doi:10.11659/jjssx.01E024136

·综 述·

甲状腺结节的影像组学研究进展

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[摘 要] 甲状腺结节近年来检出率逐渐提升,术前对其全方位准确评估、早期识别危险因素有助于临床选择治疗方案及改善预后。影像组学通过高通量挖掘肉眼不可见的图像特征从医学图像中提取定量特征对甲状腺结节进行评估,在甲状腺结节良恶性鉴别、甲状腺癌淋巴结转移、腺外侵犯、分子生物学改变、复发和预后等领域广泛开展且效能优异,但也存在各机构模型间效能差异大等不足。本文针对影像组学在甲状腺结节的应用价值、局限性和未来发展前景等方面进行综述,为临床实践及研究提供新思路。

[关键词] 影像组学;甲状腺结节;甲状腺癌;超声影像;机器学习
[中图分类号] R736.1;R445 [文献标志码] A [收稿日期] 2024-01-29

Research progresses of radiomics in thyroid nodules

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Abstract: The detection rate of thyroid nodules has gradually increased in recent years. Comprehensive and accurate preoperative evaluation and early identification of risk factors help doctors to choose treatment options and improve prognosis. Radiomics extracts quantitative features from medical images for evaluation of thyroid nodules through high-throughput mining of invisible image features, which has been widely used and has excellent performance in the identification of benign and malignant thyroid nodules, lymph node metastasis, extrathyroidal extension, molecular biological changes, recurrence and prognosis of thyroid cancer. However, there are also shortcomings such as large differences in performance among models from different institutions. This article reviews the application value, limitations and future development prospects of radiomics in the thyroid nodules, so as to provide new ideas for clinical practice and research.

Keywords: radiomics; thyroid nodules; thyroid cancer; ultrasonic image; machine learning

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[24] Çalışkan B, Besir Z, Sen Ö. Pain monitoring in intensive care: how does the nociception level index affect treatment and prognosis? A randomized, controlled, double-blind trial [J]. Ulus Travma Acil Cerrahi Derg,2024,30(6):415-422. doi:10.14744/tjtes.2024.95533.

[25] Choi BM, Shin H, Lee JH, et al. Performance of the surgical pleth index and analgesia nociception index in healthy volunteers and parturients[J]. Front Physiol, 2021, 12:554026. doi:10.3389/fphys.2021.554026.

[26] Koschmieder KC, Funcke S, Shadloo M, et al. Validation of three nociception indices to predict immediate postoperative pain before emergence from general anaesthesia: a prospective double-blind, observational study[J]. Br J Anaesth, 2023, 130(4):477-484. doi:10.1016/j.bja.2022.11.024.

[27] Mannes AJ, Martin BM, Yang HYT, et al. Cystatin C as a cerebrospinal fluid biomarker for pain in humans[J]. Pain, 2003, 102(3):251-256. doi:10.1016/S0304-3959(02)00403-7.

[28] Mogil JS. Pain genetics: past, present and future[J]. Trends Genet, 2012, 28(6):258-266. doi:10.1016/j.tig.2012.02.004.

[29] Packiasabapathy S, Horn N, Sadhasivam S. Genetics of perioperative pain management[J]. Curr Opin Anaesthesiol, 2018, 31(6):749-755. doi:10.1097/ACO.0000000000000660.

[30] Savignac C, Ocay DD, Mahdid Y, et al. Clinical use of electroencephalography in the assessment of acute thermal pain: a narrative review based on articles from 2009 to 2019[J]. Clin EEG Neurosci, 2022, 53(2):124-132. doi:10.1177/15500594211026280.

[31] Ryu S, Gwon D, Park C, et al. Resting-state frontal electroencephalography (EEG) biomarkers for detecting the severity of chronic neuropathic pain[J]. Sci Rep, 2024, 14(1):20188. doi:10.1038/s41598-024-71219-3.

[32] Segning CM, da Silva RA, Ngomo S. An innovative EEG-based pain identification and quantification: a pilot study[J]. Sensors, 2024, 24(12):3873. doi:10.3390/s24123873.

