

Application of MRI Radiomics in Clinical Evaluation of Glioma

综 述

LIU Shu-han, ZHOU Qing*

Department of Ultrasound Imaging, Renmin Hospital of Wuhan University, Wuhan 430060, Hubei Province, P.R.C

ABSTRACT

Through high-throughput computing, radiomics is to mine a large number of (200+) quantitative image features from medical images, and use statistical / machine learning methods to select the most valuable imaging features for clinical decision support system, in order to improve the accuracy of diagnosis, prognosis and molecular level prediction, it is becoming more and more important in tumor research. Magnetic resonance imaging (MRI) has been widely studied in central nervous system tumors because of its high spatial resolution and MRI image features extracted by radiomics group. This article reviews the research and application of MRI radiomics in the clinical evaluation of gliomas.

Keywords: Glioma; Magnetic Resonance imaging; Radiomics

MRI影像组学在脑胶质瘤临床评估中的研究应用

刘书涵 周 青*

武汉大学人民医院超声影像科
(湖北 武汉 430060)

【摘要】影像组学是通过高通量计算,从医学影像中挖掘大量(200+)的定量影像特征,使用统计学/机器学习方法,筛选出最有价值的影像组学特征,用于临床决策支持系统,以提高诊断、预后和分子水平预测的准确性,在肿瘤研究中越来越重要。磁共振成像(MRI)由于其空间高分辨率的优势,影像组学提取MRI图像特征,在中枢神经系统肿瘤得到了更广泛的研究。本文就MRI影像组学在脑胶质瘤临床评估中的研究应用,予以综述。

【关键词】胶质瘤;磁共振成像;影像组学

【中图分类号】R445.2

【文献标识码】A

DOI:10.3969/j.issn.1672-5131.2023.03.061

脑胶质瘤主要起源于神经胶质细胞,是最常见的颅内原发肿瘤,每年全球发病率约为7/100000^[1]。在中国,胶质瘤发病率呈现逐年上升趋势,该趋势在中老年男性群体中尤为显著^[2]。胶质瘤表现出很大程度的异质性,具有复发率高、死亡率高、治疗手段有限的特点,尤其体现在恶性程度最高的胶质母细胞瘤(GBM)的治疗上。一项研究表明^[3],经综合手段治疗的胶质母细胞瘤患者,生存结果仍不尽人意,1年生存率为39.7%,5年生存率仅为5.5%。因此,早期发现、早期诊断、早期治疗是提高胶质瘤患者总体生存率的关键。

磁共振成像技术(MRI)广泛应用于中枢神经系统肿瘤的筛查、诊断及治疗评估。近年来,先进的磁共振新技术应用,如酰胺质子转移成像(amide proton transfer, APT)、体素不相干运动(intravoxel incoherent motion, IVIM)、磁共振扩散成像技术(diffusion MRI, dMRI)、血氧水平依赖功能磁共振成像(blood oxygen level dependent fMRI, BOLD-fMRI)等,不仅可以提供脑肿瘤的解剖结构信息,还可以反应肿瘤微环境、潜在的肿瘤生物学和病理过程^[4]。尽管如此,磁共振成像对胶质瘤分子表型、基因型状态的预测及治疗反应的评估仍具有较大挑战^[5]。

2012年荷兰学者Lambin教授^[6]首次并完善地提出影像组学(radiomics)概念,从而为胶质瘤的组织定性研究、基因型分析、病情预后及疗效评估等方面,开启了一个崭新的研究模式。具体来说,影像组学是通过高通量计算,从医学影像中挖掘大量(200+)的定量影像特征,使用统计学/机器学习方法,筛选出最有价值的影像组学特征,用以解析临床信息。影像组学的工作流程包括获取高质量标准化图像、感兴趣区(region of interest, ROI)分割、影像组学特征提取、影像组学特征降维、模型设计优化及验证这五个步骤,其最终目标是构建将影像特征纳入治疗结果的预测模型,提供临床准确的风险分层,并评估其对常用预测指标的附加价值^[7]。本文就MRI影像组学在脑胶质瘤临床诊断及治疗评价方面的研究应用,予以综述。

1 MRI影像组学在脑胶质瘤诊断及鉴别诊断中的应用

随着MRI技术的发展和不断完善,常规序列与先进的技术手段相结合,大大提高了胶质瘤影像学诊断的准确率。常规MRI序列提供了脑肿瘤精细的解剖细节,钆剂增强评估血脑屏障受损区域的范围,而先进的磁共振技术如MR灌注加权成像(PWI)、磁共振波谱(MRS)及扩散张量成像(DTI)等,可提供有关肿瘤浸润、侵袭性和潜在的肿瘤生物学特征,有助于胶质瘤的诊断及鉴别诊断^[8]。在影像学中,胶质瘤主要与颅内转移瘤、原发性中枢神经系统淋巴瘤、颅内感染(脑炎、脑脓肿)及肿瘤样脱髓鞘病变(TDL)相鉴别。

