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新型冠状病毒肺炎(COVID-19)医学影像 AI 诊断研究进展

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摘　要:　2020 年 3 月,世界卫生组织(World Health Organization,WHO)宣布新型冠状病毒肺炎(corona virus disease 2019,COVID-19)为世界大流行病,疫情的爆发给世界各地医疗系统带来巨大压力。现有的 COVID-19 诊断标准是核酸检测阳性,然而核酸检测假阴性率高达 17%～25.5%,为避免漏诊,需要采用基于影像学的 AI 诊断方法筛查大量疑似病例,扼制疾病传播。本综述将回顾疫情爆发数月以来,基于医学影像的新冠肺炎 AI 辅助诊断的研究成果。首先介绍 CT(computed tomography)和 X 光片的优缺点,以及 COVID-19 的放射学特征,然后对数据准备、图像分割和分类识别等 AI 诊断的关键步骤分别进行阐述,最后介绍 COVID-19 的跟踪和预后(预先对疾病后续发展过程及结果的判断和估计)。本文还整理了部分公开的 COVID-19 相关数据集,并对数据标注不足的问题提供了弱监督学习和迁移学习等解决方案。实验验证,AI 系统诊断 COVID-19 的敏感性达到 97.4%,特异性达到 92.2%,优于放射科医生的诊断结果。其中表现尤为突出的是基于语义分割网络检测 COVID-19 感染区域,由此可以定量分析感染率。AI 系统可以辅助医生诊断和治疗 COVID-19,提高放射科医生阅读 X 光片和 CT 的效率。

关键词: 人工智能;新型冠状病毒肺炎(COVID-19);图像分割;计算机辅助诊断;感染区域分割

Progress of artificial intelligence diagnosis and prognosis technology for COVID-19 medical imaging

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Abstract: In March 2020, the World Health Organization (WHO) declared the new corona virus pneumonia (COVID-19) as a world pandemic, which means that the epidemic has broken out worldwide. The outbreak of COVID-19 threatens the lives and property safety of countless people and brings great pressure to medical systems. The main clinical symptoms of COVID-19 are fever, cough, and fatigue, which may lead to a fatal complication: acute respiratory distress syndrome. The main challenge in inhibiting the spread of this disease is the lack of efficient detection methods. Although reverse transcription-polymerase chain reaction (RT-PCR) is the gold standard for confirming COVID-19, it takes 4-6 h to obtain the results, and the false-negative rate of RT-PCR detection is as high as 17%-25.5%. Therefore, multiple RT-PCR detections at intervals of several days must be performed to confirm the diagnostic result. In addition, RT-PCR reagents are lacking in many severe epidemic areas. By contrast, X-ray and CT (computed tomography) examination equipment have been