[33] Teixeira M, Mancini C, Wicht CA, et al. Beta electroencephalographic oscillation is a potential GABAergic biomarker of chronic peripheral neuropathic pain[J]. Front Neurosci, 2021, 15:594536. doi:10.3389/fnins.2021.594536.

[34] Voepel-Lewis T. Can pain assessment tools accurately measure pain experience of disabled individuals?[J]. Dev Med Child Neurol, 2019, 61(1):8-9. doi:10.1111/dmcn.14033.

(编辑:贺绍梅)

随着高频超声在甲状腺疾病筛查中的应用,甲状腺结节,尤其是恶性结节的检出率明显提高,甲状腺癌发病率居女性恶性肿瘤第5位,居50岁以下女性恶性肿瘤第3位[1-2]。超声可对甲状腺结节形态进行评估,但其准确性受机器及操作者手法[3]等影响,导致同质性降低。近年来,影像组学的临床应用已经成为热点。与人工阅片相比,影像组学通过计算机以图像最小构成单元为基础的定量分析读取图片信息,以机器学习模型进行训练和升级,计算图片间宏观异质性的定量特征,捕获结节微观异质性和微小标记,可以微观量化不同结节特征,进行定量赋能[4]。影像组学在鉴别甲状腺结节良恶性、甲状腺癌淋巴结转移、腺外侵犯、分子生物学改变、复发和预后等领域广泛开展且效能优异,本文就影像组学在甲状腺癌领域的研究进展进行综述。

1 影像组学与甲状腺影响报告和数据系统(thyroid imaging reporting and data system,TI-RADS)鉴别甲状腺结节的性能比较

甲状腺结节的术前超声评估通常基于TI-RADS分级系统,然而其一致性及特异性较低,经验较少的外科医师对于报告中TI-RADS分级较高的结节,倾向于给予患者穿刺或手术等诊疗建议,增加不必要的心理负担。影像组学在超声的基础上给予更为精准的客观量化指标评估,提高了甲状腺结节筛查的准确性。研究发现,影像组学模型诊断敏感度及特异度均显著高于TI-RADS分级系统,尤其能为低风险结节提供更多的诊断依据[5-6]。研究发现,影像组学模型诊断效能高于初级医师的分级评分,甚至优于中高级医师,提示影像组学评分模型有助于提高初级医师对于甲状腺结节恶性程度的辨别能力[6-7]。Gild等[8]研究发现,影像组学模型对低风险结节(TI-RADS 2~3级)的诊断敏感度(100%)及特异度(80%)显著高于TI-RADS分级;与根据恶性征象赋分的TI-RADS分级相比,影像组学模型判断低风险结节效能可靠,提供了与之互补的参考,二者结合有助于相互印证。值得关注的是,目前超声影像组学大多聚焦于2D静态图片(表1),有学者对890例甲状腺结节的超声动态视频和静态图像进行综合研究发现,基于动态视频超声的影像组学模型的诊断效能优于超声静态图像影像组学[9]。因此,影像组学特征结合超声自身特征和临床因素综合判断甲状腺结节良恶性的准确性是值得肯定的。

