



电子科技大学 健康大数据研究所



人工智能+医疗

蒲晓蓉 博士 计算机专业首席教授
任亚洲 博士 计算机专业副教授

2021. 12

目录

- √ 面向临床的医学图像深度降噪
- √ 空气污染与儿童呼吸系统疾病关联性分析
- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ 5G+医疗健康应用试点
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目

10月13日是世界血栓日。崴一下脚竟引发肺栓塞，坐飞机时间长了出现下肢血栓，术后长时间卧床也会引发血栓……血栓常常谜一样地存在，且严重威胁着我们的健康。血栓究竟是什么？对人体有哪些危害？又该如何预防呢？

“血管就好比河道一样，血栓就如同堵在河道主干上的船，严重时会导致整个运河体系瘫痪。”兰州大学第一医院普外科一病区、血管外科副主任舒小军介绍，**血栓是指在一定条件下，血液中的有形成分在血管内形成栓子，造成血管部分或完全堵塞，从而导致与其相对应的器官或组织的血液供应或血液回流障碍的过程。**

舒小军医生表示，血栓性疾病包括动脉血栓与静脉血栓两大类。血栓栓塞在动脉会引起脑卒中、心肌梗死、下肢动脉坏死等情况，而栓塞在静脉会引起相应器官或组织的淤血、水肿等情况。

人民健康
一切为了
老百姓

常规胸片，包括你们常说的胸透，已经不能满足大部分人群的需求了！部分人群需要选择低剂量CT代替胸片。

常规胸片是肺、纵隔、骨骼及软组织的重叠影像，对比度差，因此容易造成误诊和漏诊，而CT是人体断层影像，密度分辨率高，影像后处理功能强大，对病变显示更加清楚、全面，对病灶定位、定性更有帮助。通俗一点讲，常规的照片“啪”一声，一秒钟的成像结果，怎么能比你躺在CT床上扫描一分钟所获得的信息更全面呢？

低剂量CT，顾名思义即扫描剂量低，**由于肺实质含气，肺内结构自然对比度高，研究表明，胸部CT可以充分地降低剂量而不影响肺内结节的发现和疾病的诊断，已有的研究均证明低剂量胸部CT对直径10mm以上结节的检出率与常规剂量没有差别，检出率均为100%。**

Background

- √ 20世纪90年代，肺癌筛查：低剂量LDCT (Low-Dose Computed-Tomography)
- √ 2011年，美国国家肺癌筛查试验 (National-Lung Screening Trial, NLST) 显示，相比X胸片，LDCT筛查肺癌高危人群，死亡率下降20%
- √ LDCT肺癌筛查：医学+工学，多学科协同
- √ LDCT的巨大挑战——**噪声**（量子噪声 + 电子高斯噪声）
- √ 深度学习：LDCT图像降噪和去除伪影
 - **致命缺陷**：**外观模糊、缺少病灶细节**，不利于临床诊断！

Highlights

√ 我们提出 **面向临床应用的LDCT图像降噪系列深度学习方法**

① 提出噪声估计/学习/扩充新方法，即插即用无配对**LDCT**降噪通用架构

- 利用正常剂量NDCT样本获得伪LDCT配对，解决临床采集LDCT样本难题；
- 2020年图像计算与数字医疗国际会议，竞赛**冠军**
- 发表学术会议论文2篇

② 提出医学图像降噪与病灶检测有机结合框架，及多损失集成+网络协同训练新方法

- 关注感兴趣区域(ROI)
- 将降噪与高阶任务（如病灶检测等）紧密关联
- 论文发表在**CCF A类国际会议 2021ACM MM**

主要研究1： NDCT-LDCT样本对生成

Quality Degradation

Dose Reduction

CT



Normal-dose Abdomen CT



Quarter-dose Abdomen CT

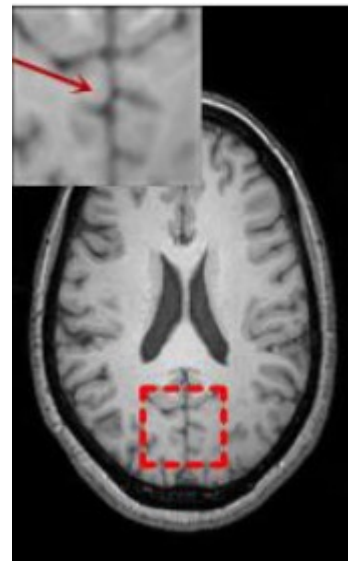
Artifacts

Noise

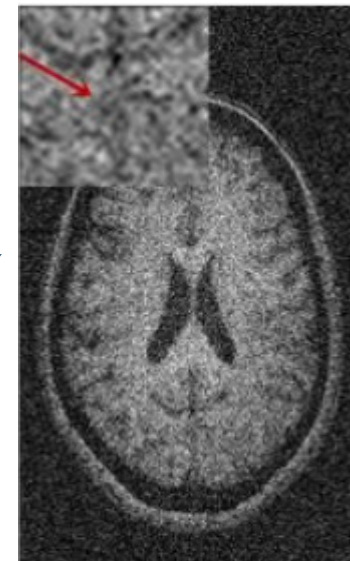
MRI

Quality Degradation

Imperfection of radio
frequency coils/movement of
the patient



T1w example of Noisy-free MRI



T1w example of Noisy MRI

主要研究1：

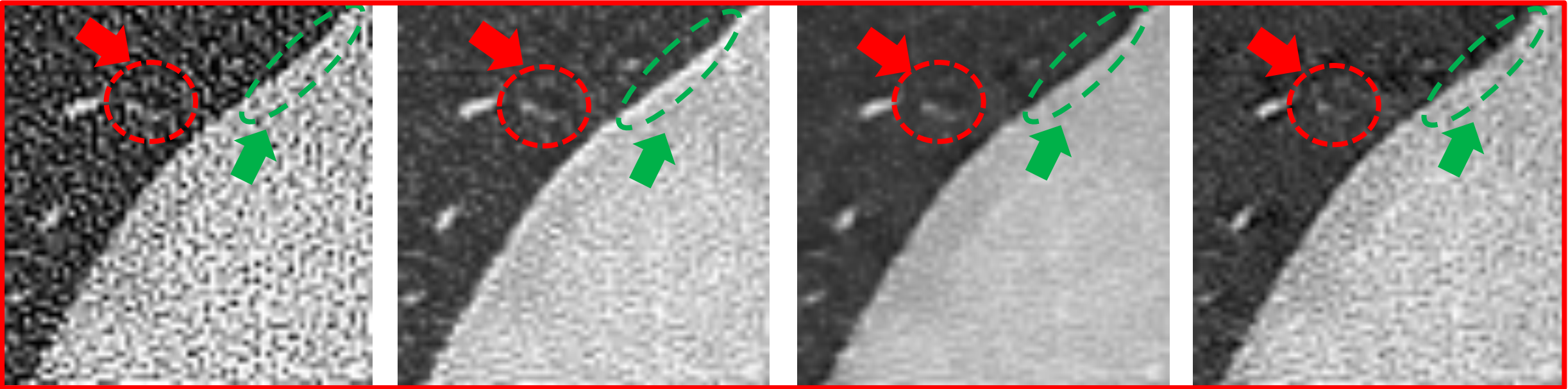
NDCT-LDCT样本对生成

Goals of LDCT denoising:

- ✓ Noise suppression (噪声抑制)
- ✓ Structure retention (结构保持)
- ✓ Artifacts suppression (伪影抑制)

Clinical-oriented LDCT quality optimization: *Unpaired Issue*

Example: Zoomed-in Denoising Results for Chest LDCT



LDCT

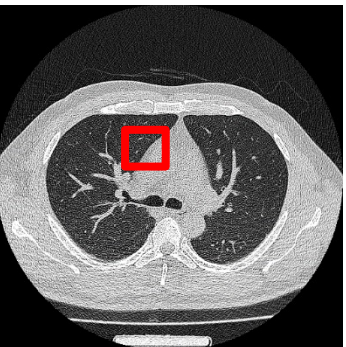
TDDL- Ours

TDDL-RED-CNN

TDDL-CPCE

CNN-based Models

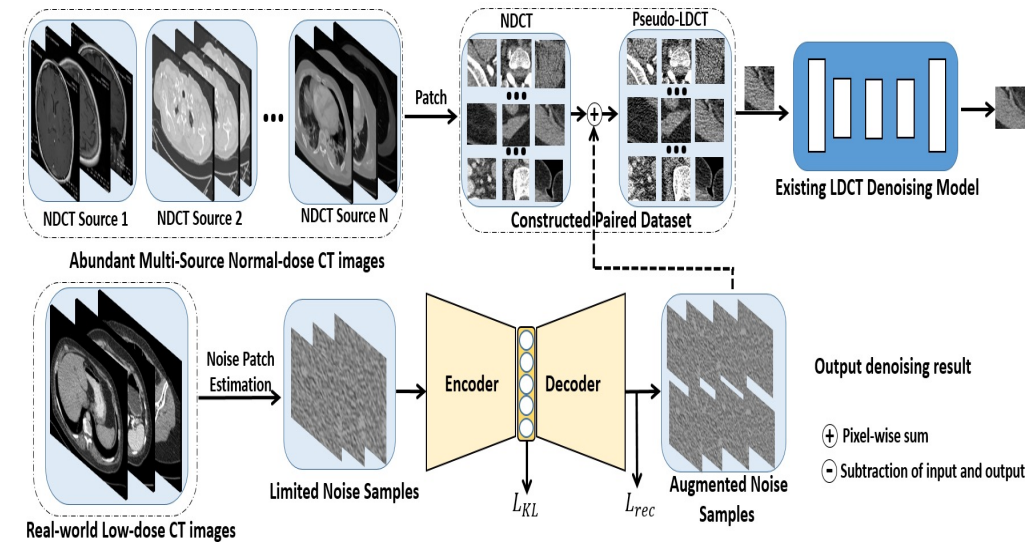
+ GCN



Award



Championship: The Challenge LDCT Quality Optimization of ISICDM



Publications

ICONIP 2020



Low-Dose CT Image Blind Denoising with Graph Convolutional Networks

Kecheng Chen¹, Xiaorong Pu^{1(✉)}, Yazhou Ren¹, Hang Qiu¹, Haoliang Li², and Jiayu Sun³

¹ School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China
puxiaor@uestc.edu.cn

² Rapid-Rich Object Search Lab, Nanyang Technological University, Singapore, Singapore

³ West China Hospital, Sichuan University, Chengdu, China

Abstract. Convolutional Neural Networks (CNNs) have been widely applied to the Low-Dose Computed Tomography (LDCT) image denoising problem. While most existing methods aim to explore the local self-similarity of the synthetic noisy CT image by injecting Poisson noise to the clean data, we argue that it may not be optimal as the noise of real-world LDCT image can be quite different compared with synthetic noise (e.g., Poisson noise). To address these issues, instead of manually distorting the clean CT to construct paired training set, we estimate

[arXiv](#)

GCN: 局部+非局部特征

Chen K., Pu X., Ren Y., Qiu H., Li H., Sun J. (2020) Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP 2020. Lecture Notes in Computer Science.

