基于人工智能技术在颞叶癫痫 ^{18}F-FDG PET/MRI 多模态影像研究

博士论文预答辩

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第一章　基于文献计量分析的癫痫影像学与人工智能的研究

引言 I

图 1.1（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

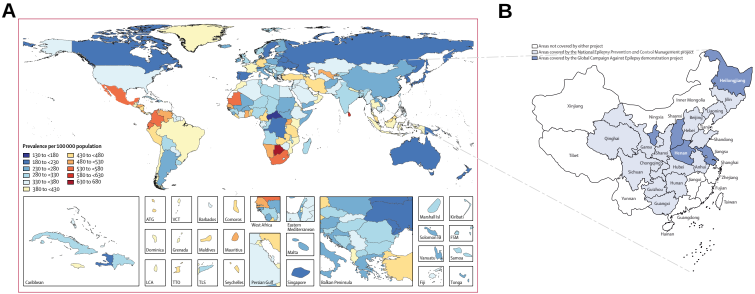

图 **1:** Epilepsy Epidemiology

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引言 II

图 1.2 癫痫疾病不同影像检查技术时空分辨率比较[23]

图 1.3 ^{18}F-FDG PET 成像原理图
图 1.4 18F-FDG PET/MRI 多模态融合示例图

材料与方法 I

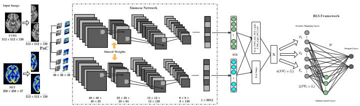

图 **2:** Black-box of AI

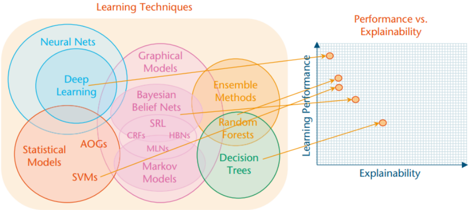

图 **3:** Learning Performance Versus Explainability Trade-Off of AI

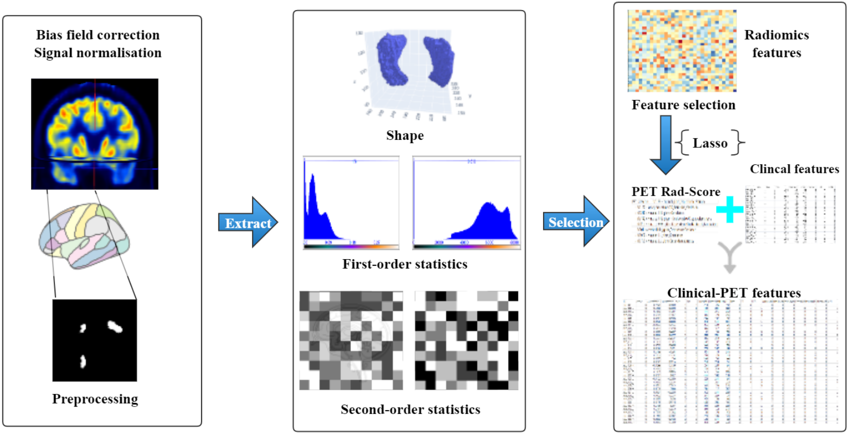

图 **4:** PET Radiomics Score and Clinical-PET Features

相关热图

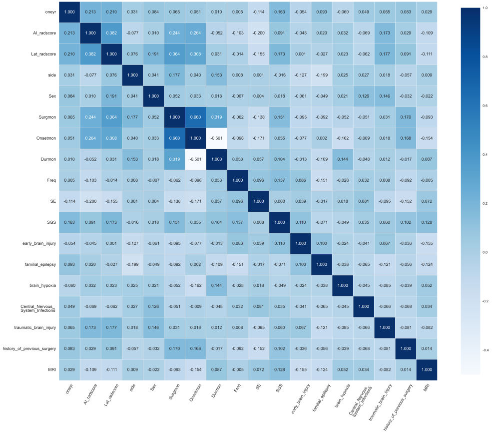

图 **5:** Heatmap of Clinical-PET Features

实验结果

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shiyan

讨论

小结

第二章 颞叶癫痫患者术前定位研究

引言

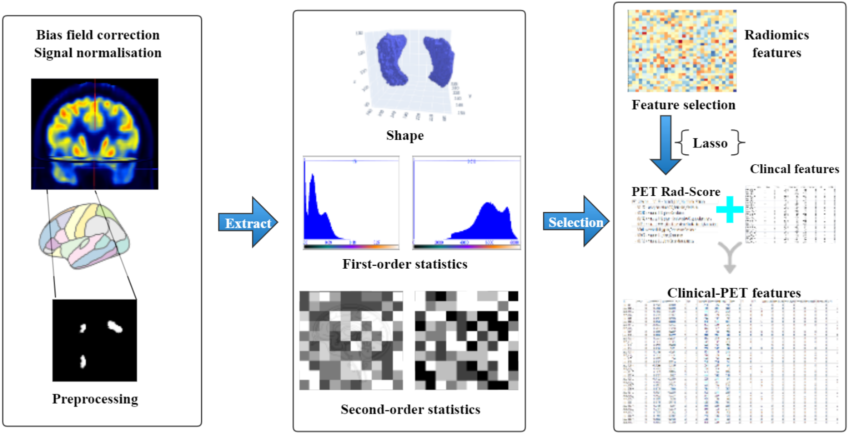

图 **6:** PET Radiomics Score and Clinical-PET Features

材料与方法

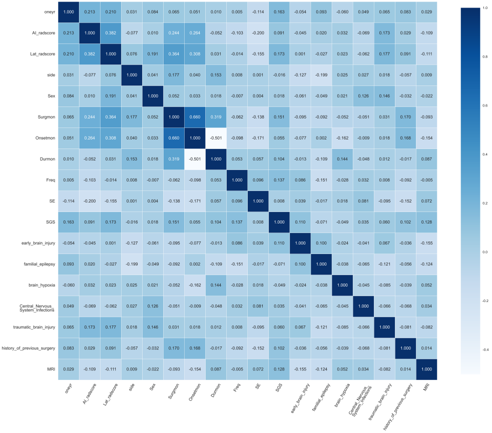

图 **7:** Heatmap of Clinical-PET Features

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实验结果

Table 1: Performance Comparison Eleven ML Algorithms

Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	APC
Ada Boost Classifier	0.883	0.789	0.4	0.433	0.393	0.345	0.357	0.59
Extreme Gradient Boosting	0.884	0.777	0.3	0.4	0.333	0.287	0.295	0.607
Random Forest Classifier	0.884	0.763	0.2	0.35	0.25	0.217	0.23	0.612
Gradient Boosting Classifier	0.89	0.762	0.35	0.483	0.39	0.346	0.36	0.591