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widely popularized in hospitals. In clinical practice, by combining clinical symptoms and travel history, CT is an efficient and safe method to diagnose COVID-19. Compared with CT, X-ray examination has faster scanning speed and lower radiation amount. Moreover, X-ray and CT images are important tools for doctors to track and observe the condition and evaluate the efficacy. In summary, medical imaging plays a vital role in limiting the spread of viruses and treating COVID-19. During the outbreak of the epidemic, medical imaging-based AI-assisted diagnostic technology has become a popular research direction. Computer-aided diagnostic technology improves the sensitivity and specificity of doctors' diagnosis and is accurate and efficient, which helps rapid diagnosis of a large number of suspicious cases. For example, the out preformed AI-assisted diagnosis system can achieve an accuracy rate comparable to that of radiologists, and it take less than 1 second to perform a diagnosis. The system has been used in 16 hospitals, with more than 1 300 diagnoses performed daily. This article reviews the latest research works on AI-assisted diagnosis of COVID-19 and analyzes and summarizes them on the basis of four aspects: data preparation, image segmentation, diagnosis, and prognosis. First, this article organizes some public data sets to support the AI-assisted diagnostic technology of COVID-19 and provides several solutions to insufficient datasets, such as the human-in-the-loop strategy, which improves the efficiency of data set production. Using transfer learning, weakly supervised or unsupervised learning can reduce model's dependence on the COVID-19 dataset. Second, the semantic segmentation network is also an indispensable part of the intelligent diagnosis of COVID-19. Segmenting the lung region from the original image is a key pre-processing step, which can reduce the calculation amount of subsequent algorithms. The lesion area helps the doctor to track the condition of the disease, and the infection rate can be calculated according to the size of the infected area. U-Net, U-Net ++, and attention U-Net are suitable for the segmentation of medical images because of the small number of parameters, which is not easy to overfit. Furthermore, training the semantic segmentation network with the idea of the generative adversarial network (GAN) can improve the Dice coefficient. Third, this article introduces the AI diagnostic system from two aspects of CT images and X-rays. Comparing different diagnostic schemes, the method of diagnosis based on the segmentation images is better than that based on the original images. Among the classification networks, ResNet and VGG19 (visual geometry group 19-layer net) perform better. Methods such as GAN, location attention mechanisms, transfer learning, and combining 2D and 3D features can be used to improve accuracy. In addition, clinical information (travel and contact history, white blood cell count, fever, cough, sputum, patient age, and patient gender) can be used as a basis for diagnosis. For example, algorithm D_ FF_ Conic uses clinical information as a diagnostic basis and has reached an accuracy rate of 90%. Clinicians will consider medical imaging and clinical information in the process of diagnosis, but the current AI diagnostic system cannot integrate multiple types of data for diagnosis. Although some algorithms can fuse the diagnostic results of medical images with the diagnostic results of clinical information, the simple fine-tuned algorithm haven't learned the deep internal connection between different types of data. Fourth, AI technology can also predict high-risk patients on the basis of infection rates and clinical information. Some research predicted the survival rate of COVID-19 patients on the basis of age, syndrome, and infection rate. Such algorithms can help doctors find and treat high-risk patients early, thereby reducing mortality, which is of great significance. This article shows the latest progress of COVID-19's medical imaging-based AI diagnosis. Although some AI-assisted diagnostic systems have been deployed in hospitals to play a practical role, these algorithms still have some problems, such as insufficient training data, a single diagnostic basis, and the ability to distinguish between non-COVID-19 pneumonia and COVID-19.

Key words: artificial intelligence; COVID-19; image segmentation; computer aided diagnosis; infection region segmentation

0 引 言

2019 年 12 月,中国武汉爆发了新型冠状病毒(Huang 等,2020; Lu 等,2020),这种冠状病毒感染的传染病被世界卫生组织命名为 2019 年冠状病毒病(corona virus disease 2019, COVID-19)(WHO, 2020a)。新型冠状病毒肺炎主要的临床症状为发热、咳嗽和乏力(国家卫生健康委员会办公厅和国家中医药管理局办公室,2020),可能会引发致命的急性呼吸窘迫综合征(acute respiratory distress syndrome, ARDS)(Chen 等,2020b)。

控制这种疾病传播的主要障碍是缺乏高效的检测方法。尽管逆转录聚合酶链式反应(reverse transcription-polymerase chain reaction，RT-PCR) 是确认 COVID-19 的金标准(Ai 等,2020) ，但获得结果需要 4 ～6 个小时，且 RT-PCR 测试还具有较高的假阴性率，需要间隔几天多次进行 RT-PCR 检测才能确定诊断结果(国家卫生健康委员会办公厅和国家中医药管理局办公室,2020) 。此外，在很多疫情严重地区 RT-PCR 试剂也严重不足。相比之下，X 射线和 CT(computed tomography) 检查设备在各大医院已广泛普及。在临床实践中，通过结合临床症状和体征，CT 是识别 COVID-19 的更高效、更安全的方法。与 CT 相比，X 射线检查具有扫描速度更快、辐射量更低的优点。同时，X 射线和 CT 图像还可应用在 COVID-19 的跟踪和预后: 轻型和普通型患者的肺部影像表现为肺部的多发性小斑片影及间质改变，以肺外带明显; 重型和危重型患者，多发展为双肺多发性的毛玻璃表现与浸润影，重者可出现肺实变(国家卫生健康委员会办公厅和国家中医药管理局办公室,2020) 。综上所述，医学影像在限制病毒传播以及治疗 COVID-19 的过程中起着至关重要的作用。

