复地预测PTC患者颈部淋巴结转移,并辅助提高超声医师的诊断性能。可见,基于动态视频的AI模型能对甲状腺结节进行更为精准的诊断,在未来有着较为广阔的应用前景。

### 2.3 基于CT图像的AI模型

由于CT不作为甲状腺结节筛查的常规检查,基于CT图像开发的用于鉴别甲状腺结节良恶性的AI模型相对较少。Zhao等<sup>[24]</sup>设计5个卷积神经网络模型和1个集成模型诊断甲状腺结节,均表现出比影像医师更好的性能。Li等<sup>[25]</sup>开发的基于卷积神经网络的自动识别分类系统表现良好。Wu等<sup>[26]</sup>通过分析直径<1 cm的结节CT图像,综合影像组学特征与临床预测因素,构建的影像组学列线图亦性能优异。

### 2.4 基于MRI图像的AI模型

MRI检查具有多种模态,能反映病变结构的微观特性,对诊断恶性肿瘤具有明显优势。Naglah等<sup>[27]</sup>与Sharafelddeen等<sup>[28]</sup>均通过MRI图像构建模型鉴别甲状腺结节并取得理想效果。王庆军等<sup>[29]</sup>为鉴别桥本甲状腺炎性结节与甲状腺微小乳头状癌,构建机器学习模型,其分类准确率接近90%。因此,基于多模态MRI图像构建AI模型,提取到肉眼无法观察到的深层次特征,可作为评估DTC的新思路。

## 3 AI在DTC分期中的应用

### 3.1 预测DTC包膜及腺外侵犯

术前准确评估DTC的包膜侵犯及腺外延伸仍具挑战性。董彬<sup>[30]</sup>通过超声影像组学分析技术对包膜侵犯进行判断,与高年资医师相比,优势明显(敏感度:83.5% vs. 76.9%; 特异度:87.0% vs. 77.7%; 准确率:85.7% vs. 77.4%)。卢文洁<sup>[31]</sup>联合临床风险预测因子与三维超声影像组学标签构建列线图模型,其诊断性能明显优于彩超医师。Wu等<sup>[32]</sup>研发的结合有CT影像组学特征及临床危险因素的联合模型,以及Yu等<sup>[33]</sup>设计的结合有影像组学特征和医师解释的影像组学列线图,均显示对DTC包膜侵犯的良好预测能力。Chen等<sup>[34]</sup>联合CT影像组学特征与临床危险因素设计影像组学列线

图,显著提高了术前预测DTC腺外侵犯的准确性。由此可见,联合模型的构建尤为常见,由于CT在清楚显示甲状腺的解剖结构、判断甲状腺结节对邻近器官组织的影响方面具有独特优势,其在进一步研究中的优势较超声更为显著。

### 3.2 预测DTC淋巴结转移

虽然PTC恶性程度低,但容易发生颈部淋巴结转移。淋巴结转移是评估PTC手术途径、手术范围及预后的重要指标,亦是该病复发率高、生存率低的重要危险因素<sup>[35]</sup>,包括中央区淋巴结转移和颈侧区淋巴结转移,转移淋巴结通常先出现在中央区(Ⅵ区),后出现在颈侧区(Ⅱ、Ⅲ和Ⅳ区)<sup>[36]</sup>。

**3.2.1 预测中央区淋巴结转移** 超声检查仅探测到20%~31%的中央区淋巴结转移,且只改变20%患者的手术过程<sup>[37]</sup>,迫切需要一种无创且有效的方法预测PTC淋巴结转移并指导临床诊疗。Wu等<sup>[38]</sup>利用7种机器学习算法,结合超声与临床特征创建AI模型,7种模型的表现均优于超声医师,证明此类研究的可行性。Li等<sup>[39]</sup>进行多中心研究,亦证实包含CT影像特征与临床危险因素的联合模型预测中央区淋巴结转移的临床实用性。Yu等<sup>[40]</sup>基于超声图像开发迁移学习影像组学模型,其诊断性能优于传统组学模型及非迁移组学模型,能用于多中心、跨机器、多操作员的场景中,在术前预测淋巴结转移。Chang等<sup>[41]</sup>结合深度学习、临床特征和超声特征构建的列线图,作为预测PTC中央区淋巴结转移的无创工具,辅助提升了低年资超声医师的诊断准确性。

