

基于人工智能技术的颞叶癫痫

¹⁸F-FDG PET/MRI 多模态影像研究

博士论文答辩

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绪论

第一章 基于孪生神经网络的颞叶癫痫术前定位研究

第二章 基于深度残差网络的颞叶癫痫术后复发预测研究

总结与展望

绪论

引言 I

1.1 癫痫影像学研究背景

引言 II

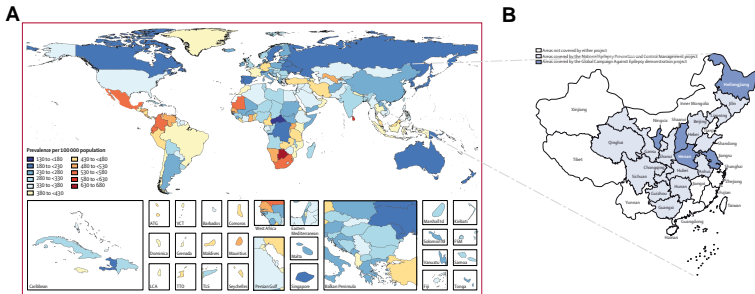


图 1: 图 1 (A) 2016 年全球特发性癫痫的年龄标准化流行率地图和 (B) 中国国家癫痫预防和控制管理项目覆盖的农村地区

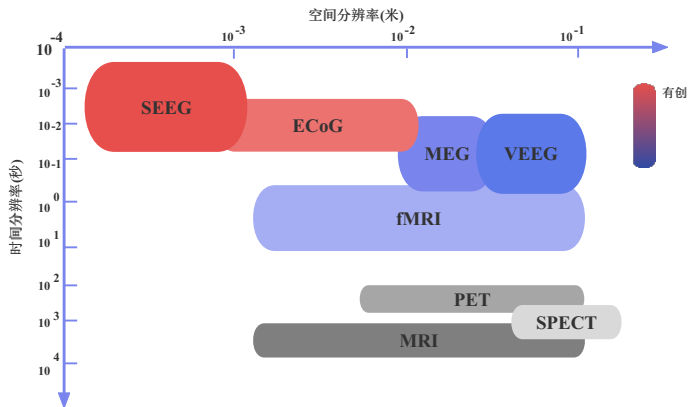


图 2: 图 2 癫痫疾病不同影像检查技术时空分辨率比较

1.2 人工智能概述

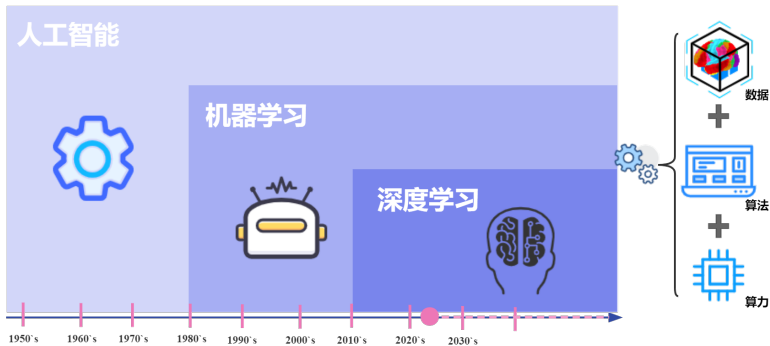


图 3: 人工智能技术简介及发展历程

1.3 研究目的

- 旨在对癫痫影像学与人工智能领域研究进行系统综述和趋势展望，
- 拟将文献计量分析方法应用于癫痫影像学与人工智能的研究中，
- 探讨当前的研究动态及热点，挖掘分析尚需改进的内容，
- 对癫痫影像学与人工智能研究领域的探索提供理论依据，确定研究方向及目标。