在 COVID-19 的医学影像诊断方面，由于需要筛查和治疗大量的病患，为减轻放射科医生的阅片工作量，可以用人工智能技术对医学影像进行自动诊断，计算感染严重程度。Jin 等人(2020) 设计了一个 AI 辅助诊断系统，可以实现与放射科医生相媲美的性能，该系统已被部署到 16 家医院。此外，AI 技术还可以根据 COVID-19 的临床特征，预测高危病患，帮助医生及早发现并治疗，降低死亡率(Yan 等，2020) 。本文重点关注基于医学影像的 AI 辅助诊断，从数据准备、图像分割、分类、跟踪和预后方面分别进行阐述。最后提出了几个尚未解决的问题和挑战。

1 数据准备

1.1 公开的数据集

训练深度学习网络模型需要有大规模高质量的数据集，由于迫切需要数据集来支持人工智能技术进行 COVID-19 的辅助诊断，部分公开的数据集见表 1。

表 1 公开的数据集

Table 1 Public dataset

数据集名称	类型	组成	描述	文献
COVID-19 CT segmentation dataset	CT	COVID-19	COVID-19 感染区域分割数据集	MedSeg(2020)
JSRT Dataset	X 光片	正常	肺部区域分割数据集	Shiraishi 等人(2000)
COVID-19 BSTI Imaging Database	CT	COVID-19	帮助医生了解 COVID-19 影像	BSTI(2020)
COVID-CT-Dataset	CT	COVID-19 其他	349 幅 COVID-19 的 CT 影像	He 等人(2020)
covid-chestxray-dataset	X 光片，CT	COVID-19 非 COVID-19 肺炎健康	一个可用于计算机分析 COVID-19 的大型 X 和 CT 数据集	Cohen 等人(2020)
COVIDx	X 光片	COVID-19 非 COVID-19 肺炎正常	13 975 幅 X 光片	Wang 和 Wong(2020a)
Open source ultrasound (POCUS) data collection initiative for COVID-19	超声波数据	COVID-19 非 COVID-19 肺炎正常	COVID-19 超声波检测数据集	Born 等人(2020)
COVID-19 Chest X-ray Database	X 光片	COVID-19 非 COVID-19 肺炎正常	2 905 幅 X 光片	Chowdhury 等人 (2020)
Augmented COVID-19 X-ray Images Dataset	X 光片	COVID-19 其他	COVID-19 和非 COVID-19 的数据增强	Alqudah 等人(2020a)
Chest X-Ray Images (Pneumonia)	X 光片	细菌/病毒性肺炎、正常	有 5 863 幅 X 射线图像	Kermany 等人(2018)
COVID-19 Open Research Dataset Challenge (CORD-19)	论文		文本挖掘数据集	Allen Institute for AI 等人(2020a)
COVID-19 Open Research Dataset (CORD-19)	论文		文本挖掘数据集	Allen Institute for AI 等人(2020b)
LITCOVID	论文		根据不同的主题和地区做了分类	Chen 等人(2020c)
Global research on COVID-19	论文		WHO 全球研究数据	WHO(2020b)

尽管已经有一些 COVID-19 的公开数据集,但数据量与训练神经网络所需的相比还是很缺乏,可以综合使用上面几个数据集,如 COVIDx 整合了 3 个开源数据集构成,并补充了 JSRT Dataset、Chest X-Ray Images (Pneumonia) 这些非 COVID-19 的肺部数据集。列出的论文数据集,一方面可以帮助学者跟踪 COVID-19 研究进展;另一方面可以作为文本挖掘数据集,帮助医学界寻找一些问题的答案。