Light Gradient Boosting Machine	0.859	0.749	0.25	0.325	0.267	0.211	0.221	0.512
Logistic Regression	0.878	0.669	0.05	0.1	0.067	0.055	0.059	0.448
Extra Trees Classifier	0.884	0.662	0.1	0.2	0.133	0.118	0.127	0.443
K Neighbors Classifier	0.865	0.646	0.2	0.2	0.183	0.14	0.149	0.283
Linear Discriminant Analysis	0.884	0.642	0.1	0.2	0.133	0.119	0.128	0.418
Naive Bayes	0.251	0.586	0.9	0.129	0.226	0.014	0.072	0.332
Decision Tree Classifier	0.798	0.584	0.3	0.264	0.259	0.158	0.167	0.218
Std	0.047	0.172	0.320	0.490	0.367	0.368	0.384	0.200

讨论

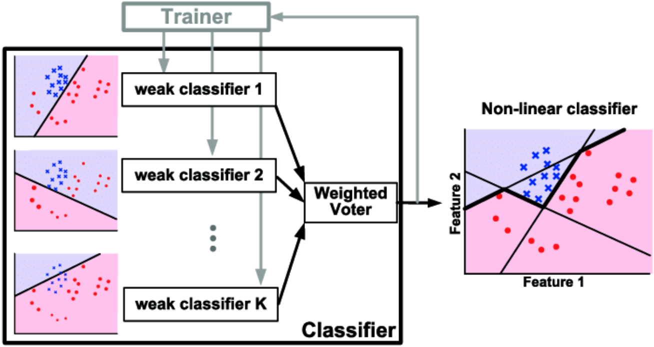

图 8: Illustration of AdaBoost Algorithm

- 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

第三章 颞叶癫痫患者术后复发预测研究

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 **9:** Permutation Importance of AdaBoost

材料与方法

PDP plots:

材料与方法

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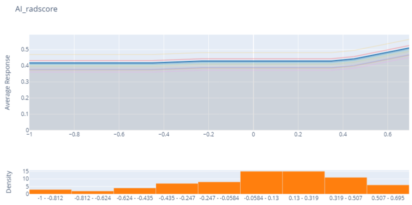
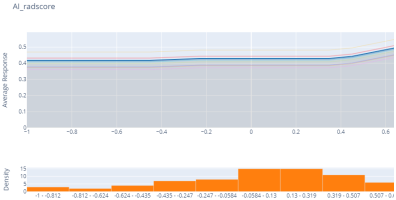
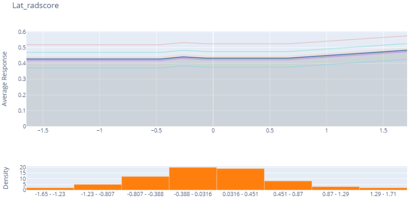
PDP plots:



材料与方法

PDP plots:





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第四章　总结与展望

结论

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

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- Combination of PET Radiomics and Clinical Features are more robust;

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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;

研究领域展望

- More data, especially external validation cohort;
- 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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