表1 近年甲状腺结节影像组学部分相关研究及主要结果

参考文献	预测目标	患者(例)	成像方法	影像组学特征(个)	主要分析方法	准确度
Gild等[8]	结节良恶性鉴别	88	超声	7	LASSO,RF	0.330~0.860
Yoon等[10]	结节良恶性鉴别	154	超声	15	LASSO,回归分析	0.841
De Koster等[11]	结节良恶性鉴别	84	PET/CT	6	LASSO,回归分析	0.727~0.999
Li等[12]	结节良恶性鉴别	407	CT	12	LASSO,回归分析	0.804
Li等[13]	甲状腺外侵犯	164	超声	16	SVM,KNN,RF,LightGBM	0.720~0.780
Kwon等[14]	甲状腺外侵犯	169	超声	6	mRMR,LASSO,SVM	0.860
Wu等[15]	甲状腺外侵犯	412	CT	24	LASSO,KNN,SVM	0.820
Dai等[16]	甲状腺外侵犯	107	MRI	5	LASSO,回归分析	0.930
Yu等[17]	淋巴结转移	1 013	超声	NM	迁移学习	0.840~0.860
Tong等[18]	淋巴结转移	886	超声	21	mRMR,LASSO	0.819
Zhu等[19]	淋巴结转移	306	超声	58	LASSO	0.830
Kong等[20]	淋巴结转移	271	CT	30	mRMR,LASSO	0.880~0.940
Zhang等[21]	淋巴结转移	61	MRI	10	LASSO,RF,SVM	0.870
Yu等[22]	RET重排	650	超声	19	LASSO,LR,SVM,RF	0.876
Wang等[23]	BRAFV600E突变	138	B型/弹性超声	8/5	mRMR,LASSO	0.969
Kwon等[24]	BRAFV600E突变	96	超声	2	mRMR,LASSO,SVM,RF	0.643
Lu等[25]	术后复发	361	超声	7	mRMR,LASSO	0.845
Park等[26]	预后	768	超声	40	LASSO,回归分析	*C-index*:0.721*

注:最小冗余最大相关性(maximum relevance and minimum redundancy,mRMR);最小绝对收缩和选择算子(least absolute shrinkage and seletionoperator,LASSO);逐步回归(backward stepwise Logistic regression,LR);轻量级梯度提升树(light gradient boosting machin,Light GBM);支持向量机(support vector machines,SVM);K近邻算法(K-nearest neighbors,KNN)随机森林(random forest,RF);*表示作者将放射组学特征与临床病理特征相结合发现,纳入基于治疗前超声图像的放射组学特征(Rad-score)能够显著提高经典PTC患者无病生存率的预测准确性

2 甲状腺癌侵袭性及腺外侵犯的影像组学预测评估

术前科学、量化地评估恶性甲状腺结节的侵袭性,直接影响手术方式、切除范围、是否淋巴结清扫等的决策。由于超声探头压迫扭曲肿瘤周围薄壁组织,导致经验欠缺的超声科医师对甲状腺组织和包膜关系判断相对困难[27];影像组学量化评价的特点能够有效规避这种主观上的识别不清,提升预测价值。一项关于儿童甲状腺癌腺外侵犯的研究获得了4个基于不同分类器的影像组学模型,其判断甲状腺外侵犯效能显著优于彩超医师人工判断曲线下面积(*area under the curve*,*AUC*)最高为0.832,敏感度和特异度相较于人工判断均有20%以上的提升[13];另一项研究预测了161例甲状腺乳头状癌(papillary thyroid carcinoma,PTC)患者甲状腺外侵犯,最终得到了*AUC*为0.824的超声组学模型,同样佐证了其预测价值[28]。由于超声检查本身存在的特点和局限,评估甲状腺癌腺外侵犯的检查手段还应综合考虑CT等,大部分影像组学研究倾向于同时纳入多种影像学方法的影像组学联合预测模型及临床数据模型等的综合分析,这种综合模型的评估更全面,效能更高。如Lee等[27]报道,超声和CT联合预测甲状腺癌腺外侵犯的准确率更高(敏感度92.9%,特异度70.4%,*AUC*=0.744)。同时,也有研究认为,采用一种影像学方法的影像组学预测模型效能同样值得肯定。如Zhou等[29]研究显示,基于双能CT的碘图影像组学预测模型表现出了优良的预测能力,其模型*AUC*达0.847。此外,单独使用MRI组学模型对于甲状腺癌腺外侵犯的评估准确率也相对较高,一项纳入60例患者的研究获得了高质量的影像组学模型(*AUC*=0.906)[30],为MRI影像组学预测甲状腺癌腺外侵犯供了参考。另一项关于MRI影像组学的研究前瞻性纳入了120例患者的MRI图像数据,采用预测机器学习模型评估PTC的侵袭性,*AUC*为0.920,但其综合价值还应在大样本研究中进一步确认[31]。上述研究表明,基于机器学习的超声、MRI、CT等影像组学在术前辅助评估甲状腺癌侵袭性中具有显著优势。