1.2 缓解数据不足问题

COVID-19 感染区域分割数据集匮乏的原因之一是标注数据是一项劳动密集型工作——放射科医生手动标注出 CT 影像的感染区域需要 1—5 h。为了提高放射科医生的标注效率,Shan 等人(2020)提出了"人工在环(human-in-the-loop, HITL)"策略和 VB-Net 语义分割网络模型,HITL 策略让放射科医生先手动标注一小部分 CT 图像以初步训练 VB-Net,然后用 VB-Net 自动分割感染区域,经医生校正后作为新的数据再次训练 VB-Net,操作流程如图 1。自动分割出的结果和手动分割相比,Dice 相似系数为 91.6% ±10.0%;HITL 策略可以将标注时间大幅减少到 4 min,体现了医生与算法专家深度合作的优势,这种策略也可以应用在其他图像分割数据集的制作上。

尽管 COVID-19 的数据集很缺乏,但有大量其他数据集可以进行迁移学习。Zhang 等人(2020b)提出一种深度领域自适应法,进行普通肺炎到 COVID-19 的领域适应,采用 ResNet18 模型达到了 98.2% 的精确率和 88.33% 的敏感性。迁移学习可以将有大量标签的源域知识迁移到只有少量标签或无标签的目标域,同时利用开源的预训练模型缩短训练时间。值得注意的是,弱监督或无监督学习也可缓解数据不足问题,如 Zheng 等人(2020)训练了一个弱监督二分类网络,该模型仅需要每位患者是否为阳性的标签。具体工作如下:训练一个无监督学习网络,对肺部区域进行分割,然后用提出的 DeCoVNet 判断是否为 COVID-19 阳性。

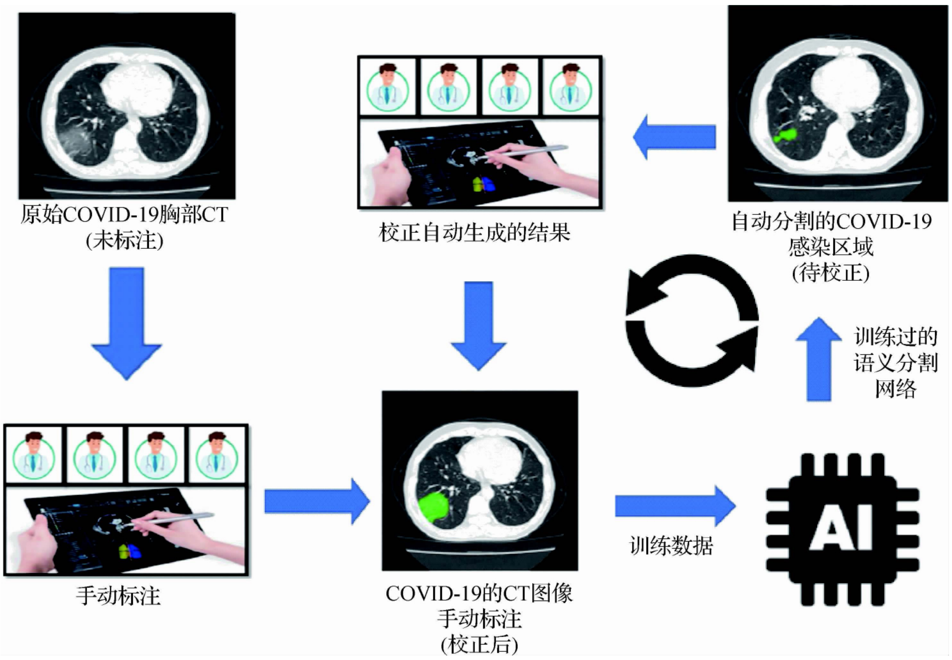

图 1 "人工在环"工作流程(Shan 等,2020)

Fig. 1 The human-in-the-loop workflow(Shan et al., 2020)

2 图像语义分割

在 COVID-19 的 AI 辅助诊疗中,从原始影像中分割出肺部区域是一项关键的预处理步骤,可以减少后续算法的计算量;而分割出病变区域,有助于医生跟踪观察病情,同时可根据感染区域的大小计算出感染率。由于医学影像数据集的限制,相对于 DeepLab 和 DenseNets 等语义分割模型而言,U-Net 参数量更少,不容易过拟合,因此 U-Net 及其变体网