2 文献计量分析

2.1 数据来源

实验结果

表 1: WoSCC 数据库检索流程及结果

步骤	结果	定义
# 1	132,750	TS = (“Epileps*”) Timespan:2000-01-01 to 2023-03-01
# 2 Timespan:2000-01-01 to 2023-03-01	592,310	TS = (“PET” or “PET/MR*” or “MRI” or “neuroimaging”)
# 3	534,113	TS = (“machine learning” or “deep learning” or “deep neural networks” or
# 4	240	#3 AND #2 AND #1
# 5	168	#3 AND #2 AND #1 and Article (文献类型) and English (语言)

步骤	结果	定义
# 1	132,750	“Epileps*” Timespan:2000-01-01 to 2023-03-01
# 2	592,310	“PET” or “PET/MR*” or “MRI” or “neuroimaging” Timespan:2000-01-01 to 2023-03-01
# 3	534,110	“machine learning” or “deep learning” or “deep neural networks” or “convolutional neural networks” or “artificial intelligence”) Timespan:2000-01-01 to 2023-03-01
# 4	240	#3 AND #2 AND #1
# 5	168	#3 AND #2 AND #1 and Article (文献类型) and English (语言)

讨论及小结

论文研究内容及组织结构

第一章 基于孪生神经网络的颞叶癫痫术前定位研究

引言

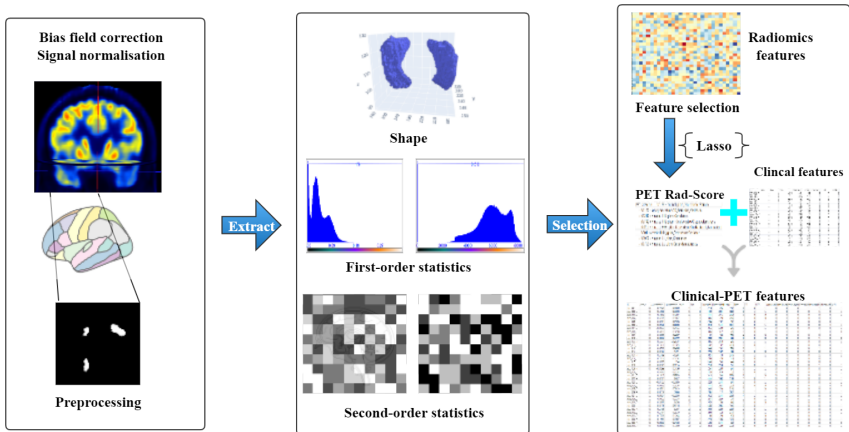


图 4: PET Radiomics Score and Clinical-PET Features

绪论

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第一章

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第二章

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总结

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材料与方法

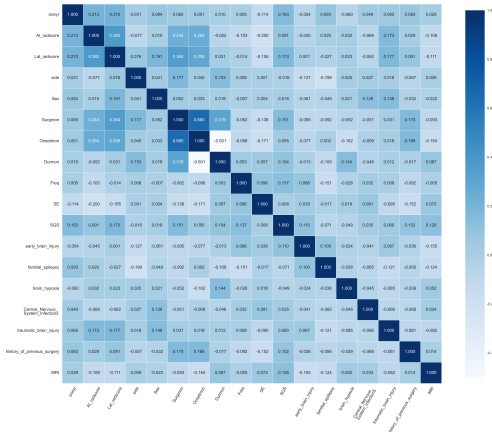


图 5: Heatmap of Clinical-PET Features

讨论

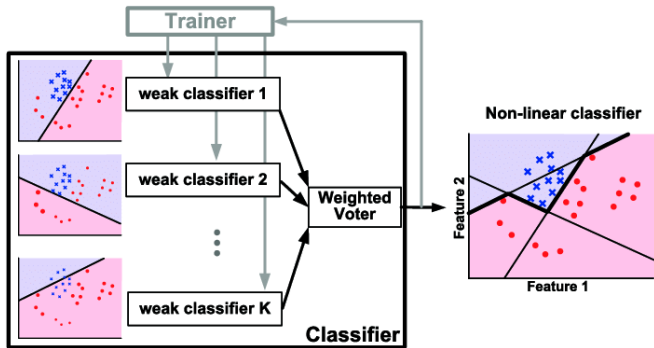


图 6: Illustration of AdaBoost Algorithm

- `AdaBoostClassifier(algorithm='SAMME',
base_estimator=None, learning_rate=0.2,
n_estimators=230, random_state=123)`