**3.2.2 预测颈侧区淋巴结转移** 研究<sup>[42]</sup>表明,存在颈侧区淋巴结转移的PTC在疾病持续、复发和远处转移方面的风险高于仅有中央淋巴结转移者。此外,颈侧区淋巴结清扫术常伴随甲状旁腺功能减退、颈部疼痛及乳糜渗漏等并发症<sup>[43]</sup>。因此,开发可靠的模型在术前预测颈侧区淋巴结转移尤为必要。既往有研究<sup>[44]</sup>利用多种临床因素构建了PTC患者颈侧区淋巴结转移风险预测列线图模型,但预测效果有限。Feng等<sup>[45]</sup>综合临床与超声特征,构建了8种预测算法,以随机森林算法表现最佳,其敏感度与特异度分别为0.903和0.959,其AUC高达0.975。Lai等<sup>[46]</sup>通过分析超声图像、临床特征及实验室检查结果,开发了6种机器学习模型,并与传统的基于逻辑回归列线图进行比较,随机森林

算法仍表现最佳,其AUC为0.80,准确率为0.74,敏感度为0.89。鉴于颈侧区淋巴结转移对PTC患者的危害较中央区更为严重,未来应加强对该领域的AI模型研究,特别是随机森林算法的应用值得进一步探索。

### 3.3 预测DTC远处转移

DTC远处转移主要累及肺,其次为骨,且FTC较PTC更易发生。远处转移显著降低DTC患者的生存率,例如骨转移患者的5年生存率仅为61%,10年生存率低至27%<sup>[47]</sup>。Liu等<sup>[48]</sup>从美国国家卫生研究院的监测、流行病学和最终结果(Surveillance, Epidemiology, and End Results, SEER)数据库中提取DTC患者的人口统计学与临床病理学数据,开发6个机器学习模型来预测肺转移,所有模型均表现良好,其中随机森林算法表现尤为突出。随后,Liu等<sup>[49]</sup>从该数据库再次提取数据,构建用于预测骨转移的随机森林模型,其性能优于传统逻辑回归模型。多数DTC在远处转移初期无明显症状,而AI技术的应用有助于早期发现转移瘤,从而为患者制定个体化诊疗策略。因此,建立符合我国人口特点的数据库并开展此类研究或在国内进行多中心、大样本研究,显得十分必要。

## 4 AI在预测DTC基因突变中的应用

### 4.1 预测BRAF基因突变

BRAF<sup>V600E</sup>突变是DTC常见的基因突变,对PTC具有高度特异性<sup>[50]</sup>,研究<sup>[51]</sup>发现,DTC的超声特征与BRAF基因突变密切相关,故预测基因突变成为研究的新方向。Kwon等<sup>[52]</sup>纳入96例PTC患者的96枚癌结节,从灰阶超声提取5个影像组学特征,建立3个机器学习模型来预测BRAF<sup>V600E</sup>突变,三者性能中等(平均AUC、准确率、敏感度、特异度分别为0.654、64.3%、66.8%、61.8%),但证实了使用超声图像进行分析的可行性。Yoon等<sup>[53]</sup>则通过分析超声图像,基于深度神经网络开发CAD系统,进行类似研究,尽管性能一般(AUC为0.706),但同样证明了此类研究的潜力。Wang等<sup>[54]</sup>进一步表明,结合灰阶超声与超声弹性成像图像的AI模型在预测BRAF<sup>V600E</sup>突变上展现出更高价值(训练集、测试集的AUC分别为0.985、0.931)。除研究影像图像外,Wang等<sup>[55]</sup>首次对118张FNAB