ISICDM 2020

Task-Driven Deep Learning for LDCT Image Denoising

Kecheng Chen
University of Electronic Science and
Technology of China
Chengdu, Sichuan, China

Jiabin Huang
University of Electronic Science and
Technology of China
Chengdu, Sichuan, China

Jiayu Sun
Sichuan University
Chengdu, Sichuan, China

Yazhou Ren*
University of Electronic Science and
Technology of China
Chengdu, Sichuan, China
yazhou.ren@uestc.edu.cn

Xiaorong Pu*
University of Electronic Science and
Technology of China
Chengdu, Sichuan, China
puxiaor@uestc.edu.cn

ABSTRACT

Compared with normal-dose computed tomography (NDCT), low-dose CT (LDCT) images have lower potential radiation risk for patients while suffering from the degradation problem by noise. In the past decades, deep learning-based (DL-based) methods have achieved impressive denoising performances in comparison to traditional methods. However, most existing DL-based methods typically preform training on a specific pairs of LDCT/NDCT images and aim to generalize well on clinical scenarios with LDCT images only. It is a difficult task and challenge, denoising LDCT images with various noise characteristics due to different imaging protocols. We propose a task-driven deep learning framework for LDCT image denoising. Specifically, the variational autoencoder (VAE) is leveraged to learn noise distribution. By utilizing abundant open-source NDCT images as the latent references, we then construct pairs of induced-LDCT (namely pseudo-LDCT)/NDCT images rather than simply using pairs of non-induced-LDCT/NDCT images. Thus, the denoising model can perceive the noise within LDCT images directly.

1 INTRODUCTION

Computed tomography (CT) is the most widely adopted imaging technology in clinical diagnosis, as it was the first method to noninvasively acquire images of the inside of the human body that were not biased by superposition of distinct anatomical structures [2]. However, epidemiologic studies have indicated that the radiation dose from even two or three CT scans results in a detectable increase in the risk of cancer, especially in children [1]. In the past decades, compared with normal-dose CT (NDCT) imaging, low-dose CT (LDCT) imaging technology enables a lower radiation dose and has been used to preliminary screening of high risk disease [15], such as lung cancer. The main crucial limitation for LDCT is that the imaging quality will inevitably be degraded due to complex noise (caused by the negative impact of dose reduction).

To improve the quality of LDCT image, many studies perform noise removal from LDCT images, which can be roughly categorized into three streams [6], i.e., sinogram filtration based methods, iterative reconstruction based methods and post-processing based

LDCT噪声学习、构建带噪声图像对

Chen K., Huang J., Sun J. Ren Y., Pu X., (2020) Task-Driven Deep Learning for LDCT Denoising. ISICDM 2020

主要研究2：LDCT图像降噪与病灶检测结合

Clinical-oriented LDCT quality optimization



② Disconnection between Quality Optimization and High-level Tasks

χ 图像降噪与高阶任务（如病灶检测等）无关

Step 1

AI-based Quality Optimization Process



Step 2

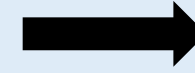
AI-based Lesion Detection/Segmentation



Disconnection



Detection



segmentation

- ⊗ Unknown Usability for Step 2 in clinic
- ⊗ Don't orient practical high-level tasks
- ⊗ Evaluated Difficulty for optimized image

Clinical-oriented LDCT quality optimization : Disconnection Issue

Connection between LDCT Quality Optimization and Lesion Detection

Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection

Kecheng Chen^{1*}, Kun Long^{1*}, Yazhou Ren^{1†}, Jiayu Sun², Xiaorong Pu^{1†}

¹ School of Computer Science and Engineering,

University of Electronic Science and Technology of China, Chengdu, 611731, China

²West China Hospital, Sichuan University, Chengdu, 610044, China

ABSTRACT

Deep learning has achieved notable performance in the denoising task of low-quality medical images and the detection task of lesions, respectively. However, existing low-quality medical image denoising approaches are disconnected from the detection task of lesions. Intuitively, the quality of denoised images will influence the lesion detection accuracy that in turn can be used to affect the denoising performance. To this end, we propose a play-and-plug medical image denoising framework, namely Lesion-Inspired Denoising Network (LIDnet), to collaboratively improve both denoising performance and detection accuracy of denoised medical images. Specifically, we propose to insert the feedback of downstream detection task into existing denoising framework by jointly learning a multi-loss objective. Instead of using perceptual loss calculated on the entire feature map, a novel region-of-interest (ROI) perceptual loss induced by the lesion detection task is proposed to further connect these two tasks. To achieve better optimization for overall framework, we propose a customized collaborative training strategy for LIDnet. On consideration of clinical usability and imaging characteristics, three low-dose CT images datasets are used to evaluate the effectiveness of the proposed LIDnet. Experiments show that, by equipping with LIDnet, both of the denoising and lesion detection performance of baseline methods can be significantly improved.

on Multimedia (MM '21), October 20–24, 2021, Virtual Event, China. ACM, New York, NY, USA, 10 pages. <https://doi.org/10.1145/3474085.3475480>

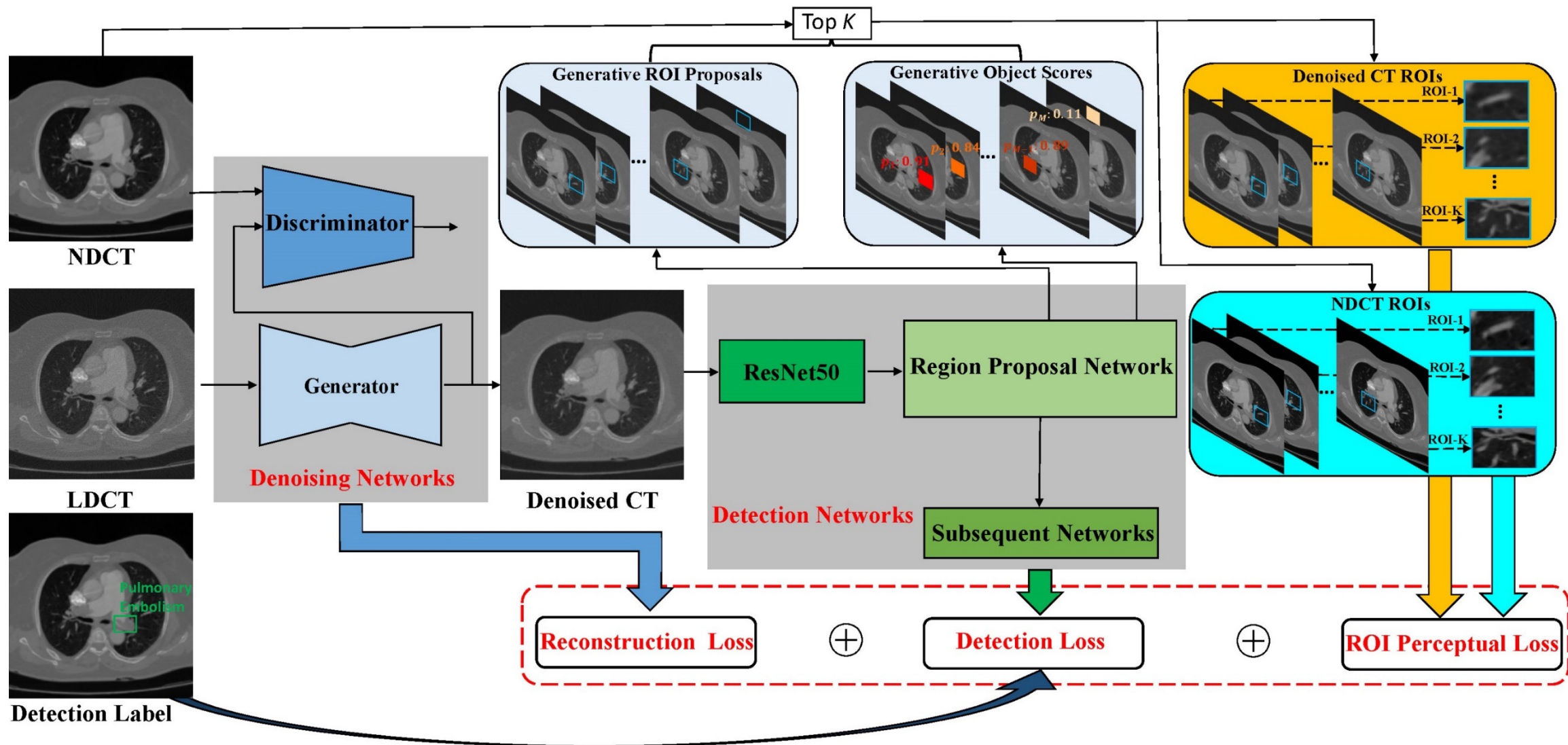
1 INTRODUCTION

The quality of medical images is crucial for the accurate diagnosis by the physicians [1, 7]. For medical artificial intelligence (AI) community, quite a few high-level medical image tasks (such as concerned lesion detection [32, 49], anatomical segmentation [21, 45], and multi-modal image registration[4, 20]) rely heavily on extremely high-quality input images, because 1) slight noise perturbation in low-quality images may take unexpected model degradation [18], and 2) some small lesions (e.g., the minute pulmonary nodules) in low-quality images will suffer from severe noise [10], leading to the difficulties of the post-processing and the diagnosis. The low-quality medical image will be disturbed by noise and artifacts [35]. The researchers therefore focus on low-quality medical image restoration such that the improved images can be used well in potential downstream tasks.

On consideration of clinical usability and imaging characteristics, the noise removal is the mainstream task for the medical image restoration [22, 40]. In various medical images, e.g., computed tomography (CT) image, magnetic resonance imaging (MRI) image, and ultrasonic image, CT image is most sensitive to the noise because the imaging quality will be greatly influenced by the

Kecheng Chen, Kun Long, Yazhou Ren*, Jiayu Sun, **Xiaorong Pu***. 2021. Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection. ACM MM, 2021. (CCF-A)

主要研究2：LDCT图像降噪与病灶检测结合



Kecheng Chen, Kun Long, Yazhou Ren*, Jiayu Sun, **Xiaorong Pu***. 2021. Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection. ACM MM, 2021. (CCF-A)

Conclusion

Clinical-oriented LDCT quality optimization:

- ① Unpaired Data Set in Clinic
- ② Disconnection between Quality Optimization and High-level Tasks



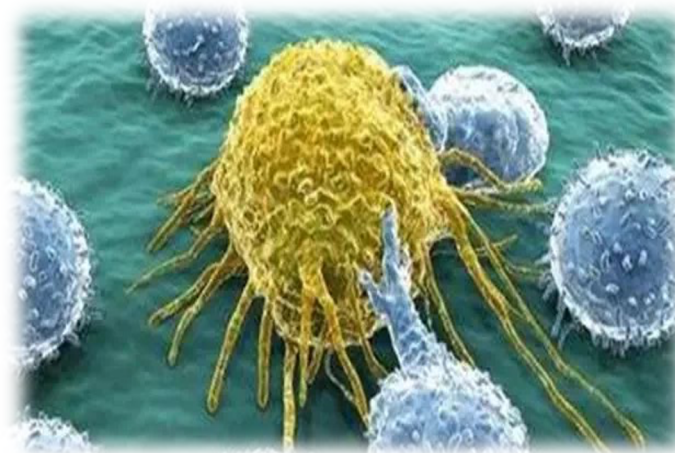
AI-based Quality Optimization of Medical Image

1. Chen K., **Pu X. ***, **Ren Y.**, Qiu H., Li H., Sun J. Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP (**CCF C**), 2020.
2. Chen K., Huang J., Sun J., **Ren Y.***, Qiu H., **Pu X.***, Task-Driven Deep Learning for LDCT Denoising. ISICDM (**EI**), 2020.
3. The **Championship**: The Challenge for LDCT image quality optimization, 2020.12
4. K Chen, **X Pu***, **Y Ren***, H Qiu, F Lin, S Zhang. TEMDnet: A Novel Deep Denoising Network for Transient Electromagnetic Signal With Signal-to-Image Transformation. TGRS (**JCR Q1**), 2020.
5. K Chen, K Long, **Y Ren***, J Sun, **X Pu***. Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection. ACM MM (**CCF A**), 2021.