小结

Table 2: K-folds Cross-validation of the Selected AdaBoost

Tuned_Ada	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	APC
1	0.882	0.733	0.000	0.000	0.000	0.000	0.000	0.361
2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3	0.824	0.550	0.000	0.000	0.000	-0.085	-0.091	0.183
4	0.875	0.893	0.000	0.000	0.000	0.000	0.000	0.500
5	0.938	0.929	0.500	1.000	0.667	0.636	0.683	0.750
6	0.938	0.964	0.500	1.000	0.667	0.636	0.683	0.833
7	0.875	0.554	0.000	0.000	0.000	0.000	0.000	0.321
8	0.938	0.964	0.500	1.000	0.667	0.636	0.683	0.833
9	0.938	1.000	0.500	1.000	0.667	0.636	0.683	1.000
10	0.938	0.679	0.500	1.000	0.667	0.636	0.683	0.591
Mean	0.914	0.827	0.350	0.600	0.433	0.410	0.432	0.637
Std	0.047	0.172	0.320	0.490	0.367	0.368	0.384	0.200

第二章 基于深度残差网络的颞叶癫痫术后复发预测研究

引言

Weight Feature	
0.0394 ± 0.0329	AI_radscore
0.0197 ± 0.0138	Lat_radscore
0.0085 ± 0.0138	Durmon
0.0085 ± 0.0138	SGS
0.0028 ± 0.0113	Onsetmon
0 ± 0.0000	Freq
0 ± 0.0000	side
0 ± 0.0000	Sex
0 ± 0.0000	MRI
0 ± 0.0000	history_of_previous_surgery
0 ± 0.0000	early_brain_injury
0 ± 0.0000	familial_epilepsy
0 ± 0.0000	brain_hypoxia
0 ± 0.0000	Central_Nervous_System_Infections
0 ± 0.0000	traumatic_brain_injury
0 ± 0.0000	SE
-0.0028 ± 0.0113	Surgmon

图 7: Permutation Importance of AdaBoost

材料与方法

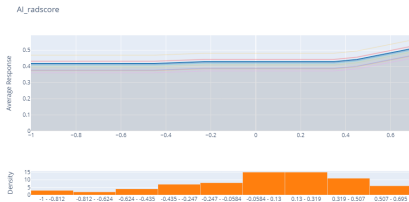
PDP plots:

材料与方法

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PDP plots:



PDP plots:



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讨论

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- Metabolic radiomics are helpful to predict the postsurgical seizure outcomes;

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- Metabolic radiomics are helpful to predict the postsurgical seizure outcomes;
- Combination of PET Radiomics and Clinical Features are more robust;
- IML technique can further deepen the understanding of the principle of ML models and the decision-making process for professional and intuitive interpretation

研究领域展望

- More data, especially external validation cohort;

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- Fusion of PET/MRI multimodal imaging;

研究领域展望

- More data, especially external validation cohort;
- Fusion of PET/MRI multimodal imaging;
- Other subtypes of drug-resistant epilepsy

For more theoretical approaches to machine learning model explanation, see [Interpretable Machine Learning: A Guide for Making Black Box Models Explainable](#), refer to (Beghi et al., 2019), (Rajpurkar, 2021), (Marc Becker, 2022), (Molnar, 2022).

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THANKS!

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Molnar, C. (2022). *Interpretable Machine Learning*. 2 edition.

Rajpurkar, P. S. (2021). *Deep Learning for Medical Image Interpretation*. Stanford University.