

• 临床研究 •

深度学习重建算法在胰腺 HASTE-T2WI 序列中的临床应用价值

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[摘要] 目的: 探讨基于深度学习(deep learning, DL)重建算法的半傅立叶采集单次快速自旋回波(half-Fourier acquisition single-shot turbo spin echo, HASTE)T2WI序列在胰腺磁共振成像(magnetic resonance imaging, MRI)中的临床应用价值。方法: 应用3.0T磁共振对69例患者进行胰腺常规BLADE-TSE-T2WI和基于DL的HASTE-DL-T2WI序列扫描。采用Likert Scale量表5分法对两组图像总体质量、胰腺锐利度、胆管显示清晰度、伪影进行主观评分; 测量并比较两组图像同层面的胰腺正常组织、病灶的对比噪声比(contrast to noise ratio, CNR)和信噪比(signal to noise ratio, SNR), 并记录扫描时间。结果: HASTE-DL序列的图像总体质量、胰腺锐利度以及胆管显示清晰度评分均优于BLADE-TSE序列($P < 0.001$), 两组图像伪影评分差异无统计学意义($P > 0.05$)。HASTE-DL序列图像的正常胰腺组织SNR、病灶SNR和CNR均优于BLADE-TSE序列图像($P < 0.001$), HASTE-DL序列的扫描时间较BLADE-TSE序列缩短了78%。结论: 与BLADE-TSE序列图像相比, HASTE-DL序列图像总体质量更好, 胰腺锐利度及胆管显示清晰度更高、SNR和CNR更优, 并且扫描时间更短, 在胰腺MRI扫描中有很好的临床应用价值。

[关键词] 胰腺; 磁共振成像; 图像质量; 深度学习**[中图分类号]** R445.2**[文献标志码]** A**[文章编号]** 1007-4368(2025)06-810-07**doi:** 10.7655/NYDXBNSN241084

The clinical value of deep learning reconstruction algorithm in pancreatic HASTE-T2WI sequence

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[Abstract] **Objective:** To evaluate the clinical value of deep learning (DL)-based reconstruction algorithm for half-Fourier acquisition single-shot turbo spin echo (HASTE) T2-weighted imaging (T2WI) in pancreatic magnetic resonance imaging (MRI). **Methods:** A total of 69 patients underwent pancreatic conventional BLADE-TSE-T2WI and based on deep learning HASTE-DL-T2WI sequences scanning using 3.0T MR. The overall image quality, pancreatic sharpness, biliary duct clarity, and artifacts were subjectively scored using a Likert 5-point scale. The contrast to noise ratio (CNR) and signal to noise ratio (SNR) of normal pancreatic tissue and the lesion in both sequences were measured and compared, and the scan time was recorded. **Results:** The HASTE-DL sequence scored significantly higher in overall image quality, pancreatic sharpness, and bile duct clarity than the BLADE-TSE sequence ($P < 0.001$), with no statistical difference in artifact scores ($P > 0.05$). The SNR of normal pancreatic tissue, lesion SNR, and CNR in HASTE-DL images were superior to those of BLADE-TSE sequence ($P < 0.001$). Additionally, the scanning time of HASTE-DL was reduced by 78% compared to BLADE-TSE. **Conclusion:** Compared to BLADE-TSE sequence, HASTE-DL provides better overall image quality, superior pancreatic sharpness and bile duct clarity, higher SNR and CNR, and significantly shorter scan time. Thus, HASTE-DL T2WI demonstrates excellent clinical utility in pancreatic MRI.

[Key words] pancreas; magnetic resonance imaging; image quality; deep learning

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胰腺位于腹腔深部,且胰腺相关疾病,特别是胰腺肿瘤起病时症状常较为隐匿,因此实现对胰腺疾病的早期诊断具有一定的困难与挑战^[1]。胰腺影像学检查是目前临床上用于诊断胰腺疾病的常用方法,特别是胰腺MRI,可以从形态学和功能学等多角度评估病灶,在胰腺病变的诊断和评估中发挥越来越重要的作用^[2]。T2加权成像(T2 weighted imaging, T2WI)序列是胰腺MRI的常规序列之一,它在胰腺病灶的定位和定性评估中有不可替代的作用。目前临床上常用的胰腺T2WI序列多采用快速自旋回波(trubo spin echo, TSE)序列,并联合呼吸门控技术和螺旋桨K空间填充方式的刀锋(BLADE)技术以减少呼吸运动伪影,加之胰腺结构精细,常需设置薄层、高分辨率的扫描参数,因此常规的胰腺T2WI序列扫描时间较长,对患者的呼吸配合度要求较高。对于呼吸配合欠佳或者不能耐受长时间扫描的患者可采用半傅立叶采集单次激发快速自旋回波(half-Fourier acquisition single-shot turbo spin-echo, HASTE)序列作为BLADE-TSE-T2WI序列的补充^[3-5]。HASTE序列利用1次激励脉冲产生的多个回波信号填充K空间,并辅以部分傅里叶图像重建技术,可以有效减少数据采集量及时间,但是该采集方式牺牲了一定的图像质量^[6]。