目录

- √ 面向临床的医学图像深度降噪
- √ 空气污染与儿童呼吸系统疾病关联性分析
- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ 5G+医疗健康应用试点
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目

- 基于跨域大数据的疾病与环境关联性分析



空气污染与儿童呼吸系统疾病关联性分析



四川省儿童呼吸道疾病大 数据分析



电子科技大学大数据研究中心

1. 跨域数据关联分析
2. 机器学习预测模型
3. 分析结果多维展现

四川省卫生和计划生育信息中心

1. 数据清洗
2. 统计分析
3. 业务指导

呼吸系统疾病

- 上呼吸道感染
- 下呼吸道感染
- 哮喘

循环系统疾病

- 脑血管疾病
- 高血压
- 冠心病

代谢疾病

- 糖尿病

空气污染与儿童呼吸系统疾病关联性分析

跨域大数据分析

1



患者信息 医疗机构信息 疾病诊断

病案首页数据

2015,2016年LRI住院患者

共计**233183**人次

2



PM2.5

PM10

CO₂

AQI

环境监测数据

2015.1.1—2016.12.31

共计**80**个监测点

3



天气

温度

风向风力

气象数据

2015.1.1—2016.12.31

覆盖四川**18**市(州)

空气污染与儿童呼吸系统疾病关联性分析




2021-Differential effects of size-specific particulate matter on LRI-PUXR.pdf - Adobe Reader

文件(F) 编辑(E) 视图(V) 窗口(W) 帮助(H)


打开 1 / 8 99.1% 工具 填写和签名 注释 扩展功能


Environmental Research 193 (2021) 110581

Contents lists available at ScienceDirect

 Environmental Research

journal homepage: www.elsevier.com/locate/envres





Differential effects of size-specific particulate matter on lower respiratory infections in children: A multi-city time-series analysis in Sichuan, China

Xiaorong Pu^{a,b,1}, Liya Wang^{b,1}, Lina Chen^c, Jinping Pan^d, Lei Tang^a, Jing Wen^e, Hang Qiu^{a,b,*}

^a School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China
^b Big Data Research Center, University of Electronic Science and Technology of China, Chengdu, China
^c West China Second University Hospital, Sichuan University, Chengdu, China
^d Health Information Center of Sichuan Province, Chengdu, China
^e Glasgow College, University of Electronic Science and Technology of China, Chengdu, China

ARTICLE INFO ABSTRACT

Keywords: Evidence on the short-term effects of size-specific particulate matter with aerodynamic diameter <2.5 μm

- Xiaorong Pu, Liya Wang, Lina Chen, Jinping Pan, Lei Tang, Jing Wen, Hang Qiu, Differential effects of size-specific particulate matter on lower respiratory infections in children: A multi-city time-series analysis in Sichuan, China, Environmental Research, 193(2021),110581

目录

- √ 面向临床的医学图像深度降噪
- √ 空气污染与儿童呼吸系统疾病关联性分析
- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ 5G+医疗健康应用试点
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目

机器学习在急诊患者死亡率预测中的应用

2020年一项关于急诊相关研究文献综述的关键词词云图：

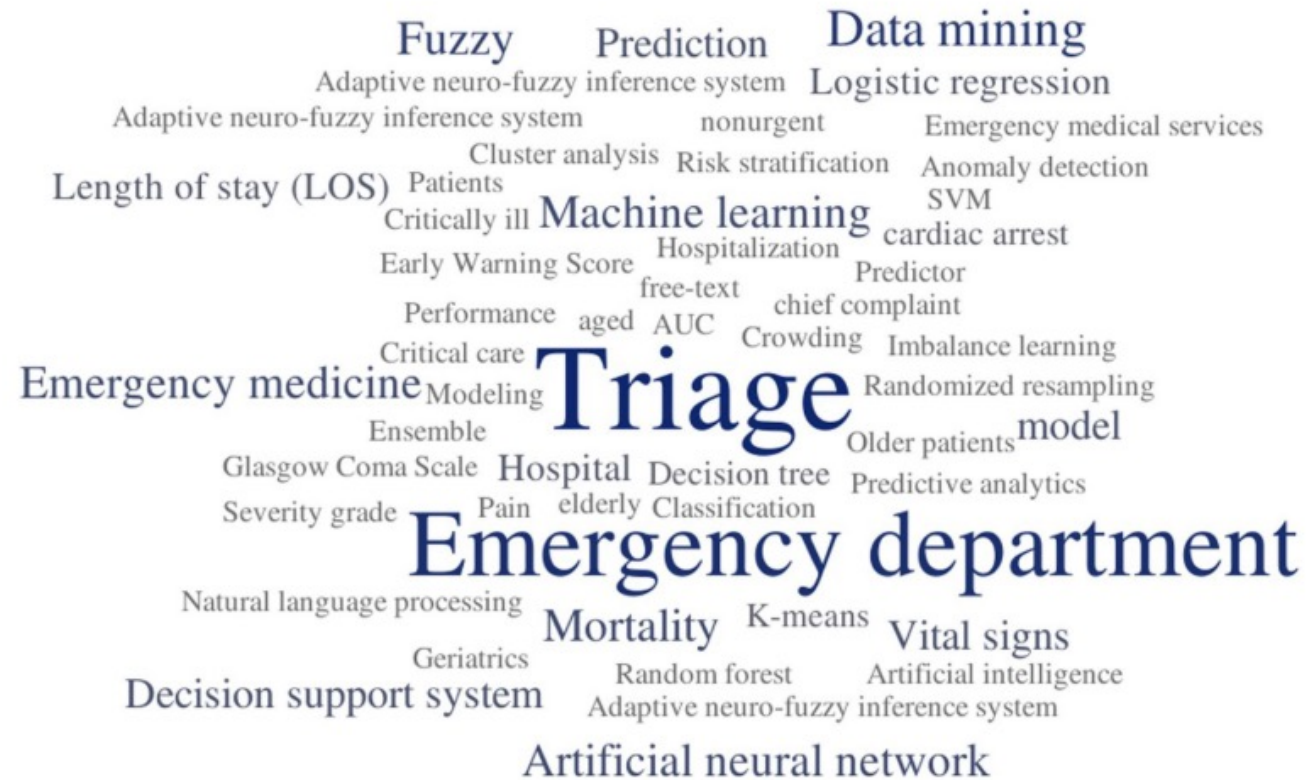


Fig. 4. Cloud of key-words of the papers selected in the review search.