全玻片图像进行研究,以尽早确定BRAF基因状态,此深度学习模型准确率为87%、精确度为94%、敏感度为91%、特异度为71%、平均敏感度和特异度为81%。在未注释的HE染色病理玻片上,Anand等<sup>[56]</sup>使用弱监督学习技术训练的深度神经网络模型,精准预测了DTC中的BRAF基因突变(AUC高达0.98),性能卓越。综上所述,相较于机器学习模型,深度学习模型在预测DTC基因突变方面性能更佳,超声新技术的应用则显著提升诊断效果。

### 4.2 预测启动子突变

端粒酶逆转录酶启动子突变在DTC患者亚群中被发现,并被证明与肿瘤侵袭性密切相关<sup>[57]</sup>。因此,明确其突变情况对判断DTC预后至关重要。Kim等<sup>[58]</sup>尝试使用病理组织图像开发深度学习模型,结果显示该模型可对端粒酶逆转录酶启动子突变进行高敏感度(99.9%)筛选,但特异度不高(60%),故未来研究可聚焦于提升此类模型的特异度,以更准确辅助DTC的诊断和预后判断。

### 4.3 预测基因重排

RET基因重排对PTC的发生与发展具有重要影响,与PTC的发病年龄、肿瘤大小、生长速度、转移能力密切相关<sup>[59]</sup>,是诊断PTC的重要指标。Yu等<sup>[60]</sup>率先在该领域进行研究,利用基于超声图像的深度学习影像组学列线图,实现了对RET基因重排的高效预测(训练集、测试集的AUC分别为0.939 6、0.954 5)。此类无创诊断方法有助于术前精准评估RET基因重排情况,进而指导分子测序和靶向治疗方案的制定,既节约医疗成本,又提升治疗效果,实现精准医疗的目标。

## 5 AI在DTC术后<sup>131</sup>I治疗中的应用

<sup>131</sup>I治疗在DTC的治疗中占据重要地位,为确保治疗效果,患者需在<sup>131</sup>I治疗前接受SPECT/CT检查以评估甲状腺组织及转移淋巴结的残余情况。然而,准确判读SPECT/CT图像对核医学医师而言颇具挑战。Guo等<sup>[61]</sup>利用诊断性<sup>131</sup>I显像图,设计了基于深度卷积神经网络的CAD系统,实现了对残留甲状腺组织的精确诊断(准确率、敏感度、特异度、精确度分别为96.69%、94.75%、99.6%、99.96%)。鉴于诊断性<sup>131</sup>I显像可能导致的“顿抑”现象对后续<sup>131</sup>I治疗效果的影响,向镛兆等<sup>[62]</sup>

对 $^{99}\text{Tc}^{\text{m}}\text{O}_4^-$ 甲状腺显像图进行深入研究,构建的神经网络模型的诊断准确率(高达91.3%)同样令人瞩目。针对 $^{131}\text{I}$ 治疗后SPECT/CT平面图像上残余甲状腺组织和摄碘性淋巴结的识别问题,Kavitha等<sup>[63]</sup>开发AI模型进行自动区分,尽管AI模型的表现优于核医学医师,但其诊断性能仍有待提高。总而言之,深度学习技术有望为核医学医师提供更准确、高效的诊断工具,从而优化DTC的诊疗过程。

## 6 小结与展望

甲状腺癌的发病率持续攀升,精准诊断与个体化治疗成为医患共同追求,亦是未来医疗的发展趋势。AI在DTC诊疗中的研究日益增多,尤其在鉴别甲状腺结节良恶性、预测DTC颈部淋巴结转移方面展现出显著优势。AI在基因突变预测方面潜力巨大,未来可在此领域进行深入研究。从研究对象来看,超声图像依然是最常见的数据来源,新型超声成像技术及动态视频的纳入均有助于优化AI模型性能,CT图像在诸多方面均可作为稳定的数据来源,而基于核医学检查图像进行AI研究同样具有广阔发展空间。未来的研究应在现有基础上,深入分析DTC的临床特点、影像及分子特征,以优化AI模型,实现对DTC更精准的诊断及个体化治疗。