深度学习(deep learning, DL)重建算法是经大量MRI图像训练优化,采用先进的卷积神经网络(convolutional neural network, CNN)提高图像质量的重建算法^[7-8]。目前有将该技术运用于腰椎^[9]、膝关节^[10]、前列腺^[11]等部位MRI的研究结果表明,DL可以在减少扫描时间的情况下,仍然能够提高图像质量。但是基于DL技术的HASTE序列在胰腺MRI扫描中的临床应用价值,国内外研究报道很少,故本研究比较结合DL技术的HASTE-DL序列和常规BLADE-TSE序列胰腺T2WI的图像质量,旨在探索HASTE-DL序列在胰腺MRI扫描中的临床应用价值。

1 对象和方法

1.1 对象

前瞻性收集2022年9月—2024年2月来南京医科大学第一附属医院就诊的患者69例,进行胰腺BLADE-TSE-T2WI序列扫描和HASTE-DL-T2WI序列扫描,其中,男30例,女39例,年龄11~85岁,平均(52.52±13.33)岁。病例纳入标准:①患者临床症状及其他辅助检查结果疑似胰腺病变,需行MRI检查进一步明确;②既往无胰腺切除或其他手术治疗

史。排除标准:①MRI禁忌证;②腹部有钛夹等金属植入物影响图像质量。所有参与本研究的患者均签署知情同意书,由南京医科大学第一附属医院医学伦理委员会审核并获批(批文号:2021-SRFA-024)。

1.2 方法

采用德国西门子3.0T skyraMR扫描设备和设备配套的18通道腹部相控阵体线圈、8通道脊柱线圈进行扫描。扫描体位采用仰卧位,头先进,双手上举,深呼气后绑紧腹带并对患者进行呼吸训练,线圈中心置于剑突下3 cm处,并设为定位中心。BLADE-TSE序列扫描参数:回波时间(echo time, TE)为98 ms,重复时间(repetition time, TR)设置为4 100 ms(但是实际由患者呼吸频率由序列自动调整),翻转角149°,视野(field of view, FOV)为340 mm×340 mm,扫描层数60,层间距为1.2 mm,层厚为3.0 mm,相位编码方向为左右方向,扫描时间依据患者呼吸频率由序列自动生成,研究中该序列平均扫描时间4 min 58 s。HASTE-DL扫描参数:TR 1 070 ms, TE 98 ms,翻转角149°,其余FOV、扫描层数、层间距、层厚等参数均与BLADE-TSE序列相同,扫描时间为1 min 6 s,分3次屏气完成。

1.2.1 图像质量主观评价

由2位具有独立审核报告资质的高年资腹部影像学医师采用Likert Scale量表5分法对同一患者同一层面BLADE-TSE图像和HASTE-DL图像进行图像质量独立双盲评价,评估指标包括:图像总体质量、胰腺锐利度、胆管显示清晰度和伪影,具体评估标准:胰腺锐利度(1分为胰腺模糊,无法诊断;2分为胰腺较模糊,影响诊断;3分为胰腺锐利度一般,不影响诊断;4分为胰腺结构良好,可以诊断;5分为胰腺结构锐利分明,可以诊断);胆管显示清晰度(1分为胆管显示模糊,无法诊断;2分为胆管显示较模糊,影响诊断;3分为胆管显示一般,不影响诊断;4分为胆管显示良好,可以诊断;5分为胆管显示清晰可见,边缘锐利);伪影(1分为重度伪影,无法诊断;2分为伪影明显,影响诊断;3分为中度伪影,尚可诊断;4分为轻微伪影,不影响诊断;5分为图像清晰无伪影);依据上述定性指标对图像的总体质量评分为:差(1分)、一般(2分)、中等(3分)、良好(4分)和优秀(5分)。