络(3D U-Net、U-Net ++ 和 Attention U-Net 等)被广泛应用于医学图像的分割。Zheng 等人(2020)采用 U-Net 模型进行肺部区域分割;V-Net 作为 U-Net 的一种 3D 变体,Butt 等人(2020)使用 V-Net 模型进行 COVID-19 感染区域的分割。

Gaál 等人(2020)采用生成对抗网络和 Attention U-Net 设计了肺部区域分割网络,在 JSRT(Japanese society of radiological technology)数据集(Shiraishi 等,2020)上实现 97.5% 的 Dice。Alom 等人(2020)使用 NABLA-N(Alom 等,2019)网络模型分割 CT 和 X 光片中的肺部受到 COVID-19 感染的区域,效果如图 2。

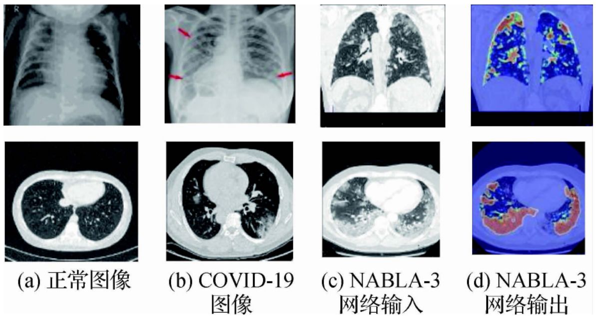

图 2 正常和 COVID-19 病例的 X 射线和 CT 图像,NABLA-3 网络的输入和输出(Alom 等,2020)

Fig. 2 X-ray and CT images of normal and COVID-19 cases, inputs and outputs of NABLA-3 network((a) normal images; (b) COVID-19 images; (c) input of NABLA-3; (d) output of NABLA-3 (Alom et al., 2020)

3 医学影像的 AI 诊断

3.1 基于 CT 的 COVID-19 诊断

CT 在诊断 COVID-19、监测疾病进展和评估疗效等方面具有重要意义(Ai 等,2020)。基于 CT 图像的 COVID-19 诊断工作有 Zheng 等人(2020)、Gozes 等人(2020)、Shan 等人(2020)、Li 等人(2020a,b)、Butt 等人(2020)、Alom 等人(2020)、Maghdid 等人(2020a)、Hu 等人(2020)、Jin 等人(2020)、Chen 等人(2020a)、Wang 等人(2020b)、Zhang 等人(2020a)以及 Bai 等人(2020)。这些算法可分为二分类和三分类,二分类算法的分类结果为 COVID-19 阳性和阴性,三分类算法的分类结果为健康、COVID-19 阳性和非 COVID-19 肺炎。

3.1.1 二分类

相对于多元分类,二元分类复杂度低,不确定性小。尽管二分类算法没有充分考虑非 COVID-19 肺炎的诊断,但是二分类可以通过平移决策边界提高敏感性。因此在疫情爆发时期,二分类算法作为一种辅助诊断方法,具有很大的应用价值。Barstugan 等人(2020)以机器学习算法对 CT 图像进行分类,该研究采用灰度共现矩阵、局部方向图、灰度游程矩阵、灰度区域大小矩阵和离散小波变换 6 种算法提取特征,用支持向量机(support vector machine, SVM)进行分类,在 150 幅 CT 图像上实验得出,最佳分类方法是以灰度区域大小矩阵进行特征提取,再用 SVM 分类,准确率为 99.68%。该研究体现了经典图像处理与机器学习算法仍有很大应用空间。

Chen 等人(2020a)使用 U-Net++(Zhou 等,2018)网络分割感染区域,再进行 COVID-19 阳性和阴性的分类,在 46 096 幅 CT 图像上实验,达到了 98.85% 的准确率。Jin 等人(2020)采用更复杂的 3D UNet++ 分割病变区域,并在分类任务中测试了 ResNet-50(He 等,2016),Inception 网络(Szegedy 等,2016),DPN-92(Chen 等,2017),Attention ResNet-50(Wang 等,2017),最终发现联合使用 3D U-Net++ 和 ResNet-50 可以达到最好的性能,在 1 136 个病例的胸部 CT 数据上实验,敏感性为 97.4%,特异性为 92.2%,AUC(area under curve)为 0.991。综上可知采用 2D 网络分析 CT 切片图像,或用 3D 网络分析 3 维 CT 数据都可以达到很好的分类准确率。

