准确度不理想.比如在第 6 行和第 7 行的眼底图中,原本是偏圆形状的视杯被简化为椭圆形状,与真实分割差异较大.另外,当把 CDR-GANs 模型与 CDR-GANs(supervised),CDR-GANs(joint)对比时可以发现:前者识别的视盘和视杯形状上更为接近圆形,边缘更光滑,比如第 4 行的分割效果图,说明半监督学习和两阶段分割设计是改善最终分割效果的有效方法.

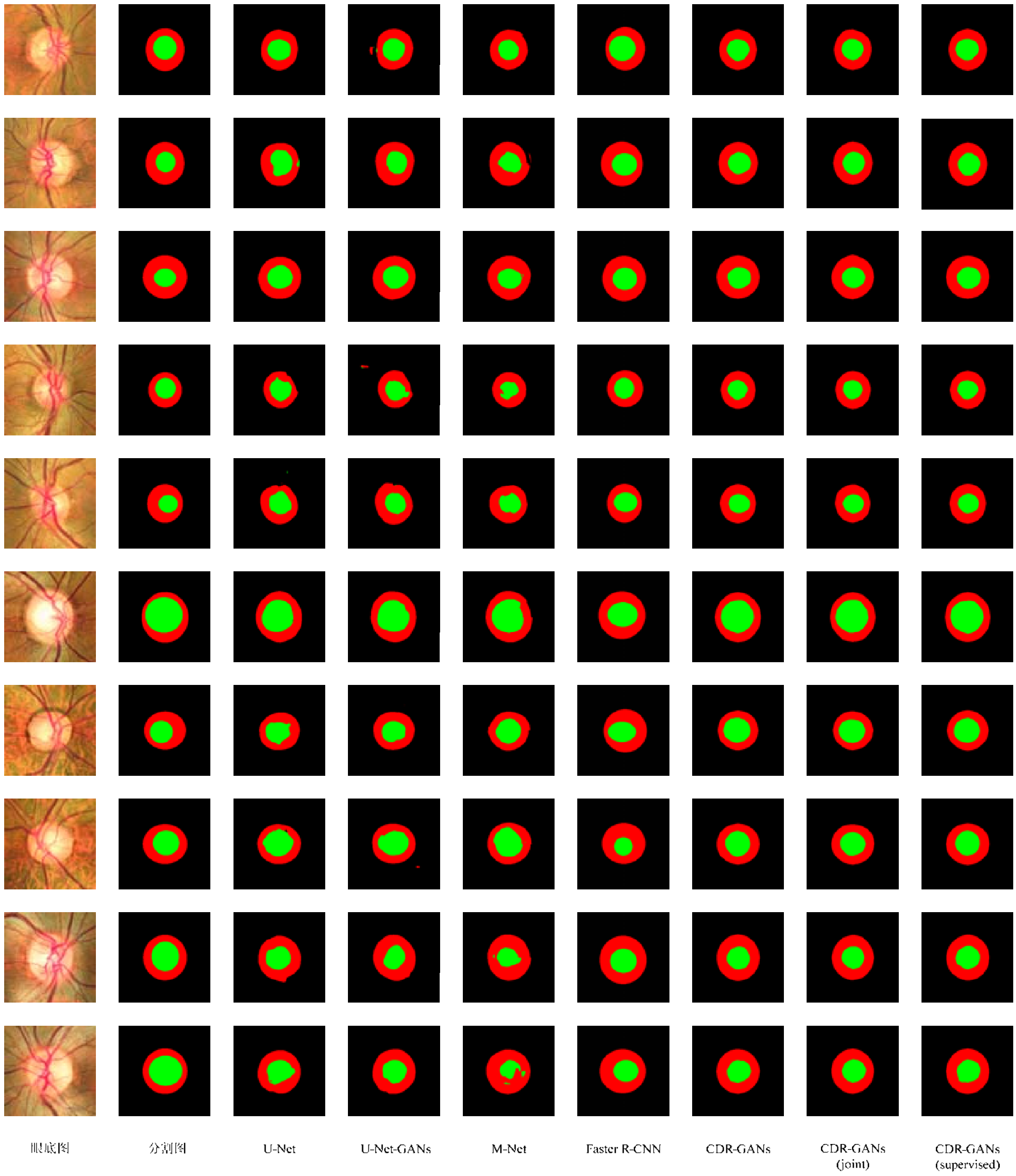

Fig.2 Optic disc and cup segmentation performances of different deep learning models on ORIGA dataset

图 2 不同深度学习模型在 ORIGA 数据集上的视盘和视杯分割效果

3.6 CDR-GANs模型的判别器激活函数讨论

CDR-GANs 模型的判别器使用 leakyReLU 而不是 ReLU 作为激活函数,主要是考虑当输入为负值时,ReLU

输出始终为 0,其一阶导数也为 0,导致神经元不能更新参数;而 leakyReLU 能够赋予较小的非零梯度值,避免出现神经元无法激活的问题.本文将 CDR-GANs 模型中的判别器激活函数替换为 ReLU,设计了 CDR-GANs(ReLU),并与 CDR-GANs 模型进行对比实验.表 5 展示了 CDR-GANs(ReLU)与 CDR-GANs 模型在 ORIGA 数据集上的 *MIoU* 指标表现情况.实验结果表明,两者性能接近.因此,选择 leakyReLU 或 ReLU 作为判别器的激活函数,实际上对模型性能并无显著影响.