机器学习在急诊患者死亡率预测中的应用



电子科技大学大数据研究中心

1. 数据清洗
2. 特征工程
3. 模型设计

基于机器学习的 急诊患者死亡率早期预测



四川大学华西第二医院

1. 数据收集
2. 数据分类
3. 医学支持

机器学习在急诊患者死亡率预测中的应用

2016年—2019年**1114例**建档急诊患者

- 登记号
- 性别
- 年龄
- 主诉
- 诊断
- 去向或死亡时间

患者基本描述**7**

- 体温
- 心率
- 呼吸率
- 收缩压
- 舒张压
- 氧饱和度

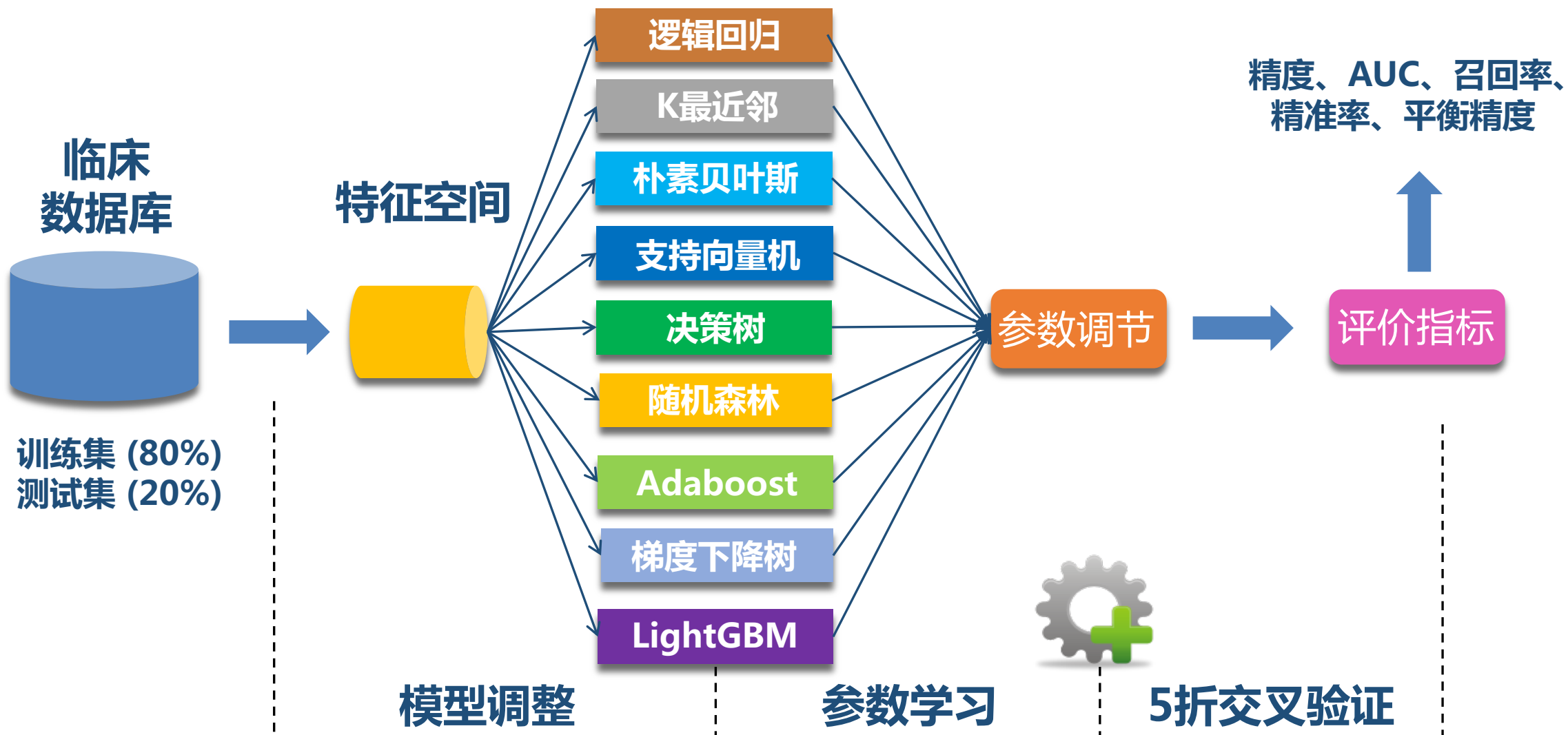
时序生命体征**6**

- 血常规
- 生化测试
- 凝血功能
- 尿钠肽
- 心肌标志物
- 检测时间

相关病理测验**68**

机器学习在急诊患者死亡率预测中的应用

死亡率预测模型构建与机器学习算法



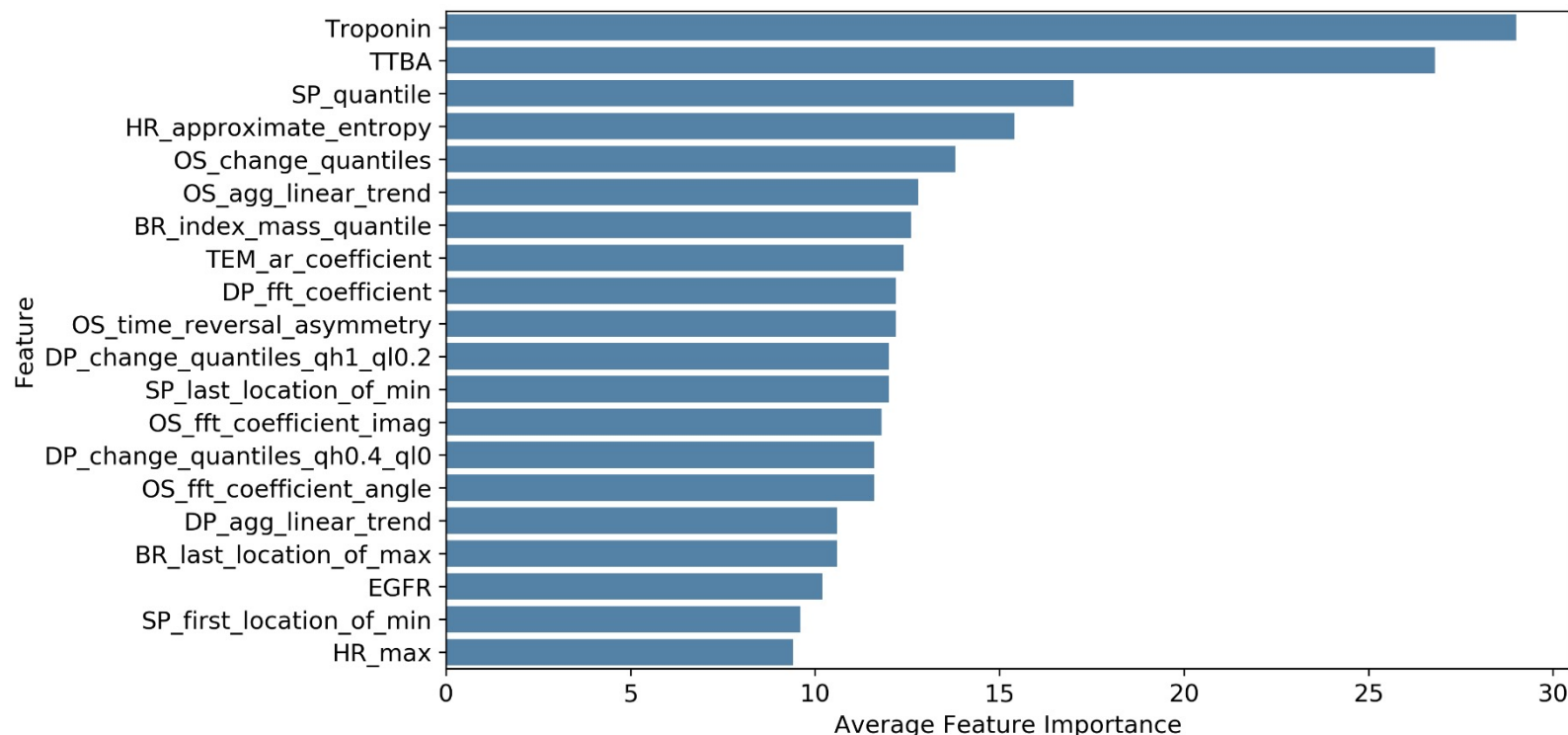
机器学习在急诊患者死亡率预测中的应用

各模型预测实验结果：

模型	准确率 (95%置信度)	AUC (95%置信度)	召回率 (95%置信度)	精准率 (95%置信度)	平衡精度 (95%置信度)
逻辑回归	0.861 (±0.010)	0.930 (±0.004)	0.867 (±0.006)	0.934 (±0.010)	0.857 (±0.014)
K最近邻	0.837 (±0.012)	0.855 (±0.010)	0.918 (±0.012)	0.864 (±0.007)	0.776 (±0.014)
朴素贝叶斯	0.790 (±0.007)	0.723 (±0.010)	0.939 (±0.006)	0.802 (±0.005)	0.676 (±0.010)
支持向量机	0.874 (±0.006)	0.931 (±0.006)	0.933 (±0.004)	0.896 (±0.005)	0.829 (±0.008)
决策树	0.817 (±0.021)	0.772 (±0.024)	0.875 (±0.020)	0.870 (±0.014)	0.772 (±0.024)
随机森林	0.882 (±0.007)	0.947 (±0.004)	0.967 (±0.003)	0.881 (±0.008)	0.818 (±0.013)
Adaboost	0.918 (±0.014)	0.964 (±0.007)	0.953 (±0.011)	0.935 (±0.013)	0.892 (±0.019)
梯度下降树	0.927 (±0.009)	0.972 (±0.004)	0.966 (±0.006)	0.934 (±0.008)	0.898 (±0.013)
LightGBM	0.936 (±0.008)	0.976 (±0.003)	0.971 (±0.008)	0.942 (±0.006)	0.910 (±0.009)

基于机器学习的急诊患者死亡率预测特征重要性分析

根据LightGBM特征重要性算法得出的最相关的前20个特征



通过机器学习和特征工程，挖掘出与急诊患者死亡率相关的临床因素，并按重要程度排序，例如：肌钙蛋白-T (Troponin)、总胆汁酸 (TTBA)、估算肾小球滤过率 (EGFR)，以及对时序生命体征数据的相关特征构建 (收缩压的分位数，心率的近似熵等)。很多特征是人工无法发现的。

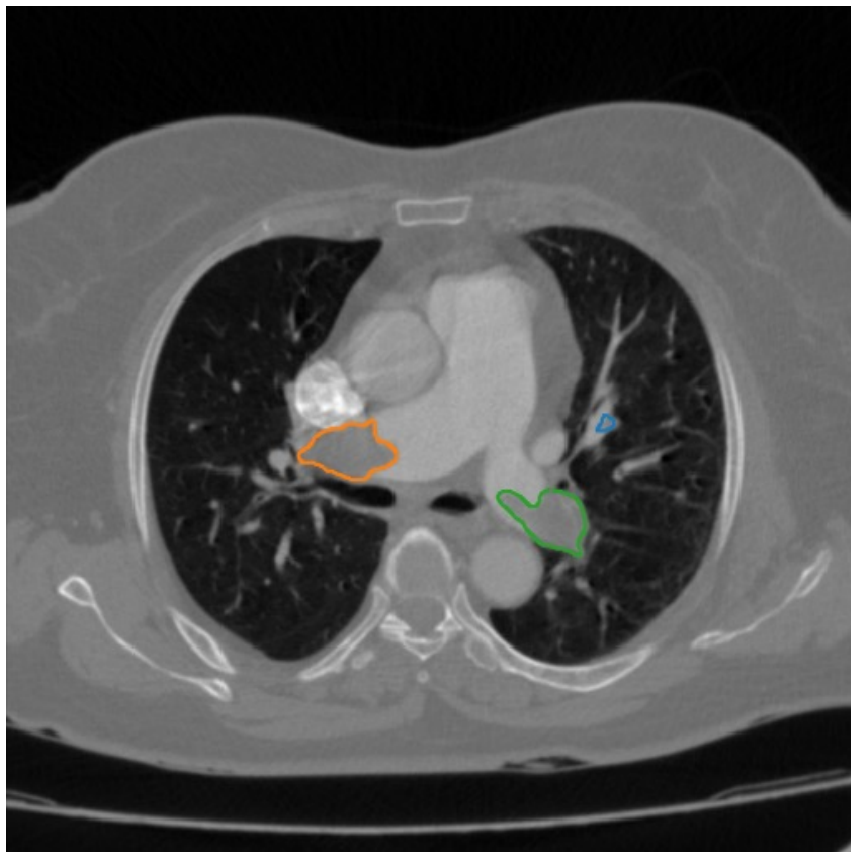
C Li, Z Zhang, Y Ren*, H Nie*, Y Lei, H Qiu, Z Xu, X Pu*. Machine learning based early mortality prediction in the emergency department. International Journal of Medical Informatics, 2021.