结合 CT 数据的 2D 和 3D 特征可达到更好的效果。Gozes 等人(2020)使用商用软件 RADLogics Inc 检测 3D 肺部 CT 扫描的结节和毛玻璃体混浊,再结合 2D 卷积神经网络进分割肺部区域并诊断是否患有 COVID-19,在 107 个病例构成的数据集上,测试达到了 0.996 的 AUC,98.2% 的敏感性,92.2% 的特异性。该算法敏感性高,更适合 COVID-19 病例的筛查。

3.1.2 三分类

COVID-19 与非 COVID-19 肺炎相比,其临床症状和放射学特征都有部分重叠,因此,许多研究设计出三分类模型。Li 等人(2020a)分割出了肺部区域作为预处理,再用 COVnet(骨干网络为 ResNet)网络进行分类,在 4 356 幅 CT 图像上实验,鉴定 COVID-19 的敏感性为 90%,特异性为 96%,AUC 为

0.96,这种设计的优点是不需要病变区域的标注信息。Zhang 等人(2020a)采用 DeepLabv3 网络,首先分割出肺部区域,再分割出病变区域,最后使用调整后的 ResNet-18 网络在 40 880 个 CT 切片上实验,达到 92.4% 的整体准确率。

由于 COVID-19 更容易引发胸膜附近的感染,且患者肺部通常不止一个独立的感染区域(Kanne,2020; Chung 等,2020)。Butt 等人(2020)根据这一特点,在分类网络中加入了位置注意力机制,用 VNET-IR(inception-resnet)-RPN(region proposal network)17(Wu 等,2019)分割网络和加入了位置注意力机制的 ResNet-18 分类网络,在 618 例 CT 样本上实验达到 86.7% 的敏感性,81.3% 的精确率。

综上所述,采用分割网络如 U-Net、V-Net 及其变体分割病变区域,再结合分类网络如 ResNet、VGG19 等,并在大规模数据集上训练,均可得到较好的分类效果,在此基础上,可以结合生成对抗网络、位置注意力机制、迁移学习以及 2D 与 3D 特征结合等方法进一步提高准确率。

3.2 基于 X 光片的 COVID-19 诊断

Ai 等人(2020)指出,在一些 COVID-19 爆发地区,可以将胸部 X 光片(chest X-Ray,CXR)检查作为 COVID-19 的主要筛查工具。Ng 等人(2020)指出了感染 COVID-19 患者的 X 光片上的特征。此外,利用 CXR 成像进行 COVID-19 筛查有以下优势:实用性(CXR 在大多数医疗保健系统中被视为标准设备)、便携性(便携式 CXR 系统可以在隔离室内执行成像,减少了成像过程中传播病毒的风险)。基于 X 光片的 COVID-19 诊断的工作有 Wang 等人(2020a)、Alqudah 等人(2020b)、Zhang 等人(2020)、Goodwin 等人(2020)、Khobahi 等人(2020)、Maghdid 等人(2020a)、Hammoudi 等人(2020)、Gaál 等人(2020)、Narin 等人(2020)和 Hemdan 等人(2020)。与基于 CT 的 COVID-19 诊断相同,面向 X 光片的算法根据分类结果也分为两部分,即二分类和三分类。

3.2.1 二分类

Hemdan 等人(2020)采用 VGG19、DenseNet201、InceptionV3、ResNetV2、InceptionResNetV2、Xception 和 MobileNetV2 这 7 种经典的深度学习模型训练二分类网络,在 50 例 X 光片上实验发现,VGG19 和 DenseNet201 达到了同样最好的性能,准确率都是 83%。Narin 等人(2020)使用经过 ImageNet 数据集预训练的 ResNet50 模型,达到 98% 的诊断准确率。实验表明使用迁移学习和更大的数据集,可以提高分类准确率。