1.2.2 图像质量客观评价

对纳入患者的BLADE-TSE图像和HASTE-DL轴位图像进行测量,步骤如下:①将所有扫描图像上传CARESTREA VUE影像归档和通信系统(picture

archiving and communication systems, PACS)进行图像分析。②分别选取同层面胰腺组织以及病灶和图像四周的空气背景作为感兴趣区域(region of interest, ROI), 尽量避免混杂组织的影响, 手绘面积35 mm²左右的圆形, 记录ROI的平均MR信号强度(signal intensity, SI)和标准差(standard deviation, SD), 每个ROI测量3次, 取均值纳入统计。③计算两组图像的信噪比(signal to noise ratio, SNR)和噪声比(contrast to noise ratio, CNR), $SNR_{胰腺} = SI_{胰腺} / SD_{背景}$, $SNR_{病灶} = SI_{病灶} / SD_{背景}$, $CNR_{病灶} = |SI_{病灶} - SI_{胰腺}| / SD_{背景}$ 。其中SI_{胰腺}为胰腺组织的平均SI, SI_{病灶}为胰腺病灶组织的平均SI, SD为图像背景空气区信号强度标准差^[12]。④病灶ROI的选取标准为: 选取病灶所显示的最大层面处, 较为均质的病灶区域作为ROI进行测量。⑤2位医师以增强扫描观察到的病灶数为标准, 分别计算两组T2WI序列上的病灶检测率, 病灶检测率为检出的病灶数与增强扫描观察到的总病灶数量的比值, 2人对病灶数量统计不一致时由另一位资深专家来确定总病灶数。

1.3 统计学方法

本研究的数据利用 SPSS27.0 及 GraphPad

Prism10.1 软件包进行分析处理, 统计学评估结果采用 Kolmogorov-Smirnov 法进行正态性检验, 符合正态分布的用均数±标准差($\bar{x} \pm s$)描述, 定量资料组间比较采用配对 *t* 检验, 分别采用 Kappa 分析和组内相关系数(intra-class correlation coefficient, ICC)评价2位医师对定性资料和定量资料评定结果的一致性, 若 Kappa 值和 ICC 值 < 0.4 为一致性差, 0.4~<0.6 为一致性中等, 0.6~<0.8 为一致性好, >0.8 为一致性优。P < 0.05 为差异有统计学意义。绘制小提琴图(violin plot)和散点柱状图分别直观展示定性和定量评价比较数据分布特点。

2 结果

2.1 图像定性分析结果

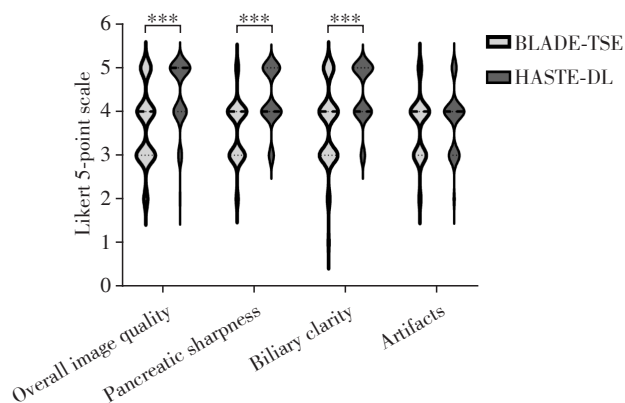
BLADE-TSE 与 HASTE-DL 扫描所得 T2WI 图像定性评分比较结果见表1, 绘制小提琴统计图展现2组图像5分法评分特征见图1。2位医师定性分析的结果一致性优(Kappa≥0.8), HASTE-DL 组的图像总体质量、胰腺锐利度以及胆管显示清晰度图像总体质量评分均优于 BLADE-TSE 组(P < 0.001, 表1), 两组图像伪影评分差异无统计学意义。

表1 HASTE-DL 和 BLADE-TSE 图像定性评分比较

Table 1 Qualitative comparison between HASTE-DL and BLADE-TSE images

($\bar{x} \pm s$)

Sequence	Overall image quality	Pancreatic sharpness	Biliary clarity	Artifacts
HASTE-DL	4.41 ± 0.73	4.29 ± 0.67	4.38 ± 0.67	3.78 ± 0.70
BLADE-TSE	3.68 ± 0.88	3.57 ± 0.68	3.71 ± 0.89	3.65 ± 0.70
Z	-5.064	-5.369	-4.981	-1.304
P	<0.001	<0.001	<0.001	0.192
Kappa	0.825	0.806	0.837	0.831



The larger the belly, the more concentrated the distribution of the score segment, and vice versa. ***P < 0.001.