3 甲状腺癌淋巴结转移的影像组学预测评估

研究表明,超声对于颈部中央区淋巴结转移的评估准确率仅为20%~31%,侧方淋巴结的准确率为70%,未被有效评估的转移淋巴结显著增加了甲状腺癌术后复发以及再次手术的风险[32]。目前对于甲状腺癌颈部中央区淋巴结和侧方淋巴结转移的研究均有超声影像组学诊断效能优于传统影像学(如单纯超声报告诊断)的证据。多项预测中央区淋巴结转移的大样本研究结果支持上述结论,其中一项纳入450例患者[33]和一项纳入3家机构720例患者[34]的研究结果均显示,中央区与侧方淋巴结转移患者的影像组学模型评分较高(*AUC*分别为0.938和0.905,与之相应的基于超声报告特征及淋巴结转移情况的预测模型最大*AUC*为0.702和0.820)。这提示影像组学对于甲状腺癌颈部中央区淋巴结转移具有优异的预测性能。另外,对于甲状腺癌颈侧区淋巴结的处理,建议常规行治疗性清扫,不推荐预防性清扫[35]。黄云霞等[36]通过超声影像组学对PTC患者的Ⅳ区淋巴结的超声影像组学特性进行评估并打分,该影像组学预测模型*AUC*为0.766,可为颈侧区淋巴结清扫决策提供参考。上述研究均提示了影像组学模型在评估颈部淋巴结转移方面的优势,但在近年的研究中,无论是基于临床统计学还是放射组学,由于提取的图像特征的完整性难以保证,较多甲状腺癌淋巴结转移模型预测性能并不理想。随着技术成熟,有望依据影像组学模型的定量评估,减少不必要的淋巴结清扫,同时避免因常规超声检查未发现淋巴结转移而未行清扫的情况,降低患者再次手术风险,提高整体预后。

4 影像组学预测甲状腺癌与基因改变之间的关系

目前影像组学预测甲状腺结节基因改变的研究涉及多种基因,部分基因的预测价值尚有争议。一项研究对138例PTC患者BRAFV600E基因突变的情况进行预测[23],利用灰阶和弹性超声图像建立模型,最终得到*AUC*分别为0.952、0.792,二者联合模型的*AUC*高达0.985,该基因与PTC腺外侵犯和颈部淋巴结转移密切相关,术前准确预判其改变可辅助诊断及靶向药物选择,提高患者整体治疗效果。然而,另有2项相关研究分别纳入328例和527例接受手术治疗的PTC患者,使用术前超声图像生成影像组学评分,发现BRAFV600突变没有相关的超声特征,*AUC*分别为0.651、0.685,从结果来看,影像组学特征预测PTC是否存在BRAFV600E突变的价值有限[24,37]。PTC组织的硬度与其内部病理结构密切相关,有无基因改变的患者在弹性模量或硬度方面存在显著差异[38]。因此,弹性超声的选择可能是获得效能更佳模型的原因,但也应注意后两项研究的样本量更大,更具备代表性。另有一项纳入650例样本的研究结果显示,超声影像组学术前预测PTC患者RET重排模型的*AUC*达0.950[22]。根据以往研究结果,影像组学预测分子生物学改变可辅助诊断25%~30%细针穿刺细胞学检查不

