Interpretable Machine Learning of PET Imaging for Individualized Predictions of Seizure Outcomes after Temporal Lobe Epilepsy Surgery

2022 GDMA Nuclear Medicine Annual Conference

Huanhua Wu
Prof. Hao Xu*

The First Affiliated Hospital of Jinan University

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Introduction

Background

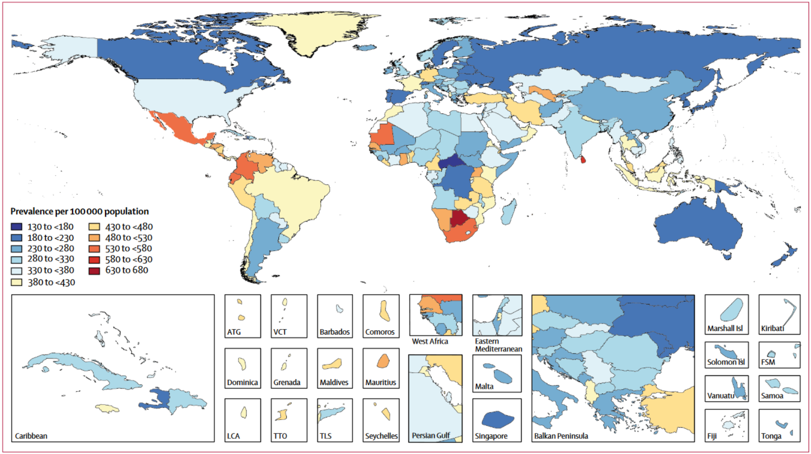
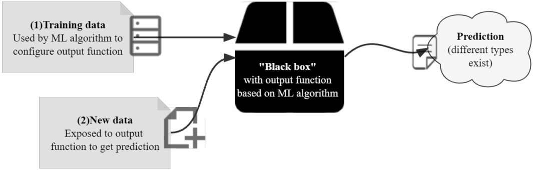