图1 五分法评分定性比较小提琴统计图

Figure 1 Violin plot of qualitative comparison using the five-point scoring method

2.2 图像定量分析结果

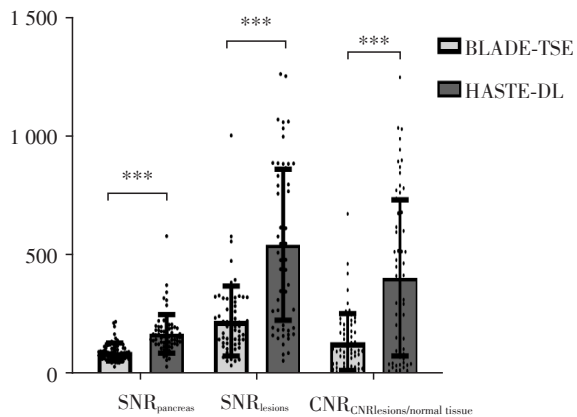
BLADE-TSE 与 HASTE-DL 扫描所得 T2WI 图像定量分析比较结果见表2, 绘制散点柱状图展示两组图像SNR和CNR的定量比较见图2。2位医师定量评估结果的一致性好(ICC≥0.60), 经配对 *t* 检验, HASTE-DL 序列图像的SNR和CNR均优于 BLADE-TSE (P < 0.001, 表2)。典型病例图像见图3~5。

2.3 病灶检测率及诊断效能

本研究中69例患者共110个病灶, 两组序列对胰腺病灶的检测率均为100%, 均没有遗漏病灶。

2.4 扫描时间

HASTE-DL 序列扫描时间为1 min 6 s, BLADE-TSE 序列平均扫描时间为4 min 58 s, HASTE-DL 序列较常规序列减少了78%的扫描时间。



The SNR and CNR of HASTE-DL sequence was higher than that of BLADE-TSE sequence. *** $P < 0.01$.

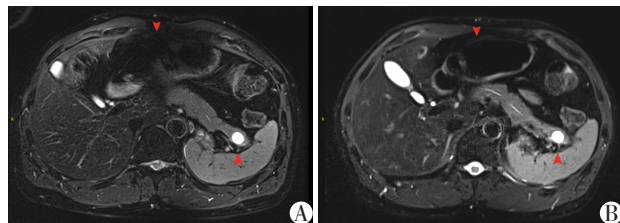
图2 SNR和CNR定量比较散点柱状统计图

Figure 2 Scattered-column statistical chart for quantitative comparison of SNR and CNR

表2 HASTE-DL和BLADE-TSE图像定量比较

Table 2 Quantitative comparison of HASTE-DL and BLADE-TSE images ($\bar{x} \pm s$)

Sequence	SNR _{pancreas}	SNR _{lesions}	CNR _{lesions/normal tissue}
HASTE-DL	166.65±81.90	568.45±370.37	417.47±346.85
BLADE-TSE	87.78±37.86	213.34±134.78	133.46±118.66
<i>t</i>	9.123	9.343	8.230
<i>P</i>	<0.001	<0.001	<0.001



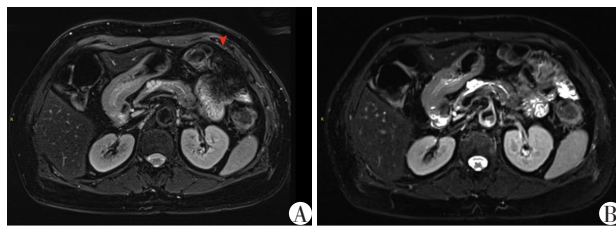
A: BLADE-TSE sequence. B: HASTE-DL sequence. The loss of signal interference caused by artifacts in A is slightly more serious than that in B (arrow above). Pancreatic duct lesions in B showed sharper, and bile duct clarity showed better than A (arrow below).