Qian等^[9]对412例孤立性脑肿瘤患者进行影像组学特征提取,经受试者工作特征(ROC)曲线分析表明,支持向量机(SVM)结合最小绝对收缩选择算子(LASSO)分类器具有最高的预测效率,其曲线下面积AUC可达0.90,有助于术前鉴别胶质母细胞瘤(GBM)和孤立性脑转移瘤(MET)。Bae等^[10]在外部验证中,发现深度神经网络(DNN)诊断GBM和MET的性能最好,其AUC、特异度和准确率分别为0.956、0.906、0.890。Sartoretti等^[11]对酰胺质子转移加权成像的脑肿瘤提取特征,进行多层感知器机器学习算法和随机森林(RF)分类器进行特征训练,均可高度准确地将原发性胶质瘤与转移瘤区分开来。

Kim等^[12]使用多参数MRI(对比增强T1加权成像、T2加权成像和扩散加权成像)进行影像组学分析,基于Logistic回归分类器可有效地鉴别原发性中枢神经系统淋巴瘤(PCNSL)与GBM,其AUC值为0.979。Xia等^[13]在Kim研究方法的基础上构建卷积神经网络(CNN)模型,发现CNN模型可以在肿瘤边界无需勾画的情况下将PCNSL与GBM鉴别开来,其准确率(0.899)与高级放射科医生(0.906, P=0.886)相媲美。

【第一作者】刘书涵,男,主治医师,主要研究方向:中枢神经系统影像诊断。E-mail: liushuhanabc@126.com

【通讯作者】周 青,女,主任医师,主要研究方向:心血管超声诊断、超声分子成像。E-mail: qingzhou128@hotmail.com

除了与肿瘤性疾病相鉴别外,影像组学在与颅内感染的鉴别诊断中也展现出较大的优势。Han等^[14]采用双样本t检验和LASSO回归方法筛选特征,建立鉴别无对比增强人群中,脑炎和低级别胶质瘤的影像组学特征模型。筛选出T2WI和联合(T1WI+T2WI)模型的诊断效果较好,AUC值分别为0.980、0.988。

此外,影像组学还应用于胶质瘤内部亚型的鉴别。Dong等^[15]利用影像组学和机器学习相结合的多模态MRI方法能较好地地区分儿童室管膜瘤和髓母细胞瘤,有助于临床诊断。另有学者^[16]从对比增强的MR图像中提取肿瘤的定量影像学特征,通过特征稳定性和Boruta算法选择特征子集,选取的特征为输入变量构建决策树模型,从而有效地鉴别GBM和毛细胞星形细胞瘤。

值得注意的是,MRI具备多参数、多方位、组织特异性的优势,还可进行功能成像,可满足大多数脑肿瘤的诊断。而影像组学相比之下,诊断模型的泛化能力具有一定的差异性,且研究成本较单模态或多模态MRI成像高。因此,在胶质瘤诊断上影像组学还未达到广泛的应用。在胶质瘤的鉴别诊断上,影像组学较多应用于与孤立性脑转移瘤、原发性中枢神经系统淋巴瘤的鉴别,而与肿瘤样脱髓鞘病变和脑脓肿的鉴别少有文献报道。

2 MRI影像组学在脑胶质瘤术前分级中的应用

根据世界卫生组织(WHO)恶性程度分级,将脑胶质瘤分为1-4级。1级恶性程度最低、预后最好,而4级肿瘤恶性程度最高、预后最差。因此,将胶质瘤按肿瘤细胞在病理学上的恶性程度进一步分类为,低级别胶质瘤(LGG,WHO 1-2级)和高级别胶质瘤(HGG,WHO 3-4级)^[17]。不同级别胶质瘤选择治疗方案不同,所以胶质瘤术前分级是关系到预后和生存的关键信息,具有重要的临床意义。