目录

- √ 面向临床的医学图像深度降噪
- √ 空气污染与儿童呼吸系统疾病关联性分析
- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ 5G+医疗健康应用试点
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目

基于P_Mask_RCNN的肺栓塞检测

肺栓塞 (pulmonary embolism)

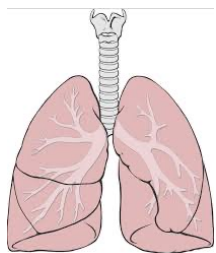


- 以**起病突然、脑缺氧**等一系列表现为主。
- 大的动脉栓塞可出现**急性右心衰竭**的症状，甚至**突然死亡**。

体循环的各种栓子脱落阻塞肺动脉及其分支引起肺循环障碍的临床病理生理综合征

基于P_Mask_RCNN的肺栓塞检测

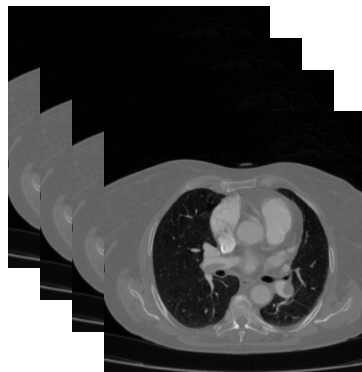
传统的肺栓塞检测手段



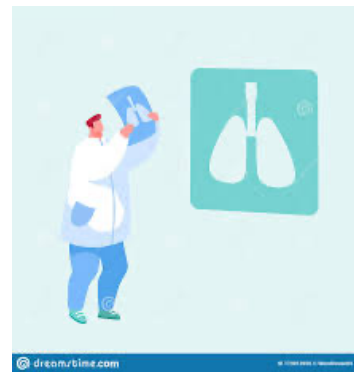
肺栓塞病例



CT扫描仪扫描



获得肺部切片序列



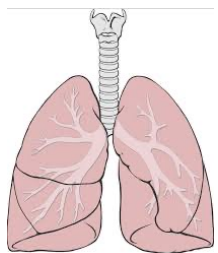
医生逐帧观察

存在的不足：

1. 对每一个病人，医生都需要观察上百张CT图像，时间成本较高。
2. 存在较高的漏诊率和误诊率。

基于P_Mask_RCNN的肺栓塞检测

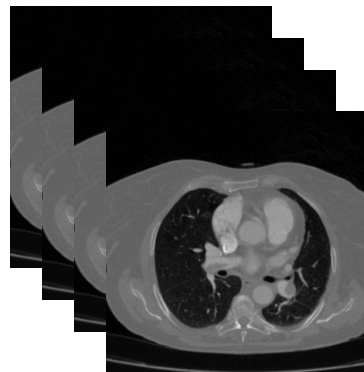
计算机辅助检测肺栓塞



肺栓塞病例



CT扫描仪扫描



获得肺部切片序列



计算机辅助诊断系统
(P_Mask_RCNN)



辅助诊断结果



医生确认检测结果

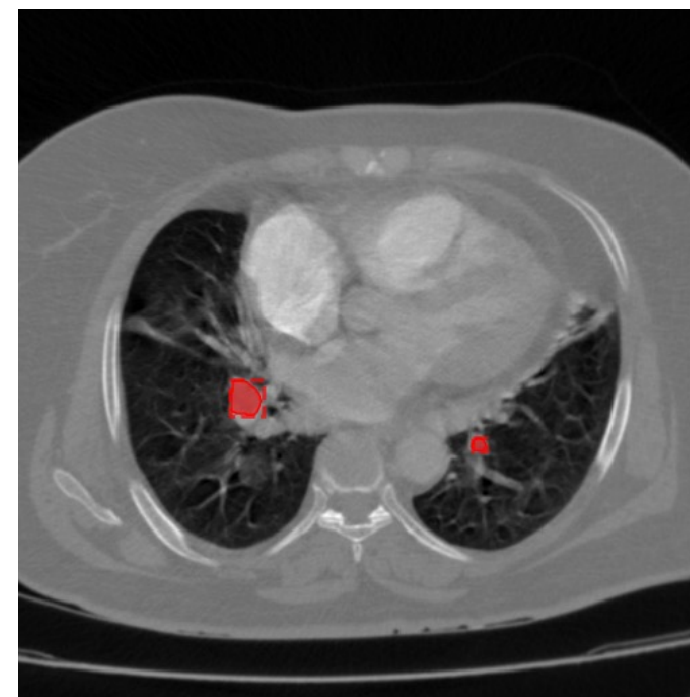
辅助诊断的优势：

1. 将医生从繁重，重复的工作中解放出来。
2. 辅助诊断可以发现一些肉眼难以确认的栓塞。
3. 提高检测的精确率和召回率。

基于P_Mask_RCNN的肺栓塞检测

肺栓塞检测的难点

- 低剂量造影剂使得CT图像噪音较高，图像质量差。
- 栓塞体积小，属于小目标。检测难度大。



图像模糊，栓塞体积小，属于小目标。

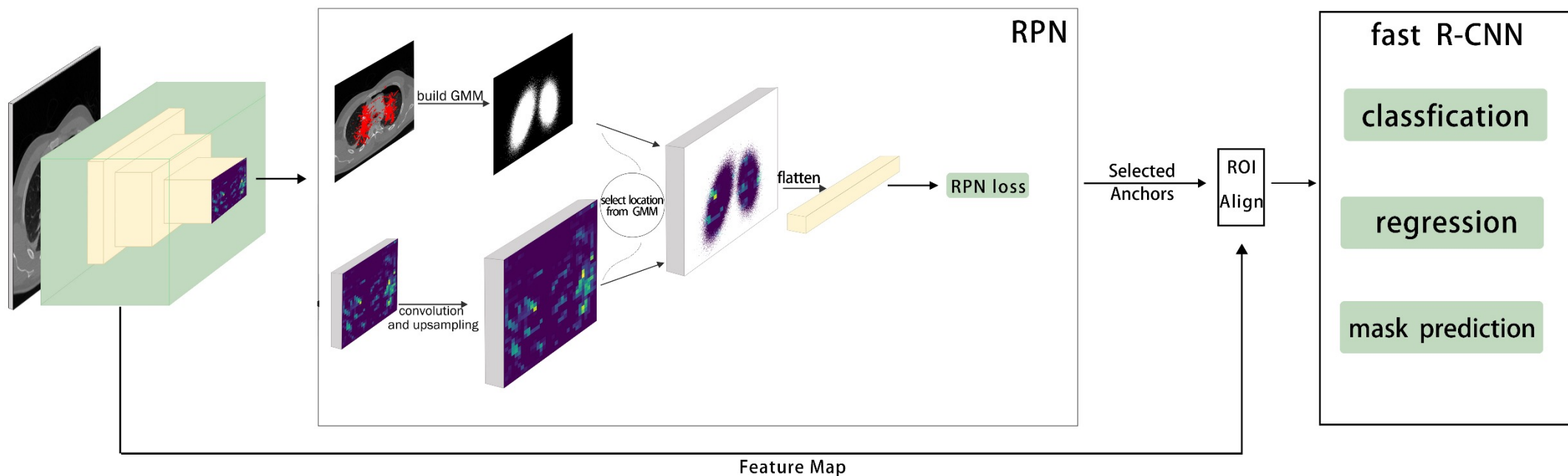
基于P_Mask_RCNN的肺栓塞检测

P_Mask_RCNN检测小目标的针对性手段

- **放大特征图，丰富小目标的特征，同时便于设置更精准的候选框。**
- **基于概率的候选框提取方法缩小检测范围，缩短检测时间。**

基于P_Mask_RCNN的肺栓塞检测

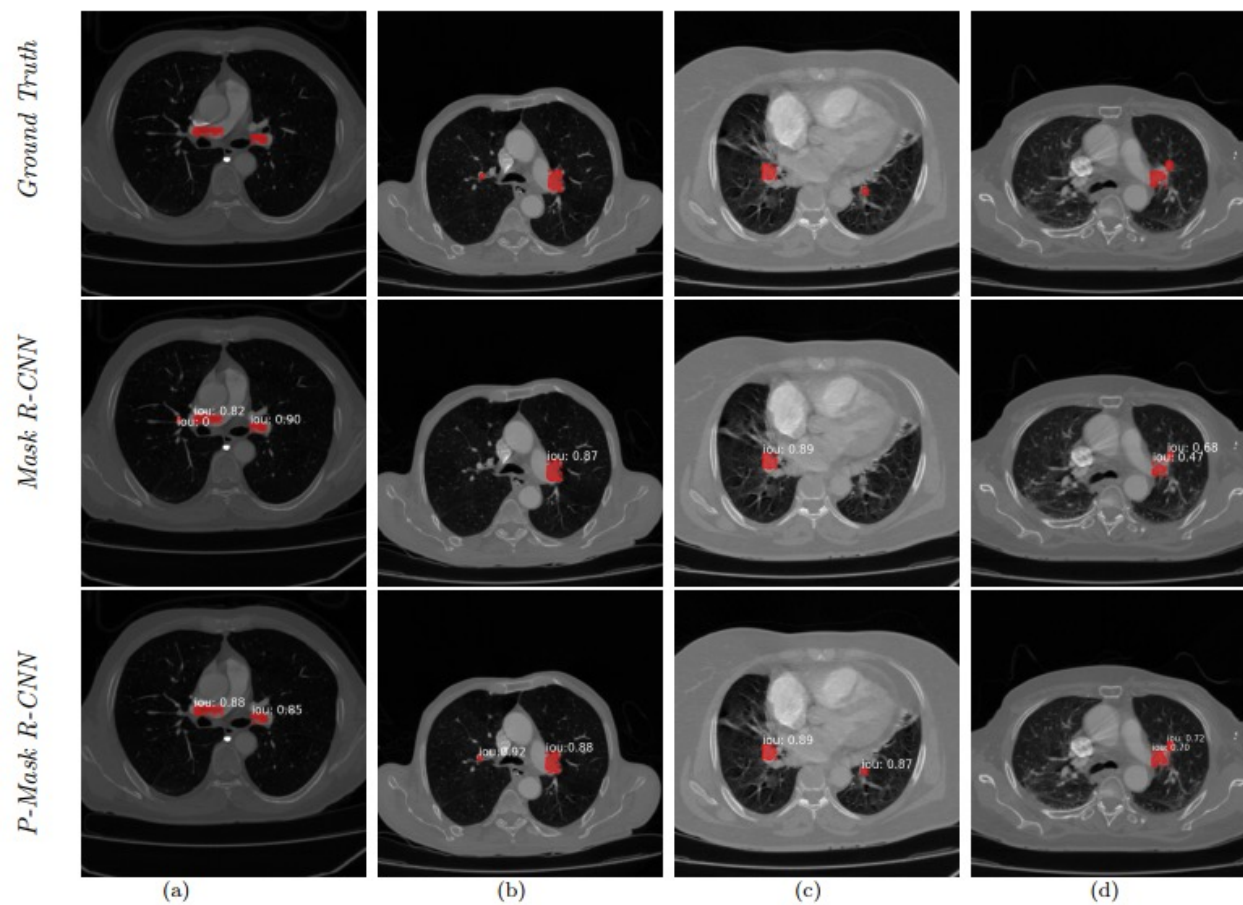
P_Mask_RCNN模型



基于P_Mask_RCNN的肺栓塞检测

实验结果对比

method	backbone	AP	AP_{50}	AP_{75}	DSC	T(h)
FCIS [32]	resnet-101	22.7	64.1	7.8	51.4	8.8
FCIS+++ [32]	resnet-101	23.1	64.3	7.8	51.9	9.0
Mask R-CNN [7]	resnet-50	19.9	45.3	14.6	47.9	4.3
Mask R-CNN	resnet-50-FPN	31.0	72.1	22.1	61.7	5.0
Mask R-CNN	resnet-101-FPN	37.5	77.4	33.2	69.8	6.2
MS R-CNN [33]	resnet-50-FPN	36.8	78.5	28.9	68.9	5.0
MS R-CNN	resnet-101-FPN	37.2	78.8	30.1	69.4	6.2
P-Mask RCNN	resnet-50-FPN	38.6	78.3	36.5	71.1	6.0
P-Mask RCNN	resnet-101-FPN	41.5	80.9	39.5	74.7	6.9