能确定的甲状腺结节[39],影像组学方法无创且价廉,可有效避免不必要的医疗支出,提高治疗效果。

5 影像组学评估PTC患者的复发和生存

PTC复发率高,对患者预后及生活质量产生负面影响[40]。因此,通过影像组学模型准确识别复发风险有利于优化随访方案。多项研究提示,基于超声的放射组学评分是PTC患者术后复发的重要预测指标,且影像组学特征可能是患者预后危险分层的潜在影像学标志物。一项研究纳入了768例常规PTC患者术前超声图像进行分析,结果提示,结合影像组学评分的预测模型对于患者无病生存率评估的准确性(*C-index*:0.777)高于单纯临床病理模型(*C-index*:0.721)[26]。Lu等[25]的研究亦得出类似的结果,该研究纳入361例PTC患者的超声资料进行分析,结果显示,预测模型在建模组和验证组中的预测精度分别比美国癌症联合委员会分期系统提高了约65.4%和43.9%。

6 挑战与前景

目前,影像组学模型预测研究存在一定局限性:第一,绝大多数研究局限于单中心、固定机器,影像组学证据难以互认,且在多灶病变和跨医院集的独立测试中,模型性能大大降低。相比之下,虽然少数研究对超声影像组学在多中心、跨机器、多操作员场景下的诊断价值进行评估后表明,迁移学习的影像组学模型在数据采集机器和数据采集操作员间具有稳定性,但仍需要更多的研究支持[17]。第二,各机构模型间效能差异大,不同成像方式导致结论不一致等。第三,影像组学特征代表的临床意义以及机器学习黑匣子效应尚未完全得到阐述及破除。最后,现有的研究热点及重点集中在甲状腺分化型癌的各个方向,涉及甲状腺髓样癌及甲状腺未分化癌的研究甚少。

本文综述了影像组学在甲状腺结节早期诊断和淋巴结转移、腺外侵犯、分子生物学改变、复发及预后等预测中的最新进展,影像组学方法提供了一种有效、无创的辅助决策支持,基于影像组学建立的甲状腺结节预测模型及数据库将为临床甲状腺结节诊疗提供更加客观的指导。

[参考文献]

[1] Grani G, Sponziello M, Pecce V, et al. Contemporary thyroid nodule evaluation and management[J]. J Clin Endocrinol Metabol, 2020, 105(9):2869-2883. doi:10.1210/clinem/dgaa322.

[2] Vaccarella S, Lortet-Tieulent J, Colombet M, et al. Global patterns and trends in incidence and mortality of thyroid cancer in children and adolescents: a population-based study[J]. Lancet Diabetes Endocrinol, 2021, 9(3):144-152. doi:10.1016/S2213-8587(20)30401-0.

[3] Pasqual E, Sosa JA, Chen Y, et al. Trends in the management of localized papillary thyroid carcinoma in the United States(2000-2018)[J]. Thyroid, 2022, 32(4):397-410. doi:10.1089/thy.2021.0557.

[4] Antunes JT, Ofshteyn A, Bera K, et al. Radiomic features of primary rectal cancers on baseline T(2)-weighted MRI are associated with pathologic complete response to neoadjuvant chemoradiation: a multisite study[J]. J Magn Reson Imaging, 2020, 52(5):1531-1541. doi:10.1002/jmri.27140.

[5] Wei X, Gao M, Yu R, et al. Ensemble deep learning model for multicenter classification of thyroid nodules on ultrasound images[J]. Med Sci Monit, 2020, 26:e926096. doi:10.12659/MSM.926096.

[6] Li X, Zhang S, Zhang Q, et al. Diagnosis of thyroid cancer using deep convolutional neural network models applied to sonographic images: a retrospective, multicohort, diagnostic study[J]. Lancet Oncol, 2019, 20(2):193-201. doi:10.1016/S1470-2045(18)30762-9.

[7] Liang J, Huang X, Hu H, et al. Predicting malignancy in thyroid nodules: radiomics score versus 2017 American college of radiology thyroid imaging, reporting and data system[J]. Thyroid, 2018, 28(8):1024-1033. doi:10.1089/thy.2017.0525.

[8] Gild ML, Chan M, Gajera J, et al. Risk stratification of indeterminate thyroid nodules using ultrasound and machine learning algorithms[J]. Clin Endocrinol (Oxf), 2022, 96(4):646-652. doi:10.1111/cen.14612.