Cho等^[18]对285例胶质瘤(高级别210例,低级别75例)进行感兴趣区手动分割,使用最小冗余最大相关性算法在训练队列中选择对胶质瘤分级有用的特征。选取的特征分别用于构建Logistic分类器、支持向量机和随机森林三种分类器模型,其AUC值分别为0.901、0.887、0.9213。因此,结合影像组学方法,使用机器学习和特征选择技术可以准确地确定胶质瘤分级。Ditmer等^[19]通过评估肿瘤的异质性来确定放射学滤过直方图纹理分析(texture analysis,TA)鉴别高级别和低级别胶质瘤的诊断准确性。其中,直方图参数包括均值、标准差、熵、正像素均值、偏度和峰度。各参数与胶质瘤分级采用Spearman相关分析。用ROC曲线分析计算曲线下面积以区分肿瘤分级,其灵敏度和特异度分别为93%和86%(AUC为0.90)。Pei等^[20]使用常规DNN对LGG和HGG的交叉验证分类准确率为93.81%,而使用残差神经网络(ResNe)DNN对LGG 2级和HGG 3级的分类准确率为73.95%。因此,深度学习的类型对胶质瘤2-3级之间的肿瘤亚型区分有显著影响。

除对常规MRI序列提取影像组学特征外,许多学者用多模态MRI的先进技术^[21-24],如表观扩散系数(ADC)、灌注成像(脑血流量CBF图、动脉自旋标记图像)、扩散峰度和扩散张量成像(DKI、DTI)、磁共振波谱成像(1H-MRS)等,以不同技术相组合的方式,来评价各种基于放射学的机器学习分类模型,均对预测胶质瘤分级具有较高的准确性。因此,多模态、多参数MRI影像组学和深度特征相结合可作为术前预测胶质瘤分级的重要补充工具。

3 MRI影像组学在脑胶质瘤基因表达状态预测中的应用

2016年WHO中枢神经系统肿瘤分类第四版(2016 WHO CNS4),首次使用分子标记物(基因/分子特征)来定义肿瘤实体^[25],2021年6月将此规范标准更新至第五版(2021 WHO CNS5),进一步推进分子诊断在中枢神经系统肿瘤分类中的作用^[26]。胶质瘤的分子标记物,如IDH、1p/19q、ATRX、TP53、TERT启动子、MGMT启动子、H3组蛋白基因、EGFR、MYB等,可以将胶质瘤分成不同亚型,从而有助于肿瘤分类分级、个性化治疗和预后分组。

IDH突变是胶质瘤的重要生物标志物,与IDH野生型胶质瘤对比,提示肿瘤侵袭性较弱,预后较好^[27]。Sakai等^[28]回顾性研究100例胶质瘤患者,分别用FLAIR和DWI两组序列提取的特征训练

XGBoost分类器模型,在测试集上获得ROC曲线,其AUC分别为0.97、0.95。结果表明,XGBoost分类器利用术前MRI获得的多参数放射学特征预测IDH1突变状态的准确率大于90%。而另一项前瞻性研究^[29],在59例胶质瘤患者(已知IDH1突变状态)的APTw中提取了1044个定量影像组学特征,采用SVM-RFE方法选取19个最优特征子集,建立支持向量机模型,用ROC曲线评估预测IDH1突变效果。其训练集和测试集的AUC值分别为0.892、0.700,准确率分别为0.952、0.840。

1p/19q共缺失与少突胶质细胞起源有关,也与LGG放疗和化疗的预后改善有关^[30]。Han等^[31]对比了MRI影像组学和临床多因素组成的临床模型在无创性预测胶质瘤1p/19q共缺失状态的优势性,分别用随机森林和Logistic回归算法建立模型。结果显示,构建的影像组学特征是区分1p/19q共缺失基因型的独立预测因子,且临床因素对预测贡献不具有显著意义。Fan等^[32]通过嵌套的十倍交叉验证循环,选择了MRI图像中提取的6个有价值的影像组学特征。不同1p/19q状态患者的5项特征有显著性差异。预测模型的AUC和准确度分别为0.8079和0.758,F1得分0.6667。

MGMT启动子甲基化状态是判断GBM患者化疗耐药的重要预后指标^[33]。Le等^[34]基于影像组学的XGBoost模型,以确定IDH1野生型GBM患者的MGMT启动子甲基化状态,并通过F-Score分析来筛选最有意义的影像特征。ROC曲线的AUC值为0.896。因此,影像组学特征提取与F-core特征选择的结合显著改善了XGBoost模型的性能,为判断胶质瘤MGMT启动子甲基化的状态提供了一定的指导。

此外,还有一些学者用MRI影像组学模型对胶质瘤的分子标记物及其改变,如H3K27M突变^[35-36]、ATRX状态^[37]、TERT启动子^[38-39]、EGFR表达扩增^[40]等做出了有价值的无创预测。而对于2021WHO CNS5新增的胶质瘤分子标记物,如MYB或MYBL1突变、H3G34突变、MAPK信号通路改变等,还需要学者进一步完善影像组学在新增分子预测上的研究。