图3 1例胰腺尾部囊性病灶的45岁男性患者病灶检测比较图

Figure 3 Comparison of lesion detection in a 45-year-old male patient with a cystic lesion in the pancreatic tail

3 讨论

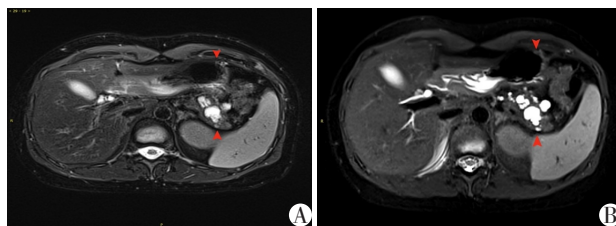
本研究通过比较 HASTE-DL 序列和 BLADE-TSE 序列胰腺 T2WI 的图像质量,包括胰腺和病灶组织 SNR、病灶 CNR、总体图像质量、胰腺锐利度、胆管显示清晰度、伪影以及病灶检出效能和扫描时



A: BLADE-TSE sequence. B: HASTE-DL sequence. The signal is missing due to the intestinal air motion artifact in A (arrow above), and image B has slightly better artifact suppression. The lesion and pancreatic duct in B have higher SNR and sharper contrast.

图4 1例胰腺导管内乳头状黏液瘤68岁女性患者病灶检测比较图

Figure 4 Comparison of lesion detection in a 68-year-old female patient with IPMN of the pancreas



A: BLADE-TSE sequence. B: HASTE-DL sequence. Both A and B can clearly see the lesion (arrow below); the contrast between pancreatic duct and lesion in B is sharper and the lesion boundary is clearer, which is conducive to the display and measurement of lesion. Both sets of sequences had comparable artifact suppression (arrow above).

图5 1例多发胰腺导管内乳头状黏液瘤(IPMN)34岁女性患者病灶检测比较图

Figure 5 Comparison of lesion detection in a 34-year-old female patient with multiple IPMN of the pancreas

间,探讨DL在胰腺MRI临床应用中的价值。本研究表明,HASTE-DL-T2WI序列能够获得优于常规BLADE-TSE-T2WI序列的胰腺T2WI图像,图像SNR和CNR更高,组织之间的锐利度更加优秀,伪影控制两者相当,并且大幅度减少扫描时间,能够为不能耐受长时间检查和呼吸配合较差的患者提供另一种扫描选择,有较高的临床应用价值。

3.1 HASTE-DL序列相比BLADE-TSE序列的扫描时间优势

目前临床上胰腺MRI的BLADE-TSE-T2WI序列为运用刀锋伪影校正(BLADE)技术的TSE序列,BLADE技术采用螺旋桨式K空间数据填充,可以减少运动伪影、提高图像质量,但这种采集模式会增加数据采集量,重复冗余的数据采集导致扫描时间长^[13],特别是应用在胰腺MRI时,需要薄层(3 mm)扫描才能满足临床诊断胰腺所需的分辨率,因此不

得不增加扫描层数,这进一步增加了扫描时间。在本研究中,由于采用了呼吸导航技术,BLADE-TSE-T2WI扫描时间是由患者呼吸频率决定的,有的呼吸频率较慢病例扫描时长达到近8 min,甚至有部分体弱、呼吸受限的患者难以忍受,不能配合完成检查。传统的HASTE序列采用1次激励脉冲产生多个回波信号,有效减少数据采集量及时间,但是该采集方式信号强度弱、SNR低,且回波链过长,易造成图像模糊,半傅里叶K空间填充方式则进一步降低了图像SNR^[3-6]。

DL技术的快速发展给传统HASTE成像技术带来了新的突破。DL技术基于CNN的图像重建算法^[14]。它首先设计出专注于图像重建任务的CNN,然后通过机器学习方式让算法读取海量MR图像数据,识别和提取出图像高级特征,预测性输出图像数据,再通过反复的前馈运算和反馈运算比较预测值和实际输入图像数据的误差,逐层修正CNN中各算法函数的参数,经过多次这样的步骤后,训练出最适用于MR图像重建任务的CNN^[15]。在实际MRI扫描时,应用DL算法的HASTE序列只需要以欠采集的方式采集少量的MRI数据,算法则依据CNN预测性输出1个图像数据,再通过多次迭代收敛算法预测的数据与实际采集数据的误差,最终输出高质量的MR图像。由上述可见,HASTE-DL序列在图像采集端大大节省了扫描时间,Herrmann等^[5]将HASTE-DL技术运用在肝脏,相比T2WI扫描时间缩短了75%;Johnson等^[16]把HASTE-DL技术结合前列腺快速T2WI序列与标准的T2WI序列相比,可以缩短约65%的扫描时间。