利益冲突:所有作者均声明不存在利益冲突。

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## 参考文献

- [1] Bray F, Ferlay J, Soerjomataram I, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries[J]. CA Cancer J Clin, 2018, 68(6):394-424. doi:10.3322/caac.21492.
- [2] Howard J. Artificial intelligence: implications for the future of work[J]. Am J Ind Med, 2019, 62(11): 917-926. doi: 10.1002/ajim.23037.
- [3] Erickson BJ, Korfiatis P, Akkus Z, et al. Machine learning for medical imaging[J]. Radiographics, 2017, 37(2): 505-515. doi: 10.1148/rg.2017160130.
- [4] Choy G, Khalilzadeh O, Michalski M, et al. Current applications and future impact of machine learning in radiology[J]. Radiology, 2018, 288(2):318-328. doi:10.1148/radiol.2018171820.
- [5] Lambin P, Rios-Velazquez E, Leijenaar R, et al. Radiomics: extracting more information from medical images using advanced feature analysis[J]. Eur J Cancer, 2012, 48(4): 441-446. doi: 10.1016/j.ejca.2011.11.036.
- [6] Gillies RJ, Kinahan PE, Hricak H. Radiomics: images are more than pictures, they are data[J]. Radiology, 2016, 278(2): 563-577. doi:10.1148/radiol.2015151169.
- [7] 蹇诗婕, 卢志刚, 牡丹, 等. 网络入侵检测技术综述[J]. 信息安全学报, 2020, 5(4): 96-122. doi: 10.19363/J.cnki.cn10-1380/tn.2020.07.07.
- [8] Jian SJ, Lu ZG, Du D, et al. Overview of network intrusion detection technology[J]. Journal of Cyber Security, 2020, 5(4):96-122. doi:10.19363/J.cnki.cn10-1380/tn.2020.07.07.
- [9] Shweel M, Mansour E. Diagnostic performance of combined elastosonography scoring and high-resolution ultrasonography for the differentiation of benign and malignant thyroid nodules[J]. Eur J Radiol, 2013, 82(6):995-1001. doi:10.1016/j.ejrad.2013.02.002.
- [10] Kim GR, Lee E, Kim HR, et al. Convolutional neural network to stratify the malignancy risk of thyroid nodules: diagnostic performance compared with the American college of radiology thyroid imaging reporting and data system implemented by experienced radiologists[J]. AJNR Am J Neuroradiol, 2021, 42(8): 1513-1519. doi:10.3174/ajnr.A7149.
- [11] Zhu J, Zhang S, Yu R, et al. An efficient deep convolutional neural network model for visual localization and automatic diagnosis of thyroid nodules on ultrasound images[J]. Quant Imaging Med Surg, 2021, 11(4):1368-1380. doi:10.21037/qims-20-538.
- [12] Wu GG, Lv WZ, Yin R, et al. Deep learning based on ACR TI-RADS can improve the differential diagnosis of thyroid nodules[J]. Front Oncol, 2021, 11:575166. doi:10.3389/fonc.2021.575166.
- [13] Yang ZY, Yao SQ, Heng Y, et al. Automated diagnosis and management of follicular thyroid nodules based on the devised small-dataset interpretable foreground optimization network deep learning: a multicenter diagnostic study[J]. Int J Surg, 2023, 109(9): 2732-2741. doi:10.1097/JS9.0000000000000506.
- [14] Zhang Y, Wu Q, Chen Y, et al. A clinical assessment of an ultrasound computer-aided diagnosis system in differentiating thyroid nodules with radiologists of different diagnostic experience[J]. Front Oncol, 2020, 10: 557169. doi: 10.3389/fonc.2020.557169.
- [15] Jin Z, Zhu Y, Zhang S, et al. Ultrasound computer-aided diagnosis