4 MRI影像组学在脑胶质瘤生存风险及预后评估中的应用

胶质瘤是一种遗传和表型不同的肿瘤,尤其GBM(WHO 4级)预后很差,治疗反应率很低。手术、替莫唑胺和放疗的标准联合治疗使GBM的中位总生存期(overall survival,OS)提高到大约2年。在现有的文献中^[41-43],脑肿瘤的MR成像特征,包括其体积、强度、形状和对比增强的纹理以及肿瘤坏死、扩散、浸润和出血量的证据,已经证明与HGG的OS相关。目前,影像组学在胶质瘤的生存风险和预后评估中,已逐步得到学术界的广泛认可。Choi等^[44]构建随机生存森林(random survival forest,RSF)模型预测LGG患者的OS,用放射学特征、非影像预后因素(包括年龄、切除范围、WHO分级和IDH状态)进行训练,并在TCGA/TCIA数据集上验证。结果显示,与非影像预后参数的随机生存森林模型相比,放射学特征的加入显著提高了随机生存森林模型的总体生存预测精度。一项类似的研究,Pan等^[45]采用Kaplan-Meier生存分析验证影像学征象预测GBM患者术前放疗反应的能力,包括放射组学特征和术前临床危险因素在内的多因素Cox回归分析,结果表明当影像组学特征和术前临床危险因素相结合时,影像组学诺模图可进一步提高个体患者的OS预测性能(TCIA和测试队列中的C指数分别为0.764、0.758)。

Xu等^[46]发现结合放射学特征、室管膜和软脑膜受累(EPI)和年龄的影像组学诺模图对GBM患者长期和短期生存的分层是可靠的,其诺模图在训练集和测试集的生存预测准确率分别为0.878和0.875,特异度分别为0.875和0.583,敏感度分别为0.704和0.833。近期的一项研究^[47],通过MRI影像组学结合分子标记物对患者的预后情况进行评估预测。通过结合重要的放射学特征,建立图像融合模型。通过对分子标记的单独预测,得到预测的分子基团。再根据预测分子群和临床病理数据绘制预后诺模图,以预测无进展生存期(PFS)和OS。结果显示,基于分级和预测分子群的预后诺模图预测PFS和OS的C指数分别为0.736和0.735。因此,MRI影像组学为无创性地检测分子群并预测不同级别胶质瘤的存活率提供了一定的价值。

5 MRI影像组学在脑胶质瘤治疗相关变化的应用

胶质瘤的治疗相关变化主要包括真性进展(true progression)、假性进展(pseudoprogression, PD)和放射性坏死(radiation necrosis, RN),其中前两者在影像学上存在着鉴别困难^[48]。因为GBM患者放疗同步接受替莫唑胺(TMZ)治疗,在放疗结束后的1个月内高达30%-48%的患者会出现影像进展(与肿瘤复发所表现的强化高度一致),故而PFS、OS这类生存指标也容易受到影像表现的误解^[49],但这种“进展”却是提示肿瘤预后良好。因此,区分肿瘤真正的进展和放疗后的假性变化,对于如何选择胶质瘤患者的治疗方案至关重要。

Kim等^[50]通过多参数MRI图像(CE-T1WI、FLAIR、ADC及CBV),从肿瘤增强部分的病灶获取6472个放射学特征,使用十倍交叉验证的LASSO逻辑回归模型选择出12个显著特征。结果显示,外部验证及内部验证的ROC曲线的AUC值分别为0.85、0.96,将扩散和灌注加权MRI纳入放射组学模型可提高诊断性能,以识别假性进展,并在多中心环境中显示出稳健性。Yan等^[51]纳入57例术后经替莫唑胺同步放化疗的GBM患者(37例提取影像组学特征并用卷积神经网络进行训练和内部验证,另盲法测试20例患者作为外部验证)。结果显示,卷积神经网络可以识别瘤周真性进展区,其训练集和验证集的总体准确率分别为92.6%和78.5%。Zhang等^[52]使用基于组合特征和多模态MRI影像组学模型,提取反映胶质瘤异质性的手工特征和深度特征,对区分胶质瘤患者的放射性坏死和复发具有临床意义,其灵敏度为0.9941,特异度为0.9755。MRI影像组学在胶质瘤术后真性进展、假性进展和放射性坏死方面的鉴别研究相对较少,但通过已有文献报道均为临床后续的治疗方案提供不同程度的指导。此外,近三年文献还未发现在MRI先进技术提取影像学特征。