Table 5 Comparison of *MIoU* values for CDR-GANs (ReLU) and CDR-GANs on ORIGA dataset

表 5 CDR-GANs(ReLU)与 CDR-GANs 模型在 ORIGA 数据集上的 *MIoU* 值对比

模型	*MIoU*(视盘)	*MIoU*(视杯)	*MIoU*(总体)
CDR-GANs(ReLU)	**0.954**	0.787	**0.857**
CDR-GANs	0.953	0.787	0.856

3.7 CDR-GANs模型的生成器作用讨论

CDR-GANs 模型的视盘分割阶段和视杯分割阶段的网络框架是相同的,均是面向半监督学习的条件生成对抗网络,由语义分割网络、生成器和判别器这 3 部分组成,其优化目标是获得眼底图及其(视盘或视杯)分割图的联合分布.在第 i 个语义分割阶段中,S_i 和 G_i 分别定义了条件分布 $p_{s_i}(y_i \mid x_i) \approx p(y_i \mid x_i)$ 和 $p_{g_i}(x_i \mid y_i) \approx p(x_i \mid y_i)$.在模型训练中,$S_i$ 对 x_i 进行分割处理并输出 y_i',构成生成样本 (x_i, y_i');而 G_i 对 y_i 进行图像转换后输出 x_i',构成另一组生成样本 (x_i', y_i).标注样本(x_i,y_i)和两组生成样本均作为 D_i 输入被判定真假.经过多次对抗学习后,D_i 迫使 S_i 和 G_i 学习眼底图和(视盘或视杯)分割图的联合分布 $p(x_i,y_i)$.可见,生成器是整个模型中不可或缺的组成部分,它贡献了一组生成样本,在训对抗学习中,有助于更好地学习联合分布.如果只使用语义分割网络和判别器来构成生成对抗模型,目标也是学习联合分布,那么训练样本将明显减少,影响模型性能.

本文将 CDR-GANs 模型中的生成器剔除,得到简化版本的 CDR-GANs(no generator),并与 CDR-GANs 模型进行对比实验.表 6 展示了 CDR-GANs(no generator)与 CDR-GANs 模型在 ORIGA 数据集上的性能对比情况.实验结果表明:CDR-GANs 模型相比 CDR-GANs(no generator),*MIoU* 各项指标与δ_E 指标均略有优势.

Table 6 Model performance comparison of CDR-GANs (no generator) and CDR-GANs on ORIGA dataset

表 6 CDR-GANs(no generator)与 CDR-GANs 模型在 ORIGA 数据集上的性能对比

模型	*MIoU*(视盘)	*MIoU*(视杯)	*MIoU*(总体)	δ_E
CDR-GANs(no generator)	0.95	0.783	0.852	0.065 2
CDR-GANs	**0.953**	**0.787**	**0.856**	**0.063 1**

3.8 CDR-GANs模型的半监督学习作用讨论

CDR-GANs 模型的性能略优于 CDR-GANs(supervised),原因在于复杂的网络结构更需要大量训练样本,而有标注的眼底图数据十分有限,半监督学习可同时利用有标注和无标注数据,在一定程度提升了分割精度,并计算出更准确的 CDR 指标.为了更进一步探讨半监督学习在 CDR-GANs 模型中的作用,本文删减部分无标签数据,得到 CDR-GANs(less unlabeled data),并与 CDR-GANs 模型进行对比实验.

表 7 展示了 CDR-GANs(less unlabeled data)与 CDR-GANs 模型在 ORIGA 数据集上的性能对比情况.实验结果表明:CDR-GANs 模型相比 CDR-GANs(less unlabeled data),不管是在总体 *MIoU* 还是δ_E 指标上,均有一定的提升.综上,半监督学习有利于提升 CDR-GANs 模型的性能,且引入相关的无标签数据越多,性能提升通常越大.

Table 7 Model performance comparison of CDR-GANs (less unlabeled data) and CDR-GANs on ORIGA dataset

表 7 CDR-GANs(less unlabeled data)模型与 CDR-GANs 模型在 ORIGA 数据集上的性能对比

模型	*MIoU*(视盘)	*MIoU*(视杯)	*MIoU*(总体)	δ_E
CDR-GANs(less unlabeled data)	**0.954**	0.781	0.853	0.068 2
CDR-GANs	0.953	**0.787**	**0.856**	**0.063 1**

4 结 论

本文针对眼底图的视盘和视杯分割问题,结合半监督学习和生成对抗网络,提出一个基于半监督条件生成对抗网络的两阶段分割模型CDR-GANs.为了优化CDR-GANs模型,设计一个合理的优化目标,并给出理论分析和详细证明.大量真实数据集的实验结果表明:CDR-GANs在均交并比、CDR绝对误差和实际分割效果等指标上,明显优于现有模型,可为青光眼早期筛查提供技术支持.

考虑到视杯分割的难度远大于视盘分割,后续的研究工作将侧重提升视杯分割结果的网络结构设计,使得CDR-GANs模型能更有效地辅助青光眼早期筛查和临床诊断.另一方面,CDR-GANs模型具有可扩展性,将其改造应用于眼底图血管分割等,也是今后的研究重点.

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