基于P_Mask_RCNN的肺栓塞检测

Probability-based Mask R-CNN for pulmonary embolism detection

Kun Long*, Lei Tang*, Xiaorong Pu**, Yazhou Ren^{ab}, Mingxin Zheng*, Li Gao^d, Chunjing Song*, Su Han^f, Min Zhou^f, Fengbin Deng*

*Medical Big Data Institute, SMILE Lab, School of Computer Science and Engineering,

University of Electronic Science and Technology of China, Chengdu 611731, China

^bInstitute of Electronic and Information Engineering of UESTC in Guangdong, Dongguan 523808, China

^cSchool of Computer Science and Technology, Southwest University for Nationalities, Chengdu 610041, China

^dChengdu Third People's Hospital, Chengdu 610060, China

^eChengdu Sixth People's Hospital, Chengdu 610051, China

^fWest China School of Public Health and West China Fourth Hospital, Sichuan University, Chengdu 610041, China

^gChongqing General Hospital, University of Chinese Academy of Science, Chongqing 400010, China

Abstract

Pulmonary embolism (PE), a blockage of the lung artery, is common and sometimes fatal. Early diagnosis and treatment of PE can reduce the risk of associated morbidity and mortality. However, it is a huge challenge to accurately detect PE, particularly for the case of small segmental and subsegmental emboli. In this paper, a flexible probability-based Mask R-CNN model, namely P-Mask RCNN, is proposed for PE detection. Specifically, the feature map is firstly upsampled to enrich the local details of the small objects and to extract anchors at a higher density. Then, a candidate area is constructed based on the appearance of PE. Finally, we extract the anchors in the candidate area of the enlarged feature map for subsequent detection. Extracting anchors in the candidate area instead of the entire image can not only reduce both time and space consumption caused by the enlarging feature maps but also improve the detection performance by eliminating most invalid anchors. Compared with Mask R-CNN, the anchors extracted by the proposed P-Mask RCNN is closer to the ground truth. Extensive experimental results demonstrate the effectiveness and efficiency of the proposed approach. The source code of our method is available at https://github.com/longkun-uestc/P_Mask_RCNN.

Keywords: small object detection, pulmonary embolism, medical image, deep learning

1. Introduction

Pulmonary embolism (PE) refers to the situation that a portion of a blood clot remains in the pulmonary artery (Fig. 1), which ranks as the third most common cardiovascular disease. The small blood clots in the pulmonary arteries will block blood flow to lung, which can lead to insufficient oxygen supply to vital organs [1]. Early detection and treatment of PE could effectively decrease the mortality rate. Computed tomography pulmonary angiography (CTPA) has become one of the main methods for diagnosing PE today [2] since manual diagnosis of PE is a time-consuming and laborious task where the current best radiologists have a range of 6-23% misdiagnosis rate [3]. Computer-aided detection methods have been developed for aiding the radiologists in PE detection automatically. However, the traditional automatic PE detection methods [4, 5, 6, 7] could not perform successfully since the area of many PE lesions is generally with small size and irregular shape.

In recent years, Mask R-CNN [8], a kind of deep neural network framework, has been developed for object detection and instance segmentation. Anantharajan et al. [9] applied Mask R-CNN for the detection and segmentation of oral diseases. Johnson [10] demonstrated that Mask R-CNN can efficiently and automatically segment microscope images of various nuclei. Mask R-CNN performs well in both large and medium objects detection and segmentation, while it underperforms with small objects [10].

Small object detection can usually be addressed by enlarging feature maps of original images. Eggert et al. [11] proposed an upsampling-based anchor generation scheme using the high-resolution feature map of small objects. Mao et al. [12] designed a codec framework with symmetric convolutional deconvolution layer, which could improve the resolution of the feature map to make it better perform on small object detection. These approaches improve detection accuracy by changing the network structure to retain the information of small objects as much as possible. However, the anchor extraction strategy has a significant influence on the detection performance of small objects. Many anchor boxes with multiple scales and aspect ratios are generally designed mainly on the entire image to

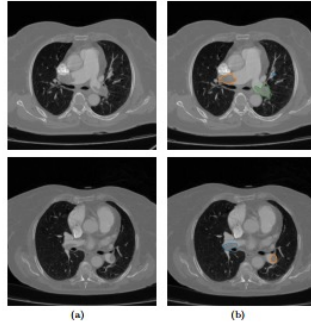


Figure 1: Pulmonary embolism. (a) The first column shows the original CTPA images. (b) The second column shows the images with marked lesions.

match objects with various aspect ratios and spatial layout [13]. Due to the limited size of the feature map, few suitable anchors match small objects. Magnifying feature maps can alleviate the issue, but it will increase both time and space consumption. In most cases, anchors are extracted on the entire image with equal strides. Thus, a large number of invalid anchors are probably generated, which will decrease the final detection performance. Most anchor extraction methods imply a hypothesis that the probability of objects appearing on an image is subject to a uniform distribution, as investigated in [14].

Clinical diagnosis based on the medical image has shown the area prone to lesions is usually a small part of the entire image. For example, in clinical coronary artery calcification quantification, calcified areas generally distribute a narrow area around the coronary artery [15]. In breast cancer examination, the diseased tissue always appears in the internal area of the breast in the image [16]. On detection of PE, most plaques in CTPAs appeared on the left or right pulmonary artery, as well as its branches. Based on the clinical medical prior knowledge, it is reasonable to take into consideration the probability of lesion's appearance at various positions in the medical image. Specifically, we construct a candidate area for the original image based on probability and then extract anchors in the corresponding candidate area of the enlarged feature map for subsequent detection and segmentation. The proposed model, namely probability-based Mask R-CNN (P-Mask RCNN), can improve small PE object detection precision without increasing time and space over-

head.

The major contributions of our work are three-fold:

- We propose that the probability distribution characteristics of lesions is a kind of significant factor to narrow the scope of detection and thus improve detection accuracy for medical image processing.
- A new framework for small object detection in the medical image is proposed. The performance of small object detection can be improved significantly by combining the probability-based anchor extraction strategy with appropriate feature map upsampling.
- Our approach upgrades the AP, AP50 and AP75 from 37.55%, 77.39% and 33.21% to 41.87%, 81.55% and 41.43%, respectively, on small PE object detection task, compared with that of Mask R-CNN.

2. Related Work

PE Detection: Computer-aided detection (CAD) plays an important role in detecting PE. Boumas et al. [17] proposed to compute circularity of the bright lumen and isophote curvature as region-level features for false-positive removal. Masutani et al. [17] detected PE regions by extracting handcrafted features based on CT values, local contrast, and the second derivatives of voxels. However, limited by the representation ability of handcrafted features, these traditional methods were apt to suffer from a high false detection rate. To address this issue, Tajbaksh et al. [18], studying the feasibility that two-dimensional Convolutional Neural Network (CNN) features eliminate false positives in PE detection, proposed a CNN based method for PE detection, and achieved higher performance than some traditional CAD methods. Huang et al. [19] applied 3D CNN for detecting PE in low dose computed tomography. These methods significantly outperformed similar hybrid systems with conventional shallow learning.

Small Object Detection: Enhancing details of small objects is a common idea for small object detection, such as enlarging the original image or feature map [20, 21], selecting a suitable anchor size [22], and increasing the proportion of small objects in the dataset [10, 23]. Liu et al. [24] proposed a network linking feature maps of different depth layers to improve the performance of small-scale object detection without sacrificing large-scale object detection performance. Eggert et al. [11] investigated the influence of feature map resolution on the performance of object detection with Faster R-CNN [25]. Krishna and Jawahar [22] formulated finding the appropriate sizes of anchor boxes mathematically to match small objects. Kisanal et al. [10] suggested oversampling images with small objects and enhancing each image by copying and pasting small objects multiple times to balance the detector's sensitivity between large and small objects.

3. Data Description

Our research includes 35 patients with pulmonary embolism between the age of 24 and 82. Each patient underwent a chest CT examination with the slice-thickness $\leq 1\text{mm}$ and slice-interval $\leq 1.5\text{mm}$. A total of 8,792 CTPA images with a size of 512×512 pixels were obtained, 2,304 of which contained lesion areas with 3781 PE regions of interest (PE-ROIs) altogether. More than 85% of these PE-ROIs are small objects with the square root of the area ≤ 32 pixels which only occupy on average 0.3% of the image area. Fig. 2 describes the size of PE-ROIs. Besides, the positional distribution of PE-ROIs on the image is also regularly searchable. Most PE-ROIs are distributed on the left or right sides of the image's central axis (the location of the left, right pulmonary arteries and their branches). Due to differences in body fat and thinness of different patients, postures during CT scan, and various random factors during scanning, all PE-ROIs present two 2-dimensional Gaussian distributions on the left and right sides of the image (Fig. 3(a)). The dataset in our research is publicly available [26], and can be downloaded from https://figshare.com/authors/Mojtaba_Masoudi/5215238.

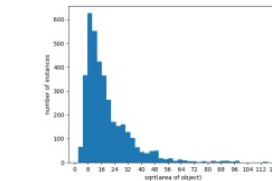


Figure 2: Size distribution in the dataset. Most PE-ROIs are too small to be detected.

4. Our Approach

Every pixel of the feature map in Mask R-CNN would generate 3 anchors with different aspect ratios, which is equivalent to anchor extraction performed on every $w_{\text{image}}/w_{\text{feature}}$ pixels (defined as sampling stride) within the original image, where w_{image} is the width of the input image and w_{feature} is the width of the feature map.

However, the anchor extraction strategy has two shortcomings: First, the sampling stride is limited by the size of the feature map so that most ground truths cannot have exactly matching anchors due to their extremely small size. Second, extracting anchors at even intervals on the entire

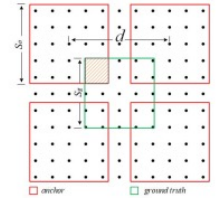


Figure 3: The minimum value of the IoU is obtained only when ground truth is in the middle of the 4 adjacent anchors.

image does not take into account the fact that the target has a different probability of occurrence at each position in the image.

4.1. Sampling stride analysis and upsampling

In the Region Proposal Network (RPN) [25] module of Mask R-CNN, an anchor is considered as a positive anchor if it has the highest intersection-over-union (IoU) with the ground truth or the IoU between the anchor and ground truth is greater than threshold t (In Mask R-CNN, $t=0.7$). Otherwise, it is a negative anchor (also named invalid anchor). Positive anchors will participate in the loss calculation. However, with the default sampling stride of Mask R-CNN, only 1.97 anchors per image are positive, and 10.41% of them have an IoU value larger than 0.7 (Table 1). This indicates that the number of positive anchors is quite small and the quality is poor. To obtain more positive anchors, the sampling stride should be adjusted.

Consider the case where both anchor and ground truth are square (Fig. 3). Let the side length of the anchor be S_a and the side length of the ground truth be S_g . To make the IoU value of the anchor and ground truth greater than the threshold t , the sampling stride d should satisfy:

$$\frac{(S_a + S_g - d)^2/4}{S_a^2 + S_g^2 - (S_a + S_g - d)^2/4} \geq t \quad (1)$$

In Eq. (1), the minimum value of the left side of the inequality is obtained only when ground truth is in the middle of the 4 adjacent anchors. Moving ground truth in any direction will increase the value of IoU. The same relationship holds for non-quadratic anchors – provided the aspect ratio of ground truth boxes and anchor boxes match [11].