综上所述,MRI影像组学在脑胶质瘤的诊断及鉴别诊断、术前分级、基因表达状态预测、生存风险及预后评估、治疗相关变化这五方面上,均表现出良好的临床应用价值。影像组学是精准医学时代下的产物,具有广阔的发展前景,但同时也面临着巨大挑战。这些挑战^[53]包括模型的可解释性、定量成像特征的重复性以及图像采集和重建参数变化的敏感性。尽管如此,随着大数据、人工智能、深度学习等技术的发展,影像组学在医学成像上的应用将成为临床医生和患者群体的宝贵财富。MRI影像组学可以成为帮助临床医生进行胶质瘤风险分层、早期诊断和改善患者预后管理的有效手段。

参考文献

- [1] Jiang Y, Uhrbom L. On the origin of glioma[J]. Upsala journal of medical sciences, 2012, 117(2): 113-121.
- [2] Chen W, Zheng R, Baade P D, et al. Cancer statistics in China, 2015[J]. CA: a cancer journal for clinicians, 2016, 66(2): 115-132.
- [3] Ostrom Q T, Gittleman H, Liao P, et al. CBRUS statistical report: primary brain and other central nervous system tumors diagnosed in the United States in 2010-2014[J]. Neuro-oncology, 2017, 19(suppl. 5): vi-v88.
- [4] Colen R R, Vangel M, Wang J, et al. Imaging genomic mapping of an invasive MRI phenotype predicts patient outcome and metabolic dysfunction: a TCGA glioma phenotype research group project[J]. BMC medical genomics, 2014, 7(1): 1-9.
- [5] Gutman D A, Cooper L A D, Hwang S N, et al. MR imaging predictors of molecular profile and survival: multi-institutional study of the TCGA glioblastoma data set[J]. Radiology, 2013, 267(2): 560-569.
- [6] Lambin P, Rios-Velazquez E, Leijenaar R, et al. Radiomics: extracting more information from medical images using advanced feature analysis[J]. European journal of cancer, 2012, 48(4): 441-446.
- [7] Gillies R J, Kinahan P E, Hricak H. Radiomics: images are more than pictures, they are data[J]. Radiology, 2016, 278(2): 563-577.
- [8] Pope W B, Brandal G. Conventional and advanced magnetic resonance imaging in patients with high-grade glioma[J]. Quarterly Journal of Nuclear Medicine & Molecular Imaging, 2018, 62(3): 239-253.
- [9] Qian Z, Li Y, Wang Y, et al. Differentiation of glioblastoma from solitary brain metastases using radiomic machine-learning classifiers[J]. Cancer letters, 2019, 451: 128-135.
- [10] Bae S, An C, Ahn S S, et al. Robust performance of deep learning for distinguishing glioblastoma from single brain metastasis using radiomic features: model development and validation[J]. Scientific reports, 2020, 10(1): 1-10.