- (CAD) based on the thyroid imaging reporting and data system (TI-RADS) to distinguish benign from malignant thyroid nodules and the diagnostic performance of radiologists with different diagnostic experience[J]. *Med Sci Monit*, 2020, 26: e918452. doi: 10.12659/MSM.918452.
- [15] He LT, Chen FJ, Zhou DZ, et al. A comparison of the performances of artificial intelligence system and radiologists in the ultrasound diagnosis of thyroid nodules[J]. *Curr Med Imaging*, 2022, 18(13): 1369–1377. doi:10.2174/1573405618666220422132251.
- [16] Peng S, Liu Y, Lv W, et al. Deep learning-based artificial intelligence model to assist thyroid nodule diagnosis and management: a multicentre diagnostic study[J]. *Lancet Digit Health*, 2021, 3(4): e250–e259. doi: 10.1016/S2589-7500(21)00041-8.
- [17] Hoang JK, Middleton WD, Farjat AE, et al. Reduction in thyroid nodule biopsies and improved accuracy with American college of radiology thyroid imaging reporting and data system[J]. *Radiology*, 2018, 287(1):185–193. doi:10.1148/radiol.2018172572.
- [18] Buda M, Wildman-Tobriner B, Hoang JK, et al. Management of thyroid nodules seen on US images: deep learning may match performance of radiologists[J]. *Radiology*, 2019, 292(3): 695–701. doi:10.1148/radiol.2019181343.
- [19] Zhao CK, Ren TT, Yin YF, et al. A comparative analysis of two machine learning-based diagnostic patterns with thyroid imaging reporting and data system for thyroid nodules: diagnostic performance and unnecessary biopsy rate[J]. *Thyroid*, 2021, 31(3): 470–481. doi:10.1089/thy.2020.0305.[PubMed]
- [20] Zhang C, Liu D, Huang L, et al. Classification of thyroid nodules by using deep learning radiomics based on ultrasound dynamic video[J]. *J Ultrasound Med*, 2022, 41(12):2993–3002. doi:10.1002/jum.16006.
- [21] Wang B, Wan Z, Li C, et al. Identification of benign and malignant thyroid nodules based on dynamic AI ultrasound intelligent auxiliary diagnosis system[J]. *Front Endocrinol (Lausanne)*, 2022, 13:1018321. doi:10.3389/fendo.2022.1018321.
- [22] 李晓宇, 刘利平, 辛雨薇, 等. 人工智能软件联合超声造影鉴别诊断甲状腺良、恶性结节[J]. *中国医学影像学杂志*, 2023, 31(3): 226–230. doi:10.3969/j.issn.1005-5185.2023.03.007.
- Li XY, Liu LP, Xin YW, et al. Diagnosis of artificial intelligence software combined with contrast-enhanced ultrasound in differentiating benign from malignant thyroid nodules[J]. *Chinese Journal of Medical Imaging*, 2023, 31(3): 226–230. doi: 10.3969/j.issn.1005-5185.2023.03.007.
- [23] Zhang MB, Meng ZL, Mao Y, et al. Cervical lymph node metastasis prediction from papillary thyroid carcinoma US videos: a prospective multicenter study[J]. *BMC Med*, 2024, 22(1):153. doi: 10.1186/s12916-024-03367-2.
- [24] Zhao HB, Liu C, Ye J, et al. A comparison between deep learning convolutional neural networks and radiologists in the differentiation of benign and malignant thyroid nodules on CT images[J]. *Endokrynol Pol*, 2021, 72(3):217–225. doi: 10.5603/EP.a2021.0015.
- [25] Li W, Cheng S, Qian K, et al. Automatic recognition and classification system of thyroid nodules in CT images based on CNN[J]. *Comput Intell Neurosci*, 2021, 2021: 5540186. doi: 10.1155/2021/5540186.
- [26] Wu X, Li J, Mou Y, et al. Radiomics nomogram for identifying sub-1 cm benign and malignant thyroid lesions[J]. *Front Oncol*, 2021, 11:580886. doi:10.3389/fonc.2021.580886.
- [27] Naglah A, Khalifa F, Khaled R, et al. Novel MRI-based CAD system for early detection of thyroid cancer using multi-input CNN[J]. *Sensors (Basel)*, 2021, 21(11): 3878. doi: 10.3390/s21113878.
- [28] Sharafeldeen A, Elsharkawy M, Khaled R, et al. Texture and shape analysis of diffusion-weighted imaging for thyroid nodules classification using machine learning[J]. *Med Phys*, 2022, 49(2): 988–999. doi:10.1002/mp.15399.
- [29] 王庆军, 程流泉, 符永瑰, 等. 桥本甲状腺炎性结节与甲状腺微小乳头状癌鉴别诊断: 基于MRI影像组学机器学习的应用[J]. *中国医学影像学杂志*, 2023, 31(3):213–219. doi:10.3969/j.issn.1005-5185.2023.03.005.
- Wang QJ, Cheng LQ, Fu YG, et al. Differentiation between hashimoto's thyroiditis nodule and papillary thyroid microcarcinoma: application of MRI radiomics-based machine learning[J]. *Chinese Journal of Medical Imaging*, 2023, 31(3):213–219. doi:10.3969/j.issn.1005-5185.2023.03.005.
- [30] 董彬. 基于多模态超声影像组学对分化型甲状腺癌包膜侵犯的研究[D]. 杭州: 浙江中医药大学, 2022. doi: 10.27465/d.cnki.gzzyc.2022.000279.
- Dong B. Research on prediction of capsule invasion in differentiated thyroid carcinoma based on multimodal ultrasound radiomics[D]. Hangzhou: Zhejiang Chinese Medical University, 2022. doi:10.27465/d.cnki.gzzyc.2022.000279.
- [31] 卢文洁. 基于甲状腺超声影像组学方法预测甲状腺乳头状癌腺外侵犯的临床研究[D]. 广州: 广州医科大学, 2022. doi:10.27043/d.cnki.ggzy.2022.000064.
- Lu WJ. Radiomics based on thyroid ultrasound for predicting extrathyroidal extension status in papillary thyroid carcinoma[D]. Guangzhou: Guangzhou Medical University, 2022. doi:10.27043/d.cnki.ggzy.2022.000064.
- [32] Wu X, Yu P, Jia C, et al. Radiomics analysis of computed tomography for prediction of thyroid capsule invasion in papillary