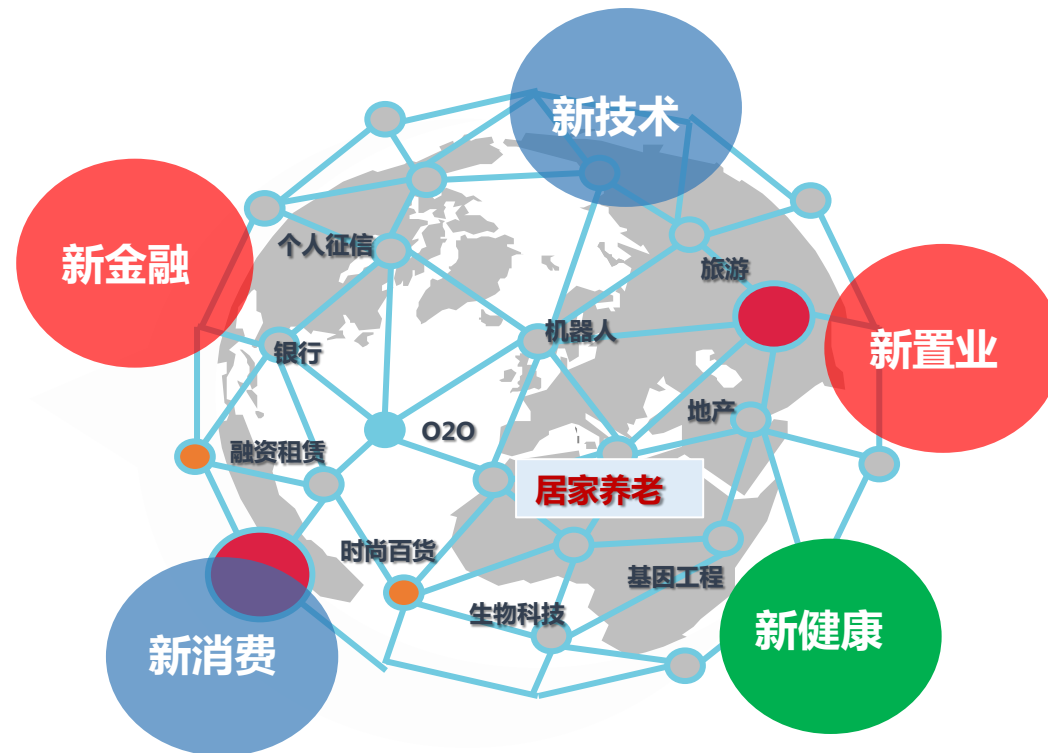
However, we found that the vast majority of positive anchors and ground truths do not satisfy Eq. (1). Thus, the sampling stride should be reduced, which is implemented by upsampling the feature map. The relationship

*Corresponding author
Email address: puiaor@uestc.edu.cn (Xiaorong Pu)

K Long, L Tang, X Pu*, Y Ren, M Zheng, L Gao, C Song, S Han, M Zhou, F Deng. Probability-based Mask R-CNN for pulmonary embolism detection. Neurocomputing, 2021.

目录

- √ 面向临床的医学图像深度降噪
- √ 空气污染与儿童呼吸系统疾病关联性分析
- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ **5G+医疗健康应用试点**
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目



- 国务院《新一代人工智能发展规划》，科技部《“十三五”卫生与健康科技创新专项规划》
 - AI+ 医疗加速融合，**万亿级的大健康产业**即将出现
- 近年来，超过90%的医院成功转用电子系统，**AI+医疗方兴未艾**
- 《新一代人工智能发展规划》的六个重点任务、九个重点产业
 - 制造、农业、物流、金融、商务、家居、教育、医疗、健康和养老
 - 其中，**医疗、健康和养老**属于大健康产业，制造、物流、金融、商务等与大健康产业息息相关。



联合申报项目：工业和信息化部、国家卫生健康委员会
5G+健康管理

基于5G通信的神经系统慢性疾病远程诊疗、照护和管理体系研发及示范项目

项目目标：

- 拟建立一个覆盖成都市、四川省范围，基于5G通信技术支持的**神经系统慢性疾病**远程诊疗、照护和管理系统
- 可应用于各级医疗机构、老龄康养机构、社区、家庭神经系统慢性疾病的远程诊疗、照护管理及健康管理。
- 改善因地域交通环境、经济发展水平、民众健康意识缺乏等诸多因素造成的看病难、看病贵、优质医疗资源配比不平衡、医疗资源应用不合理等卫生健康领域的突出问题。
- 使处于基层及偏远地区的患者得到及时有效的治疗和指导，提高患者及其家庭就医需求的满意度，减轻家庭及社会医疗的经济负担，减少医疗资源的不合理应用。



联合申报项目：工业和信息化部、国家卫生健康委员会
5G+健康管理

基于5G通信的神经系统慢性疾病远程诊疗、照护和管理体系研发及示范项目

5G+健康管理试点小镇方案

宝山集团试点总体目标：

- 旅游景区及民宿居住区域**5G全覆盖**，景区内居家人群及旅游人群**健康管理全覆盖**（预计年覆盖人群100万人以上）、实施远程健康管理、健康监测、神经慢性疾病远程诊疗、咨询、建设远程家庭病房、实现双向转诊全服务。
- 实现**5G+智慧康养产业**、**5G+智慧乡村旅游**，全面提升康养度假健康保障、提升乡村旅游品质，提升旅游观光人群及居家养老人群优质享受体验感。

基于 5G 通信的神经系统慢性疾病远程诊疗、照护 和管理体系研发及示范项目

➢ 电子科大负责人：**蒲晓蓉**

目录

- √ 面向临床的医学图像深度降噪
- √ 空气污染与儿童呼吸系统疾病关联性分析
- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ 5G+医疗健康应用试点
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目



医院开展灾害脆弱性研究的意义

➤ 风险隐患多：

来院人员复杂、流动性大、建筑密集且数量多、管道、线路密集、易燃易爆物品多……

➤ 应对和控制风险提供科学依据

➤ 不断增强软实力，进一步提高医院管理水平

脆弱性分析与评价在突发灾害性事件的预警及

处理中具有十分重要的作用！



本课题研究目的

- ◆ 通过对医院受到多种潜在灾害影响的可能性以及医院对灾害的承受能力，进行相关因素分析，帮助医院找准风险点及薄弱环节。
- ◆ 结合医院实际情况，通过循证制定策略与管理软件工具、采取必要的防范措施，对医院进行危机管理，努力将灾害带来的不良影响及损失降到最低限度，保证医院正常运转



数据采集模块

四川大学华西医院风险评估表

风险事件	风险性评估													应急准备程度									风险 优先 级	
	发生的 可能性				后果的严重性									风险 积分	需要准备						准备 积分			
					人员伤亡			财产损失			服务/声誉 影响				内部反应			外部支援				准备完毕		
	高	中	低	无	高	中	低	高	中	低	高	中	低	高	中	低	高	中	低	高	中	低		
3	2	1	0	3	2	1	3	2	1	3	2	1	3	2	1	3	2	1	3	2	1			
一、 公共卫 生事件	1. 突发公共卫生事件																							
	群体性不明原因的疾病																							
	重大传染病疫情																							
	重大食物中毒事件																							
	重大职业中毒事件																							
二、 社会安 全事件	传染病菌种或毒种丢失																							
	2. 医疗工作场所暴力事件																							
	3. 医院群体踩踏伤害事件																							
	4. 医学生、进修生意外事故																							
	5. 暴力抢劫财务室事件																							
	6. 爆炸事件																							
	7. 医疗不良事件																							
	医院感染事件																							
	(特殊)药品突发安全危害事件																							
	医疗器械突发群体不良事件																							
	8. 职业暴露事件																							
	9. 医疗紧急救援																							
	三、 事故灾难	10. 科实验室危险化学品药品事件																						
11. 放射性药品、设施安全危害事件																								
12. 生物实验室安全危害事件																								
13. 后勤、基建突发事件																								
供气(汽)故障																								
供电故障																								
供水故障																								
电梯意外事件(坠梯、锁闭)																								

人工填写



脆弱性分析 填报系统

四川大学
华西医院
WEST CHINA HOSPITAL
SICHUAN UNIVERSITY
1892

账号:
请输入电话号码

密码:
请输入密码

忘记密码 没有账号? 去注册>>

登录

线上采集

问卷中心

进行中

四川大学华西医院脆弱性分析评分表 待完成

时间: 2020-11-13至2020-12-31

四川大学华西医院应对重大新发呼吸道急性传染病的脆弱性分析评分表 已通过

时间: 2020-11-12至2020-11-14

已结束

四川大学华西医院脆弱性分析评分表 已通过

时间: 2020-11-11至2020-11-14

四川大学华西医院脆弱性分析评分表 已通过

时间: 2020-11-11至2020-11-15

四川大学华西医院脆弱性分析评分表 已通过

时间: 2020-11-11至2020-11-16

问卷中心 个人中心



数据采集模块

问卷填写

四川大学华西医院脆弱性分析评分表

感谢您能来参与本次评估，现在让我们开始吧！

一、内部：与技术相关类

离开暂存

1.1、供水短缺或中断：

既往应对的情况（既往针对风险所开展应对的情况）

不适用	低
中	高

可能性（将来发生的可能性）

不适用	低
中	高

人群影响（死亡或受伤的可能性）

不适用	低
中	高

财物影响（财物损失或损伤）

不适用	低
中	高

vConsole

问卷填写

1.23、舆情不良事件：

既往应对的情况（既往针对风险所开展应对的情况）

不适用	低
中	高

可能性（将来发生的可能性）

不适用	低
中	高

人群影响（死亡或受伤的可能性）

不适用	低
中	高

财物影响（财物损失或损伤）

不适用	低
中	高

日常运行影响（医疗服务终止）

不适用	低
中	高

vConsole

问卷填写

提交成功

问卷已提交，
后续请注意审核情况

四川大学华西医院-医院管理研究所
Fri Nov 13 2020 21:21:02 GMT+0800 (CST)