- [11] Sartoretti E, Sartoretti T, Wyss M, et al. Amide proton transfer weighted (APT_w) imaging based radiomics allows for the differentiation of gliomas from metastases[J]. Scientific reports, 2021, 11(1): 1-8.
- [12] Kim Y, Cho H, Kim S T, et al. Radiomics features to distinguish glioblastoma from primary central nervous system lymphoma on multi-parametric MRI[J]. Neuroradiology, 2018, 60(12): 1297-1305.
- [13] Xia W, Hu B, Li H, et al. Multiparametric MRI-based radiomics model for differentiating primary central nervous system lymphoma from glioblastoma: Development and cross-vendor validation[J]. Journal of Magnetic Resonance Imaging, 2021, 53(1): 242-250.
- [14] Han Y, Yang Y, Shi Z, et al. Distinguishing brain inflammation from grade II glioma in population without contrast enhancement: a radiomics analysis based on conventional MRI[J]. European Journal of Radiology, 2021, 134: 109467.
- [15] Dong J, Li L, Liang S, et al. Differentiation between ependymoma and medulloblastoma in children with radiomics approach[J]. Academic radiology, 2021, 28(3): 318-327.
- [16] Dong F, Li Q, Xu D, et al. Differentiation between pilocytic astrocytoma and glioblastoma: a decision tree model using contrast-enhanced magnetic resonance imaging-derived quantitative radiomic features[J]. European radiology, 2019, 29(8): 3968-3975.
- [17] Pedetour-Braccini Z, Burel-Vandenbos F, Goz C, et al. Microfoci of malignant progression in diffuse low-grade gliomas: towards the creation of an intermediate grade in glioma classification? [J]. Virchows Archiv, 2015, 466(4): 433-444.
- [18] Cho H, Lee S, Kim J, et al. Classification of the glioma grading using radiomics analysis[J]. PeerJ, 2018, 6: e5982.
- [19] Dittmer A, Zhang B, Shujaat T, et al. Diagnostic accuracy of MRI texture analysis for grading gliomas[J]. Journal of Neuro-oncology, 2018, 140(3): 583-589.
- [20] Pei L, Jones K A, Shboul Z A, et al. Deep neural network analysis of pathology images with integrated molecular data for enhanced glioma classification and grading[J]. Frontiers in oncology, 2021, 11: 2572.
- [21] Hashido T, Saito S, Ishida T. Radiomics-based machine learning classification for glioma grading using diffusion-and perfusion-weighted magnetic resonance imaging[J]. Journal of Computer Assisted Tomography, 2021, 45(4): 606-613.
- [22] Hashido T, Saito S, Ishida T. A radiomics-based comparative study on arterial spin labeling and dynamic susceptibility contrast perfusion-weighted imaging in gliomas[J]. Scientific reports, 2020, 10(1): 1-10.
- [23] Takahashi S, Takahashi W, Tanaka S, et al. Radiomics analysis for glioma malignancy evaluation using diffusion kurtosis and tensor imaging[J]. International journal of radiation oncology, biology, physics, 2019, 105(4): 784-791.
- [24] Vamvakas A, Williams S C, Theodorou K, et al. Imaging biomarker analysis of advanced multiparametric MRI for glioma grading[J]. Physica Medica, 2019, 60: 188-198.
- [25] Louis D N, Perry A, Reifenberger G, et al. The 2016 world health organization classification of tumors of the central nervous system: a summary[J]. Acta neuropathologica, 2016, 131(6): 803-820.
- [26] Louis D N, Perry A, Wesseling P, et al. The 2021 WHO classification of tumors of the central nervous system: a summary[J]. Neuro-oncology, 2021, 23(8): 1231-1251.
- [27] Han S, Liu Y, Cai S J, et al. IDH mutation in glioma: molecular mechanisms and potential therapeutic targets[J]. British journal of cancer, 2020, 122(11): 1580-1589.
- [28] Sakai Y, Yang C, Kihira S, et al. MRI radiomic features to predict IDH1 mutation status in gliomas: a machine learning approach using gradient tree boosting[J]. International Journal of Molecular Sciences, 2020, 21(21): 8004.
- [29] Han Y, Wang W, Yang Y, et al. Amide proton transfer imaging in predicting isocitrate dehydrogenase 1 mutation status of grade II/III gliomas based on support vector machine[J]. Frontiers in neuroscience, 2020, 14: 144.
- [30] Chai R C, Zhang K N, Chang Y Z, et al. Systematically characterize the clinical and biological significances of 1p19q genes in 1p/19q non-deletion glioma[J]. Carcinogenesis, 2019, 40(10): 1229-1239.
- [31] Han Y, Xie Z, Zang Y, et al. Non-invasive genotype prediction of chromosome 1p/19q co-deletion by development and validation of an MRI-based radiomics signature in lower-grade gliomas[J]. Journal of neuro-oncology, 2018, 140(2): 297-306.
- [32] Fan Z, Sun Z, Fang S, et al. Preoperative radiomics analysis of 1p/19q status in WHO grade II gliomas[J]. Frontiers in oncology, 2021, 11: 2582.
- [33] Mathur R, Zhang Y, Grimmer M R, et al. MGMT promoter methylation level in newly diagnosed low-grade glioma is a predictor of hypermutation at recurrence[J]. Neuro-oncology, 2020, 22(11): 1580-1590.
- [34] Le N Q K, Do D T, Chiu F Y, et al. XGBoost improves classification of MGMT promoter methylation status in IDH1 wildtype glioblastoma[J]. Journal of Personalized Medicine, 2020, 10(3): 128.
- [35] Li Q, Dong F, Jiang B, et al. Exploring MRI characteristics of brain diffuse midline gliomas with the H3 K27M mutation using radiomics[J]. Frontiers in oncology, 2021, 11: 1746.

(下转第 189 页)