- thyroid carcinoma: a multi-classifier and two-center study[J]. *Front Endocrinol (Lausanne)*, 2022, 13: 849065. doi: 10.3389/fendo.2022.849065.
- [33] Yu PY, Wu XX, Li JJ, et al. Extrathyroidal extension prediction of papillary thyroid cancer with computed tomography based radiomics nomogram: a multicenter study[J]. *Front Endocrinol (Lausanne)*, 2022, 13:874396. doi:10.3389/fendo.2022.874396.
- [34] Chen B, Zhong LZ, Dong D, et al. Computed tomography radiomic nomogram for preoperative prediction of extrathyroidal extension in papillary thyroid carcinoma[J]. *Front Oncol*, 2019, 9: 829. doi: 10.3389/fonc.2019.00829.
- [35] Zhao Q, Ming J, Liu C, et al. Multifocality and total tumor diameter predict central neck lymph node metastases in papillary thyroid microcarcinoma[J]. *Ann Surg Oncol*, 2013, 20(3):746–752. doi:10.1245/s10434-012-2654-2.
- [36] Hughes DT, Doherty GM. Central neck dissection for papillary thyroid cancer[J]. *Cancer Control*, 2011, 18(2):83–88. doi:10.1177/107327481101800202.
- [37] O'Connell K, Yen TW, Quiroz F, et al. The utility of routine preoperative cervical ultrasonography in patients undergoing thyroidectomy for differentiated thyroid cancer[J]. *Surgery*, 2013, 154(4):697–701. doi:10.1016/j.surg.2013.06.040.
- [38] Wu YJ, Rao K, Liu JH, et al. Machine learning algorithms for the prediction of central lymph node metastasis in patients with papillary thyroid cancer[J]. *Front Endocrinol (Lausanne)*, 2020, 11: 577537. doi:10.3389/fendo.2020.577537.
- [39] Li JJ, Wu XX, Mao N, et al. Computed tomography-based radiomics model to predict central cervical lymph node metastases in papillary thyroid carcinoma: a multicenter study[J]. *Front Endocrinol (Lausanne)*, 2021, 12: 741698. doi: 10.3389/fendo.2021.741698.
- [40] Yu J, Deng Y, Liu T, et al. Lymph node metastasis prediction of papillary thyroid carcinoma based on transfer learning radiomics[J]. *Nat Commun*, 2020, 11(1):4807. doi:10.1038/s41467-020-18497-3.
- [41] Chang LC, Zhang YQ, Zhu JL, et al. An integrated nomogram combining deep learning, clinical characteristics and ultrasound features for predicting central lymph node metastasis in papillary thyroid cancer: a multicenter study[J]. *Front Endocrinol (Lausanne)*, 2023, 14:964074. doi:10.3389/fendo.2023.964074.
- [42] Feng JW, Yang XH, Wu BQ, et al. Predictive factors for central lymph node and lateral cervical lymph node metastases in papillary thyroid carcinoma[J]. *Clin Transl Oncol*, 2019, 21(11):1482–1491. doi:10.1007/s12094-019-02076-0.
- [43] 王慧芳,于博,赵文君,等. cN0 甲状腺微小乳头状癌右侧喉返神经后方淋巴结转移及清扫研究进展[J]. *中国普通外科杂志*, 2020, 29(5):603–610. doi:10.7659/j.issn.1005-6947.2020.05.012.