vConsole

线上采集流程

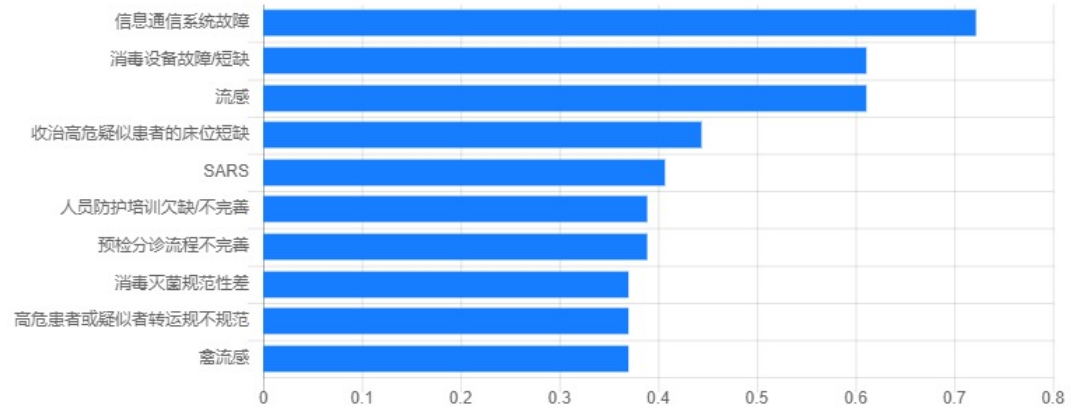


数据统计模块

统计结果预览

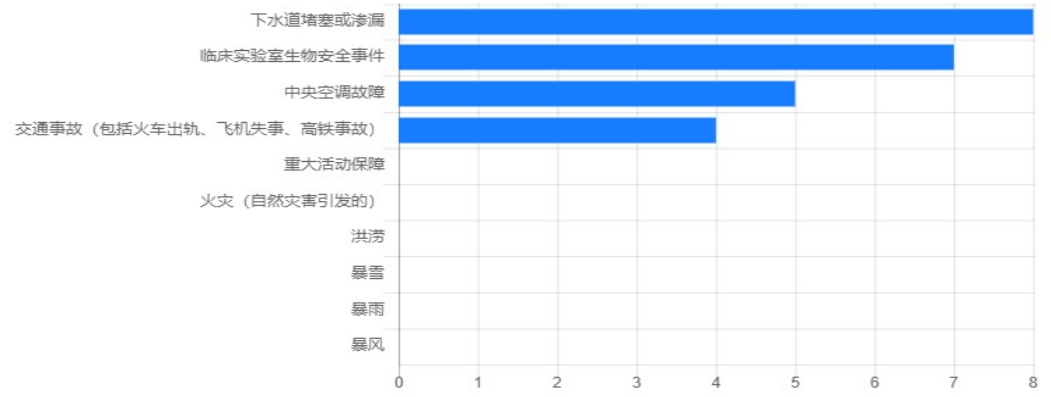
结果预览

序号	风险源	相对风险值
1	信息通信系统故障	0.722
2	消毒设备故障/短缺	0.611
3	流感	0.611
4	收治高危疑似患者的床位短缺	0.444
5	SARS	0.407
6	人员防护培训欠缺/不完善	0.389
7	预检分诊流程不完善	0.389
8	消毒灭菌规范性差	0.37
9	高危患者或疑似者转运不规范	0.37



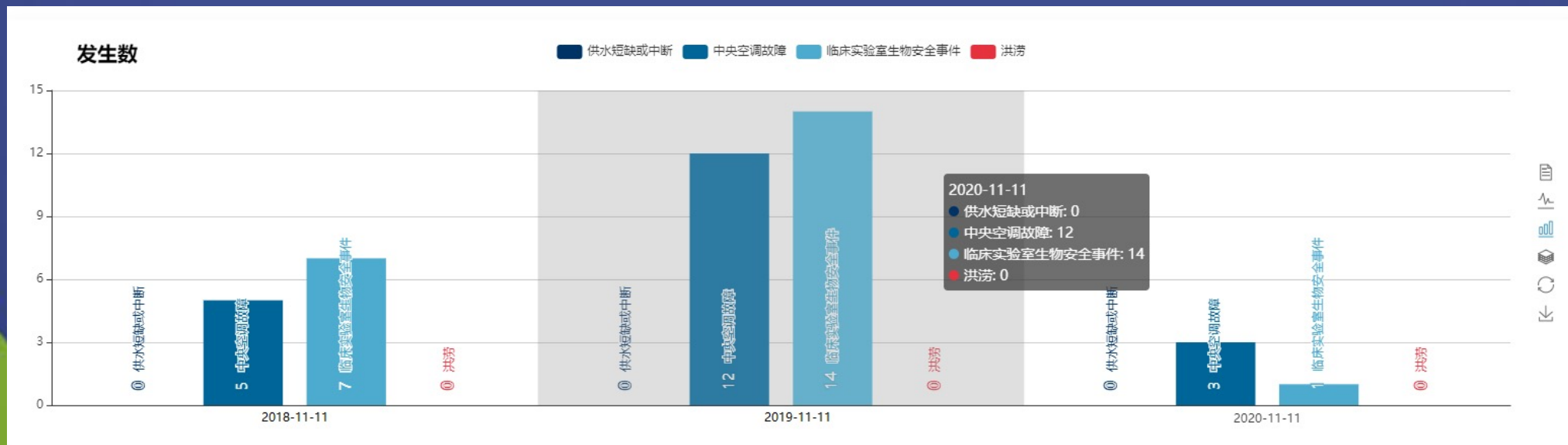
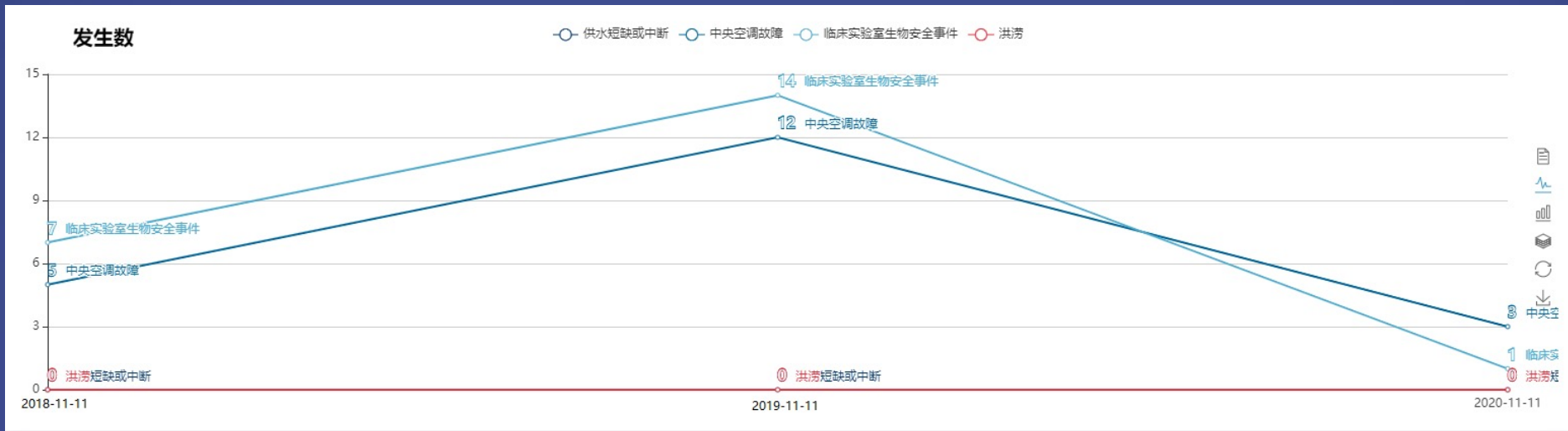
发生数

序号	风险源	发生数
1	下水道堵塞或渗漏	8
2	临床实验室生物安全事件	7
3	中央空调故障	5
4	交通事故 (包括火车出轨、飞机失事、高铁事故)	4
5	重大活动保障	0
6	火灾 (自然灾害引发的)	0
7	洪涝	0
8	暴雪	0
9	暴雨	0
10	暴风	0





结果分析展示模块



近三年某风险源（发生数）
结果对比

目录

- √ 基于机器学习的急诊患者死亡率预测
- √ 基于P_Mask_RCNN的肺栓塞检测
- √ 5G+医疗健康应用试点
- √ 医院灾害脆弱性分析系统
- √ 其他AI+医疗项目

其他AI+医疗项目

- 01/2022~12/2023 全程化多维度肿瘤放射外科精准诊疗体系的构建与实践研究
四川省重点研发计划(重大科技专项), 80万, 电子科大负责人: 任亚洲
- 07/2021~06/2023 基于临床病理学及放射组学的结直肠癌患者腹膜转移智能诊断研究
电子科技大学医工交叉联合基金, 10万, 在研, 负责人: 任亚洲
- 04/2021~03/2023 基于植物状态患者面部表情的意识智能评估研究
四川省重点研发项目, 20万, 在研, 负责人: 任亚洲
- 01/2020~12/2021 全身核素骨扫描图像自动分析与报告生成
四川省重点研发项目, 20万, 在研, 负责人: 蒲晓蓉
- 01/2017~12/2018 自步学习理论及其在阿兹海默病症诊断中的应用研究
中央高校基本科研业务费, 9万, 已结题, 负责人: 任亚洲
- 01/2017~10/2021 针对阿兹海默病症的多任务自步学习算法研究
中国博士后科学基金第60批面上资助, 5万, 已结题, 负责人: 任亚洲

骨扫描诊断分类·团体标准

ICS 11.020
CCS 61

团 体 标 准

T/SHIA 010—2021

TC-99m MDP 骨扫描结构式报告诊断分类

Structural report and diagnostic classification for Tc-99m MDP
Scintigraphy

2021-12-10 发布

2022-02-10 实施

四川省卫生信息学会 发布

T/SHIA X—2021

前 言

本标准按照 GB/T1.1-2020 给出的规则起草。

本标准由四川大学华西医院和电子科技大学共同提出。

本标准由四川省卫生信息学会提出并归口。

本标准的主要起草单位：四川大学华西医院、电子科技大学、四川省卫生信息学会、四川省卫生和计划生育信息中心。

本标准的主要起草人员：唐恭顺、蒲晓蓉、林晓东。

Tutors

puxiaor@uestc.edu.cn



Xiaorong Pu

蒲晓蓉 电子科技大学

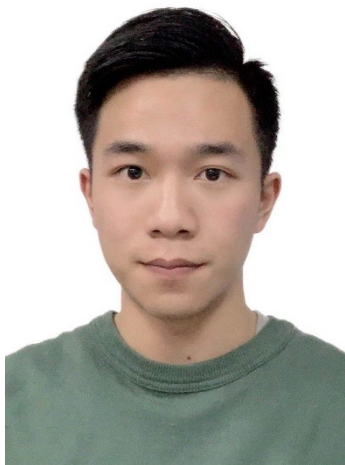


Yazhou Ren

任亚洲 电子科技大学

yazhou.ren@uestc.edu.cn

Students



Kecheng Chen



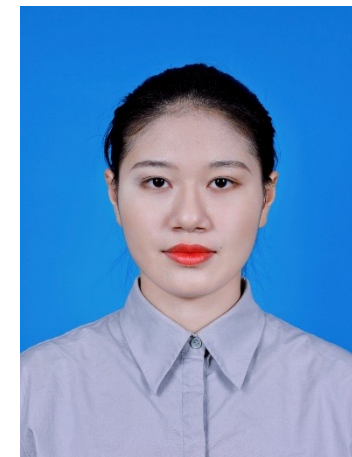
Yue Zhao



Jixiang Luo



Yuxin Zhang



Jiaxin Huang

电子科技大学

Thanks !