[9] 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.

[10] Yoon J, Lee E, Kang SW, et al. Implications of US radiomics signature for predicting malignancy in thyroid nodules with indeterminate cytology[J]. Eur Radiol, 2021, 31(7):5059-5067. doi:10.1007/s00330-020-07670-3.

[11] De Koster EJ, Noortman WA, Mostert JM, et al. Quantitative classification and radiomics of[(18)F]FDG-PET/CT in indeterminate thyroid nodules[J]. Eur J Nucl Med Mol Imaging, 2022, 49(7):2174-2188. doi:10.1007/s00259-022-05712-0.

[12] Li Z, Zhang H, Chen W, et al. Contrast-enhanced CT-based radiomics for the differentiation of nodular goiter from papillary thyroid carcinoma in thyroid nodules[J]. Cancer Manag Res, 2022, 14:1131-1140. doi:10.2147/CMAR.S353877.

[13] Li J, Xia F, Wang X, et al. Multiclassifier radiomics analysis of ultrasound for prediction of extrathyroidal extension in papillary thyroid carcinoma in children[J]. Int J Med Sci, 2023, 20(2):278-286. doi:10.7150/ijms.79758.

[14] Kwon MR, Shin JH, Park H, et al. Radiomics based on thyroid ultrasound can predict distant metastasis of follicular thyroid carcinoma[J]. J Clin Med, 2020, 9(7):2156. doi:10.3390/jcm9072156.

[15] 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.

[16] Dai Z, Wei R, Wang H, et al. Multimodality MRI-based radiomics for aggressiveness prediction in papillary thyroid cancer [J]. BMC Med Imaging, 2022, 22(1): 54. doi: 10.1186/s12880-022-00779-5.

[17] 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.

[18] Tong Y, Li J, Huang Y, et al. Ultrasound-based radiomic nomogram for predicting lateral cervical lymph node metastasis in papillary thyroid carcinoma [J]. Acad Radiol, 2021, 28(12): 1675-1684. doi: 10.1016/j.acra.2020.07.017.

[19] Zhu W, Huang X, Qi Q, et al. Artificial neural network-based ultrasound radiomics can predict large-volume lymph node metastasis in clinical N0 papillary thyroid carcinoma patients [J]. J Oncol, 2022, 2022: 7133972. doi: 10.1155/2022/7133972.

[20] Kong D, Shan W, Zhu Y, et al. Preliminary study on CT contrast-enhanced radiomics for predicting central cervical lymph node status in patients with thyroid nodules [J]. Front Oncol, 2023, 13: 1060674. doi: 10.3389/fonc.2023.1060674.

[21] Zhang H, Hu S, Wang X, et al. Prediction of cervical lymph node metastasis using MRI radiomics approach in papillary thyroid carcinoma: a feasibility study [J]. Technol Cancer Res Treat, 2020, 19: 1533033820969451. doi: 10.1177/1533033820969451.

[22] Yu J, Zhang Y, 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.

[23] Wang YG, Xu FJ, Agyekum EA, et al. Radiomic model for determining the value of elasticity and grayscale ultrasound diagnoses for predicting BRAF (V600E) mutations in papillary thyroid carcinoma [J]. Front Endocrinol (Lausanne), 2022, 13: 872153. doi: 10.3389/fendo.2022.872153.

[24] 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.

[25] Lu B, Zhou Y, Lu X, et al. An ultrasound model for predicting recurrence of papillary thyroid carcinoma after complete endoscopic resection [J]. Wideochir Inne Tech Maloinwazyjne, 2022, 17(3): 524-532. doi: 10.5114/wiitm.2022.116419.

[26] Park VY, Han K, Lee E, et al. Association between radiomics signature and disease-free survival in conventional papillary thyroid carcinoma [J]. Sci Rep, 2019, 9(1): 4501. doi: 10.1038/s41598-018-37748-4.