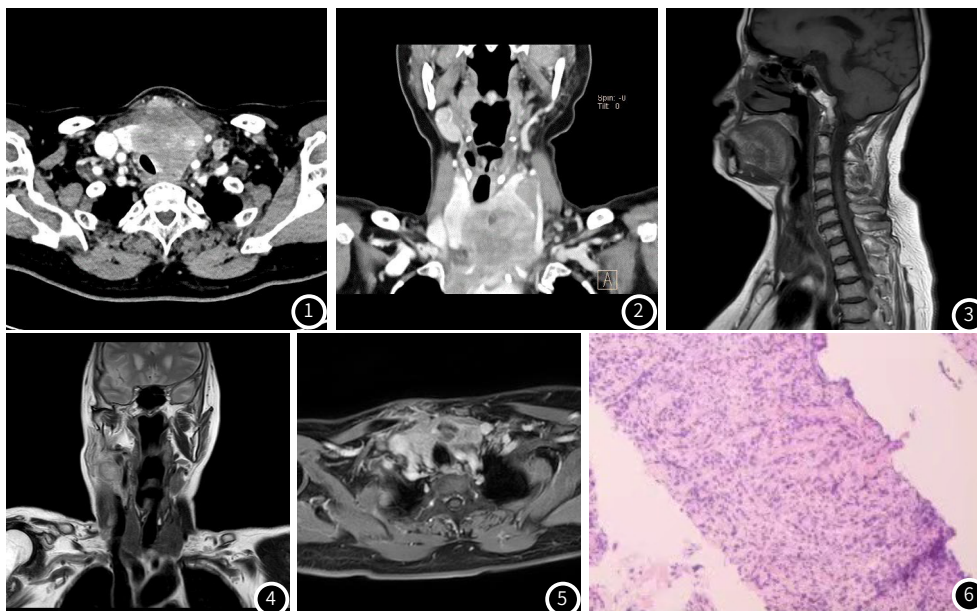


图1 CT增强扫描,横断面显示甲状腺形态失常,其内见多发稍低密度肿块,增强后不均匀强化,邻近组织受压改变。图2 CT增强扫描,冠状面显示病灶局部包绕左侧颈总动脉,向下突向纵隔内生长,气管被推压向后方移位。图3 MRT1WI失状面显示甲状腺肿块呈等信号,类似于邻近肌肉的信号。图4 MR冠状面显示病灶呈不均匀混杂信号;颈部右侧见稍高信号的肿大淋巴结。图5 MR增强横断面显示病灶明显不均匀强化,内部见坏死区域。图6 显微镜下可见纤维及挤压变形染蓝的细胞

参考文献

- [1] Pearce L. Non-Hodgkin's lymphoma. Nurs Stand, 2016 Sep 14; 31 (3): 15.
- [2] Weber AL, Rahemtullah A, Ferry JA. Hodgkin and non-Hodgkin lymphoma of the head and neck: clinical, pathologic, and imaging evaluation. Neuroimaging Clin N Am, 2003 Aug; 13 (3): 371-92.
- [3] Wirtzfeld DA, Winston JS, Hicks WL Jr, et al. Clinical presentation and treatment of non-Hodgkin's lymphoma of the thyroid gland. Ann Surg Oncol, 2001 May; 8 (4): 338-41.
- [4] Lin N, Vargas-Pinto S, Gisriel S, et al. Diffuse large B-cell and follicular lymphoma presenting as a slowly growing compressive goiter: A case report and literature review. Int J Surg Case Rep, 2020; 72: 615-619.
- [5] Lanham T, Lanham E, Sullivan A, et al. Non-Hodgkin lymphoma of the thyroid in a patient with hyperthyroidism. J Community Hosp Intern Med Perspect, 2021 Jan 26; 11 (1): 79-80.
- [6] Kleinstern G, Averbuch M, Abu Seir R, et al. Presence of autoimmune disease affects not only risk but also survival in patients with B-cell non-Hodgkin lymphoma. Hematol Oncol, 2018 Apr; 36 (2): 457-462.
- [7] Travaglino A, Pace M, Varricchio S, et al. Hashimoto Thyroiditis in Primary Thyroid Non-Hodgkin Lymphoma. Am J Clin Pathol, 2020 Jan 2; 153 (2): 156-164.
- [8] Chien S H, Liu C J, Hong Y C, et al. Development of second primary malignancy in patients with non-Hodgkin lymphoma: a nationwide population-based study. J Cancer Res Clin Oncol, 2015 Nov; 141 (11): 1995-2004.
- [9] Horeh N, Horowitz NA. Does gender matter in non-hodgkin lymphoma? Differences in epidemiology, clinical behavior, and therapy. Rambam Maimonides Med J, 2014 Oct 29; 5 (4): e0038.
- [10] Yi J, Yi P, Wang W, et al. A Multicenter retrospective study of 58 patients with primary thyroid diffuse large B cell lymphoma. Front endocrinol (lausanne), 2020 Aug 28; 11: 542.
- [11] 兰方荣. 实时超声弹性成像对鉴别甲状腺结节良恶性的诊断价值[J]. 罕少疾病杂志, 2019, 26 (2): 6-7, 12.
- [12] 杨宇凌, 郭永飞, 杨伟聪. 甲状腺乳头状癌的螺旋CT影像学表现及其病理学基础[J]. 罕少疾病杂志, 2016, 23 (2): 6-8.