- Wang HF, Yu B, Zhao WJ, et al. Progress of metastasis and dissection of the lymph nodes posterior to the right recurrent laryngeal nerve in CN0 thyroid micropapillary carcinoma[J]. *China Journal of General Surgery*, 2020, 29(5): 603–610. doi: 10.7659/j.issn.1005-6947.2020.05.012.
- [44] 马鑫雨,柴芳,肖智远,等. 甲状腺乳头状癌患者侧颈部淋巴结转移影响因素分析[J]. *中国普通外科杂志*, 2023, 32(5):682–689. doi:10.7659/j.issn.1005-6947.2023.05.007.
- Ma XY, Chai F, Xiao ZY, et al. Analysis of influencing factors for lateral neck lymph node metastasis in patients with papillary thyroid carcinoma[J]. *China Journal of General Surgery*, 2023, 32(5):682–689. doi:10.7659/j.issn.1005-6947.2023.05.007.
- [45] Feng JW, Ye J, Qi GF, et al. A comparative analysis of eight machine learning models for the prediction of lateral lymph node metastasis in patients with papillary thyroid carcinoma[J]. *Front Endocrinol (Lausanne)*, 2022, 13: 1004913. doi: 10.3389/fendo.2022.1004913.
- [46] Lai SW, Fan YL, Zhu YH, et al. Machine learning-based dynamic prediction of lateral lymph node metastasis in patients with papillary thyroid cancer[J]. *Front Endocrinol (Lausanne)*, 2022, 13: 1019037. doi:10.3389/fendo.2022.1019037.
- [47] Wu D, Gomes Lima CJ, Moreau SL, et al. Improved survival after multimodal approach with 131I treatment in patients with bone metastases secondary to differentiated thyroid cancer[J]. *Thyroid*, 2019, 29(7):971–978. doi:10.1089/thy.2018.0582.
- [48] Liu W, Wang S, Ye Z, et al. Prediction of lung metastases in thyroid cancer using machine learning based on SEER database[J]. *Cancer Med*, 2022, 11(12):2503–2515. doi:10.1002/cam4.4617.
- [49] Liu WC, Li ZQ, Luo ZW, et al. Machine learning for the prediction of bone metastasis in patients with newly diagnosed thyroid cancer[J]. *Cancer Med*, 2021, 10(8): 2802–2811. doi: 10.1002/cam4.3776.
- [50] Moon HJ, Kwak JY, Kim EK, et al. The role of BRAFV600E mutation and ultrasonography for the surgical management of a thyroid nodule suspicious for papillary thyroid carcinoma on cytology[J]. *Ann Surg Oncol*, 2009, 16(11): 3125–3131. doi: 10.1245/s10434-009-0644-9.
- [51] Kabaker AS, Tublin ME, Nikiforov YE, et al. Suspicious ultrasound characteristics predict BRAF V600E-positive papillary thyroid carcinoma[J]. *Thyroid*, 2012, 22(6):585–589. doi:10.1089/thy.2011.0274.
- [52] Kwon MR, Shin JH, Park H, et al. Radiomics study of thyroid ultrasound for predicting BRAF mutation in papillary thyroid carcinoma: preliminary results[J]. *AJNR Am J Neuroradiol*, 2020, 41(4):700–705. doi:10.3174/ajnr.A6505.