多位学者应用基于DL技术的HASTE序列采集肝脏、肌骨、前列腺和盆腔等图像^[5,17-18],证实DL技术可以缩短图像扫描时间,同时降低图像噪声,去除截断伪影,提高图像清晰度,得出较高质量的MR图像^[19]。本研究中DL技术采用传统CNN和数据一致性两个算法交错叠代的网络架构完成图像重建^[10],结果与文献报道接近,HASTE-DL序列扫描时长为1 min 6 s,比BLADE-TSE-T2WI的平均扫描时长4 min 58 s缩短了78%。

3.2 HASTE-DL与BLADE-TSE序列图像质量结果分析

本研究中,HASTE-DL序列图像的SNR胰腺、SNR病灶和CNR病灶均优于BLADE-TSE序列,这与Ginocchio等^[7]对肝脏的研究结果一致,这主要是由于一方面DL技术中的CNN通过MRI图像训练,可以识别组织信号和噪声,通过多次迭代过滤图像

噪声,从而提高图像SNR^[20];另一方面,本研究发现,由于射频能量吸收率(specific absorption ratio, SAR)保护机制,BLADE-TSE序列在超SAR时会自动降低翻转角来降低SRA值,而翻转角的降低会带来MR信号强度的降低,这也可能是BLADE-TSE序列SNR较低的原因^[11]。SNR的提高也提高了另外一个定量评估指标CNR,同样,DL技术不仅可以轻松识别噪声和组织信号,也能识别主要组织之间的信号差异,因此HASTE-DL序列的CNR也高于BLADE-TSE序列。

在实际应用场景中,本研究主观评价结果与定量评估结果相互支持:HASTE-DL序列对胰腺锐利度、胆管显示清晰度、图像总体质量的控制均优于BLADE-TSE序列,此外2位专家达成两序列的病灶发现率一致的意见,这与Herrmann等^[21]在腹部相关研究中得出的结果一致,说明DL技术可以通过算法弥补采集数据量少带来的图像质量下降,获得与常规BLADE-TSE-T2WI序列一致的诊断效能。在研究过程中,评估者发现由于HASTE-DL序列的图像SNR和CNR提高,病灶组织与正常组织之间的边缘对比更加锐利,因此病灶更容易识别和判断,避免因重复阅片造成疲劳而导致忽略部分病灶的情况,提高了综合诊断效能;但是,HASTE-DL序列对组织细节信息的显示不如BLADE-TSE序列丰富,Kaniewska等^[15]也提到此问题,这可能是DL算法结构和参数设置还有训练和提升的空间,CNN的稳定性不够,导致输入数据与CNN过度拟合所致,这方面可以通过对CNN卷积核、结构以及参数设置的优化,进一步的数据训练来解决。

3.3 局限性

本研究也存在一定局限性,首先,由于目前的DL版本仅适用于2D的TSE序列,未引入DL算法在其他序列,诸如梯度回波序列、平面回波序列的研究;其次,本研究仅是针对单序列的研究,不能全面评估DL技术对胰腺病灶的诊断效能。针对以上不足,笔者拟待DL技术进一步的开发应用,纳入更多的样本量,加入更多的序列,进一步研究DL技术提升胰腺病灶诊断的效能。

综上所述,HASTE-DL序列主观评分高,提高了胰腺T2WI的图像SNR和CNR,大幅缩短扫描时间的同时减少诊断时间,有效提升诊断效能,为临床提供优质数据支持。

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全部作者均声明无利益冲突。

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徐思雨设计本研究方案,实施研究过程,起草和撰写稿件,获取、分析或解释本研究的数据;张永杰获取、分析或解释本研究的数据,指导性支持;田水获取、分析或解释本研究的数据,对稿件重要内容进行了修改。王建伟提出研究选题,设计本研究的方案,对稿件重要的内容进行了修改,终审论文。

Author's Contributions:

XU Siyu designed the research plan, conducted the research process, drafted and wrote the manuscript, obtained, analyzed or interpreted the data of this study; ZHANG Yongjie obtained, analyzed or interpreted the data of this study, provided guiding support; TIAN Shui obtained, analyzed or interpreted the data of this study, and made significant intellectual contributions to the manuscript; WANG Jianwei proposed the research topic, designed the research plan, made significant intellectual contributions to the manuscript, and reviewed the final version of the paper.

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