(收稿日期: 2022-01-17)

(校对编辑: 姚丽娜)

(上接第 181 页)

- [36] Kandemirli S G, Kocak B, Naganawa S, et al. Machine learning-based multiparametric magnetic resonance imaging radiomics for prediction of H3K27M mutation in midline gliomas[J]. World neurosurgery, 2021.
- [37] Li Y, Liu X, Qian Z, et al. Genotype prediction of ATRX mutation in lower-grade gliomas using an MRI radiomics signature[J]. European radiology, 2018, 28 (7): 2960-2968.
- [38] Jiang C, Kong Z, Zhang Y, et al. Conventional magnetic resonance imaging-based radiomic signature predicts telomerase reverse transcriptase promoter mutation status in grade II and III gliomas[J]. Neuroradiology, 2020, 62 (7): 803-813.
- [39] Fang S, Fan Z, Sun Z, et al. Radiomics features predict telomerase reverse transcriptase promoter mutations in world health organization grade II gliomas via a machine-learning approach[J]. Frontiers in oncology, 2021, 10: 3420.
- [40] Lin Y, Liu X, Xu K, et al. MRI features can predict EGFR expression in lower grade gliomas: a voxel-based radiomic analysis[J]. European radiology, 2018, 28 (1): 356-362.
- [41] Zhou M, Scott J, Chaudhury B, et al. Radiomics in brain tumor: image assessment, quantitative feature descriptors, and machine-learning approaches[J]. American Journal of Neuroradiology, 2018, 39 (2): 208-216.
- [42] Qu J, Qin L, Cheng S, et al. Residual low ADC and high FA at the resection margin correlate with poor chemoradiation response and overall survival in high-grade glioma patients[J]. European journal of radiology, 2016, 85 (3): 657-664.
- [43] Qin L, Li A, Qu J, et al. Normalization of ADC does not improve correlation with overall survival in patients with high-grade glioma (HGG) [J]. Journal of neuro-oncology, 2018, 137 (2): 313-319.
- [44] Choi Y S, Ahn S S, Chang J H, et al. Machine learning and radiomic phenotyping of lower grade gliomas: improving survival prediction[J]. European radiology, 2020, 30 (7): 3834-3842.
- [45] Pan Z Q, Zhang S J, Wang X L, et al. Machine learning based on a multiparametric and multiregional radiomics signature predicts radiotherapeutic response in patients with glioblastoma[J]. Behavioural neurology, 2020, 2020 (4): 1-12.
- [46] Xu Y, He X, Li Y, et al. The nomogram of MRI - based radiomics with complementary visual features by machine learning improves stratification of glioblastoma patients: a multicenter study[J]. Journal of Magnetic Resonance Imaging, 2021.
- [47] Yan J, Zhang B, Zhang S, et al. Quantitative MRI-based radiomics for noninvasively predicting molecular subtypes and survival in glioma patients[J]. NPJ Precision Oncology, 2021, 5 (1): 1-9.
- [48] Delgado-López P D, Riñones-Mena E, Corrales-García E M. Treatment-related changes in glioblastoma: a review on the controversies in response assessment criteria and the concepts of true progression, pseudoprogression, pseudoresponse and radionecrosis[J]. Clinical and Translational Oncology, 2018, 20 (8): 939-953.
- [49] Pouleau H B, Sadeghi N, Balériaux D, et al. High levels of cellular proliferation predict pseudoprogression in glioblastoma patients[J]. International journal of oncology, 2012, 40 (4): 923-928.
- [50] Kim J Y, Park J E, Jo Y, et al. Incorporating diffusion- and perfusion-weighted MRI into a radiomics model improves diagnostic performance for pseudoprogression in glioblastoma patients[J]. Neuro-oncology, 2019, 21 (3): 404-414.
- [51] Yan J L, Li C, van der Hoorn A, et al. A neural network approach to identify the peritumoral invasive areas in glioblastoma patients by using MR Radiomics[J]. Scientific reports, 2020, 10 (1): 1-10.
- [52] Zhang Q, Cao J, Zhang J, et al. Differentiation of recurrence from radiation necrosis in gliomas based on the radiomics of combinational features and multimodality MRI images[J]. Computational and mathematical methods in medicine, 2019, 2019: 2893043-2893043.
- [53] Ibrahim A, Primakov S, Beuque M, et al. Radiomics for precision medicine: Current challenges, future prospects, and the proposal of a new framework[J]. Methods, 2021, 188: 20-29.

(收稿日期: 2021-10-18)

(校对编辑: 姚丽娜)