- [53] Yoon J, Lee E, Koo JS, et al. Artificial intelligence to predict the BRAFV600E mutation in patients with thyroid cancer[J]. PLoS One, 2020, 15(11):e0242806. doi:10.1371/journal.pone.0242806.
- [54] Wang YG, Xu FJ, Agyekum EA, et al. Radiomic model for determining the value of elasticity and grayscale ultrasound diagnoses for predicting BRAFV600E mutations in papillary thyroid carcinoma[J]. Front Endocrinol (Lausanne), 2022, 13: 872153. doi:10.3389/fendo.2022.872153.
- [55] Wang CW, Muzakky H, Lee YC, et al. Annotation-free deep learning-based prediction of thyroid molecular cancer biomarker BRAF (V600E) from cytological slides[J]. Int J Mol Sci, 2023, 24(3):2521. doi:10.3390/ijms24032521.
- [56] Anand D, Yashashwi K, Kumar N, et al. Weakly supervised learning on unannotated H&E-stained slides predicts BRAF mutation in thyroid cancer with high accuracy[J]. J Pathol, 2021, 255(3):232–242. doi:10.1002/path.5773.
- [57] Xing M, Liu R, Liu X, et al. BRAF V600E and TERT promoter mutations cooperatively identify the most aggressive papillary thyroid cancer with highest recurrence[J]. J Clin Oncol, 2014, 32(25):2718–2726. doi:10.1200/JCO.2014.55.5094.
- [58] Kim J, Ko S, Kim M, et al. Deep learning prediction of TERT promoter mutation status in thyroid cancer using histologic images[J]. Medicina (Kaunas), 2023, 59(3): 536. doi: 10.3390/medicina59030536.
- [59] Adeniran AJ, Zhu Z, Gandhi M, et al. Correlation between genetic alterations and microscopic features, clinical manifestations, and prognostic characteristics of thyroid papillary carcinomas[J]. Am J Surg Pathol, 2006, 30(2):216–222. doi: 10.1097/01.pas.000017643.2.73455.1b.
- [60] Yu JL, Zhang YH, Zheng J, et al. Ultrasound images-based deep learning radiomics nomogram for preoperative prediction of RET rearrangement in papillary thyroid carcinoma[J]. Front Endocrinol (Lausanne), 2022, 13:1062571. doi:10.3389/fendo.2022.1062571.
- [61] Guo Y, Xu J, Li X, et al. Classification and diagnosis of residual thyroid tissue in SPECT images based on fine-tuning deep convolutional neural network[J]. Front Oncol, 2021, 11: 762643. doi:10.3389/fonc.2021.762643.
- [62] 向镛兆, 黄秋菊, 魏建安, 等. 深度神经网络辅助评估 $^{99}\text{Tc}^{\text{m}}\text{O}^{-+4}$ 显像甲状腺癌术后残留组织[J]. 中国医学影像学杂志, 2023, 31(2):108–113. doi:10.3969/j.issn.1005-5185.2023.02.003.
- Xiang YZ, Huang QJ, Wei JA, et al. Deep neural network assisted  $^{99}\text{Tc}^{\text{m}}\text{O}^{-+4}$  imaging for evaluation of postoperative residual tissue in thyroid cancer[J]. Chinese Journal of Medical Imaging, 2023, 31(2):108–113. doi:10.3969/j.issn.1005-5185.2023.02.003.
- [63] Kavitha M, Lee CH, Shibudas K, et al. Deep learning enables automated localization of the metastatic lymph node for thyroid cancer on  $^{131}\text{I}$  post-ablation whole-body planar scans[J]. Sci Rep, 2020, 10(1):7738. doi:10.1038/s41598-020-64455-w.

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