3.2.2 三分类

由于 COVID-19 与其他肺炎的 CXR 有相似之处,而与正常人的胸片差别较大。Hammoudi 等人(2020)设计了两阶段分类方法,第 1 阶段是用 CNN 模型来区分正常还是肺炎,在第 2 阶段,用 CNN + RNN 模型区分 COVID-19 和细菌性肺炎,准确率达到了 90.7%。Wang 等人(2020a)采用 Wong 等人(2018)提出的生成合成器(generative synthesis)自动生成 COVID-Net 网络模型,测试准确率为 83.5%。

3.3 其他 COVID-19 诊断方法

由于 COVID-19 早期患者的放射学影像表现并不明显,根据临床信息(旅行和接触史、白细胞数、症状(发烧、咳嗽和痰液),患者年龄和性别等)进行早期诊断是一种快速有效的方法。Langer 等人(2020)收集了 199 个病例的 74 项临床信息,用人工神经网络算法达到了 91.4% 的准确率,94.1% 的敏感性。临床医生在诊断的过程中,会综合考虑医学影像和临床信息两方面因素。根据这一特点,Mei 等人(2020)使用 CNN 模型和多层感知机算法,结合 CT 影像和临床信息两类数据以诊断 COVID-19,该算法敏感性为 84.3%,AUC 为 0.92,优于高级放射科医生(具有 10 年经验)的诊断结果。

值得注意的是,Maghdid 等人(2020b)开发了基于智能手机的 AI 诊断系统,将 CT 影像和手机传感器数据(惯性传感器数据、咳嗽声和手指温度)上传到云服务器进行诊断。该系统具有便捷快速的优势,且随着该手机 App 的推广,数据集的规模也将不断增加,有助于进一步训练改进算法模型。

4 COVID-19 的跟踪和预后

医学影像是医生跟踪观察病情的重要工具。语义分割网络可以分割出肺部感染区域并计算出感染率,作为医生预后的参考。Gozes 等人(2020)根据 CT 切片的“特征图”和 3 维 CT 数据中检测到的不透明度测量值,提出“电晕评分”来衡量 COVID-19 患者的病情的变化。Hammoudi 等人(2020)根据年

龄,综合症和感染率来预测 COVID-19 患者的存活率。

除了根据医学图像预后,还有许多研究根据临床指标预测存活率。由于指标的数量多,变化复杂,需要智能算法来快速且敏锐地分析这些数据。Jiang 等人(2020) 根据丙氨酸转氨酶、肌痛和血红蛋白数,预测患者是否会发展为急性呼吸窘迫综合征(acute respiratory distress syndrome,ARDS)(COVID-19 可能引发的一种致命并发症),用最近邻算法和支持向量机算法达到 80% 的准确率。Yan 等人(2020) 开发了基于 XGBoost(eXtreme Gradient Boosting) 算法的预后模型,从 300 多个特征中识别出 3 个关键的临床特征,预测 COVID-19 患者的存活率,准确率超过了 90%。这些预测算法,可以帮助医生及早发现高危患者并治疗,更好地分配医疗资源,降低死亡率,具有重大意义。

5 结 语

算法专家和临床医生基于图像处理和机器学习等技术,提出各种计算机辅助诊断算法,来积极应对 COVID-19 大爆发带来的挑战。本文回顾了数月以来基于医学影像的 AI 诊断的研究成果。尽管有一些 AI 辅助诊断系统已经部署到医院中发挥实际作用,这些 AI 系统仍然具备很大的上升潜力,可以通过以下几个方面进一步提升其性能:

1) 人工智能作为数据驱动的一门学科,收集更多高质量的数据集,有助于进一步提升算法性能。

2) 现有的 AI 诊断技术多是基于医学影像的,诊断依据单一。结合临床信息、旅行接触史等多种类型数据可弥补仅用医学影像诊断的不足。

3) 由于非 COVID-19 肺炎和 COVID-19 有很多重叠的临床特征,如何更好地区分这两类肺炎也是未来的研究方向之一。

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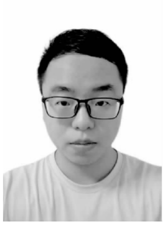

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