[27] Lee DY, Kwon TK, Sung MW, et al. Prediction of extrathyroidal extension using ultrasonography and computed tomography [J]. Int J Endocrinol, 2014, 2014: 351058. doi: 10.1155/2014/351058.

[28] Wang X, Agyekum EA, Ren Y, et al. A radiomic nomogram for the ultrasound-based evaluation of extrathyroidal extension in papillary thyroid carcinoma [J]. Front Oncol, 2021, 11: 625646. doi: 10.3389/fonc.2021.625646.

[29] Zhou Y, Su GY, Hu H, et al. Radiomics from primary tumor on dual-energy CT derived iodine maps can predict cervical lymph node metastasis in papillary thyroid cancer [J]. Acad Radiol, 2022, 29(Suppl 3): S222-S231. doi: 10.1016/j.acra.2021.06.014.

[30] He J, Zhang H, Wang X, et al. A pilot study of radiomics signature based on biparametric MRI for preoperative prediction of extrathyroidal extension in papillary thyroid carcinoma [J]. J Xray Sci Technol, 2021, 29(1): 171-183. doi: 10.3233/XST-200760.

[31] Wang H, Song B, Ye N, et al. Machine learning-based multiparametric MRI radiomics for predicting the aggressiveness of papillary thyroid carcinoma [J]. Eur J Radiol, 2020, 122: 108755. doi: 10.1016/j.ejrad.2019.108755.

[32] Zhao H, Li H. Meta-analysis of ultrasound for cervical lymph nodes in papillary thyroid cancer: diagnosis of central and lateral compartment nodal metastases [J]. Eur J Radiol, 2019, 112: 14-21. doi: 10.1016/j.ejrad.2019.01.006.

[33] Liu T, Zhou S, Yu J, et al. Prediction of lymph node metastasis in patients with papillary thyroid carcinoma: a radiomics method based on preoperative ultrasound images [J]. Technol Cancer Res Treat, 2019, 18: 1533033819831713. doi: 10.1177/1533033819831713.

[34] Tong Y, Zhang J, Wei Y, et al. Ultrasound-based radiomics analysis for preoperative prediction of central and lateral cervical lymph node metastasis in papillary thyroid carcinoma: a multi-institutional study [J]. BMC Med Imaging, 2022, 22(1): 82. doi: 10.1186/s12880-022-00809-2.

[35] 孙 颖, 赵彦广, 吴 剑, 等. 甲状腺微小乳头状癌与颈部淋巴结转移的相关性探讨 [J]. 局解手术学杂志, 2019, 28(2): 133-138. doi: 10.11659/jjssx.12E018041.

[36] 黄云霞, 周 瑾, 刘桐桐, 等. 超声影像组学与传统影像模式对甲状腺乳头状癌颈部中央区淋巴结转移的诊断价值比较 [J]. 中华超声影像学杂志, 2019, 28(10): 882-887. doi: 10.3760/cma.j.issn.1004-4477.2019.10.011.

[37] Tang J, Jiang S, Ma J, et al. Nomogram based on radiomics analysis of ultrasound images can improve preoperative BRAF mutation diagnosis for papillary thyroid microcarcinoma [J]. Front Endocrinol (Lausanne), 2022, 13: 915135. doi: 10.3389/fendo.2022.915135.

[38] Bojunga J, Mondorf A. Thyroid elastography [J]. Laryngorhinootologie, 2019, 98(3): 150-156. doi: 10.1055/a-0790-0885.

[39] 汪 金, 常 新, 韩春荣, 等. 超声造影联合血清SMURF1检测诊断甲状腺癌的临床分析 [J]. 局解手术学杂志, 2024, 33(2): 153-157. doi: 10.11659/jjssx.01E023048.

[40] 季福庆, 张明坤, 李梦斐. 手术治疗分化型甲状腺癌合并淋巴细胞性甲状腺炎的临床疗效分析 [J]. 局解手术学杂志, 2019, 28(9): 719-722. doi: 10.11659/jjssx.04E019047.

(编辑:杨 颖)