Figure 1: Epilepsy Epidemiology

Aims



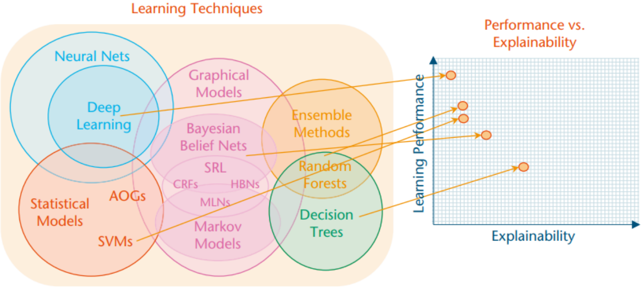


Figure 2: Focus on Interpretability of ML

Scheme

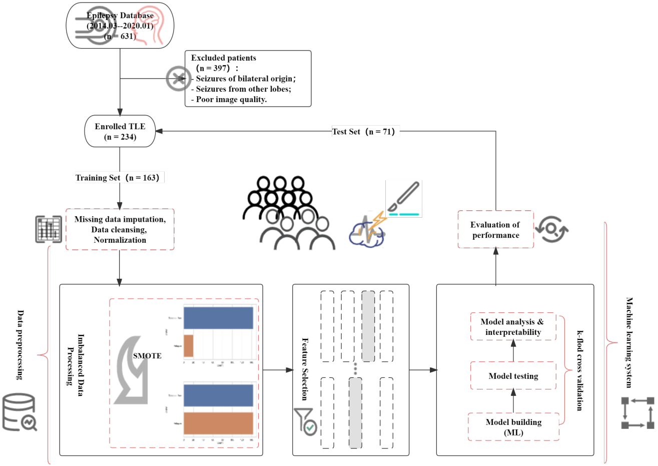


Figure 3: Flowchart of TLE Postsurgical IML

The Data

Combined of PET Radiomics and Clinical Features

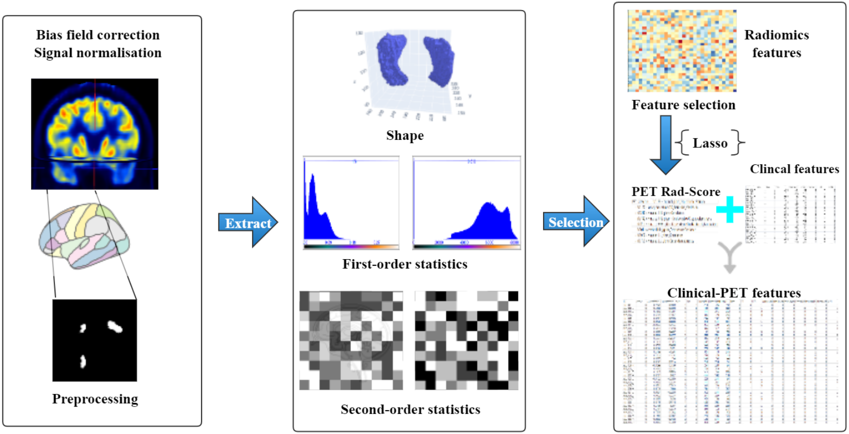


Figure 4: PET Radiomics Score and Clinical-PET Features

Exploratory Data Analysis

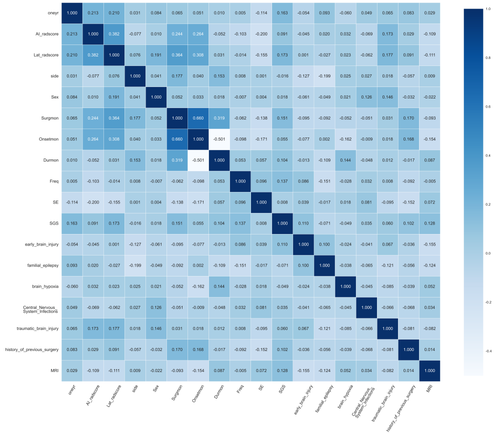


Figure 5: Heatmap of Clinical-PET Features

The Model

Benchmark

Table 1: Performance Comparison Eleven ML algorithms and K-folds Cross-validation of the Selected AdaBoost

Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Ada Boost Classifier	0.883	0.789	0.400	0.433	0.393	0.345	0.357
Extreme Gradient Boosting	0.884	0.777	0.300	0.400	0.333	0.287	0.295
Random Forest Classifier	0.884	0.763	0.200	0.350	0.250	0.217	0.230
Gradient Boosting Classifier	0.890	0.762	0.350	0.483	0.390	0.346	0.360
Light Gradient Boosting Machine	0.859	0.749	0.250	0.325	0.267	0.211	0.221
Logistic Regression	0.878	0.669	0.050	0.100	0.067	0.055	0.059
Extra Trees Classifier	0.884	0.662	0.100	0.200	0.133	0.118	0.127
K Neighbors Classifier	0.865	0.646	0.200	0.200	0.183	0.140	0.149
Linear Discriminant Analysis	0.884	0.642	0.100	0.200	0.133	0.119	0.128
Naive Bayes	0.251	0.586	0.900	0.129	0.226	0.014	0.072
Decision Tree Classifier	0.798	0.584	0.300	0.264	0.259	0.158	0.167

Folds\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

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Table 1: Performance Comparison Eleven ML algorithms

Model	Accuracy	AUC	Recall	Prec.	F1	Kapp
Ada Boost Classifier	0.883	0.789	0.4	0.433	0.393	0.345
Extreme Gradient Boosting	0.884	0.777	0.3	0.4	0.333	0.287
Random Forest Classifier	0.884	0.763	0.2	0.35	0.25	0.217
Gradient Boosting Classifier	0.89	0.762	0.35	0.483	0.39	0.346
Light Gradient Boosting Machine	0.859	0.749	0.25	0.325	0.267	0.211
Logistic Regression	0.878	0.669	0.05	0.1	0.067	0.055
Extra Trees Classifier	0.884	0.662	0.1	0.2	0.133	0.118
K Neighbors Classifier	0.865	0.646	0.2	0.2	0.183	0.14
Linear Discriminant Analysis	0.884	0.642	0.1	0.2	0.133	0.119
Naive Bayes	0.251	0.586	0.9	0.129	0.226	0.014
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AdaBoost Algorithm

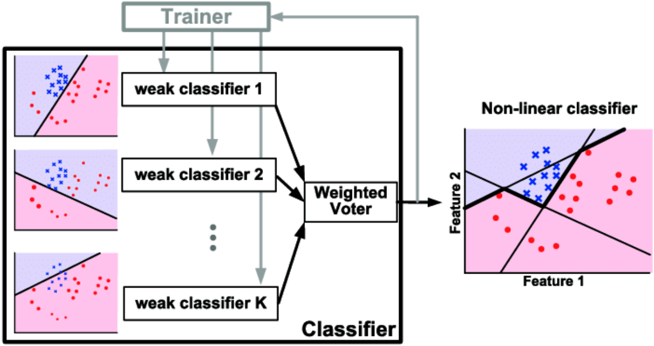

Figure 6: Illustration of AdaBoost Algorithm

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

The Explanation

Permutation Importance

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

Figure 7: Permutation Importance of AdaBoost

Partial Dependence Plot

- PDP plot:

Partial Dependence Plot

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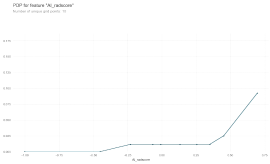

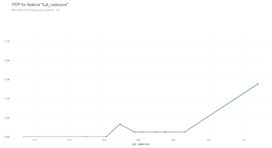

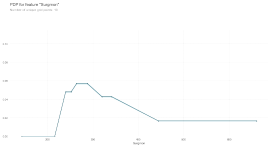

Conclusion

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

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- 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

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- More data, especially external validation cohort;

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- 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).

Email: wane199@outlook.com

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THANKS !

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