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

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Introduction

Background

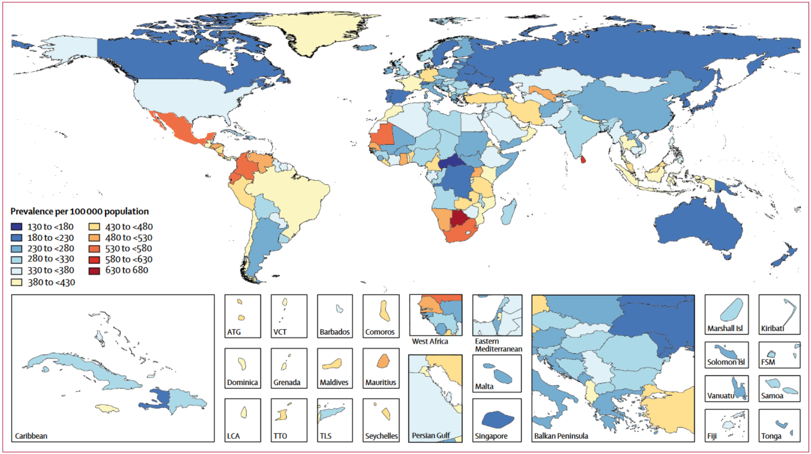

Figure 1: Epilepsy Epidemiology

Aims

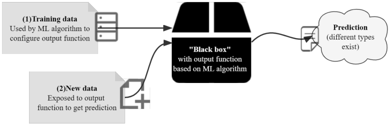

Figure 2: Black-box of AI

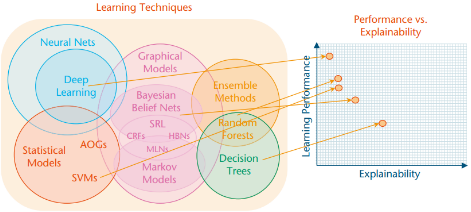

Figure 3: Learning Performance Versus Explainability Trade-Off of AI

Scheme

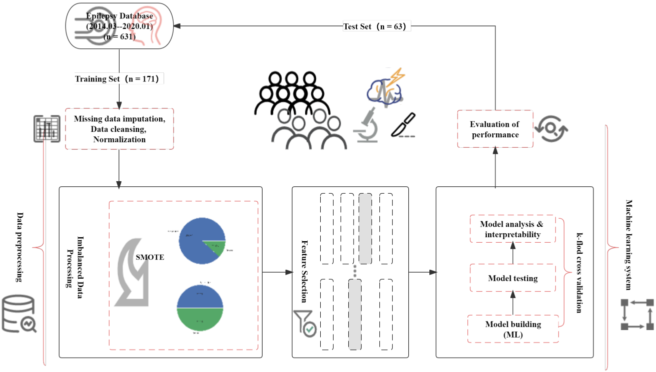

Figure 4: Flowchart of TLE Postsurgical IML

The Data

Combined of PET Radiomics and Clinical Features

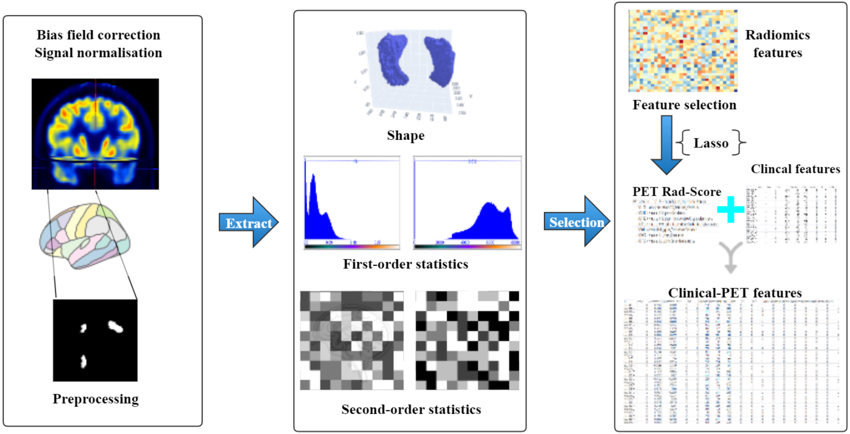

Figure 5: PET Radiomics Score and Clinical-PET Features

Exploratory Data Analysis

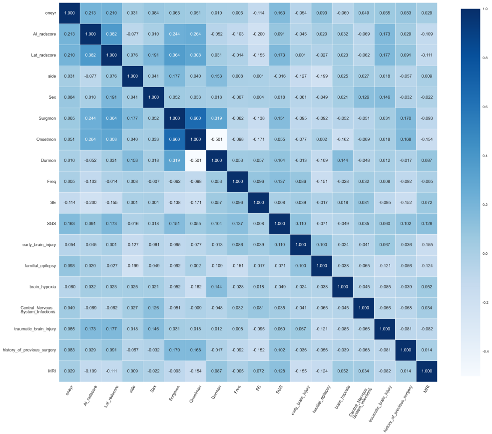

Figure 6: Heatmap of Clinical-PET Features

The Model

Benchmark

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

AdaBoost Algorithm

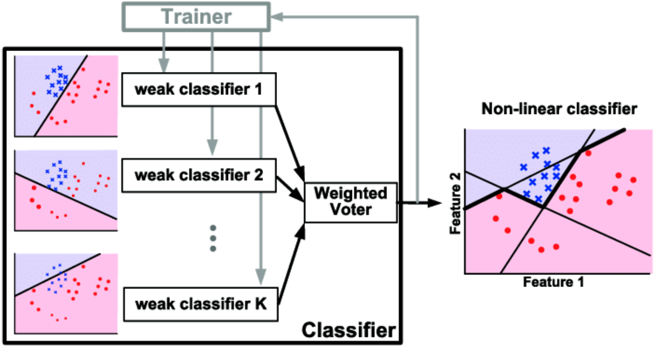

Figure 7: Illustration of AdaBoost Algorithm

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

Tuned AdaBoost

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

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 8: Permutation Importance of AdaBoost

Partial Dependence Plot

PDP plots:

Partial Dependence Plot

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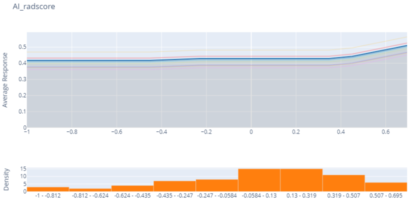
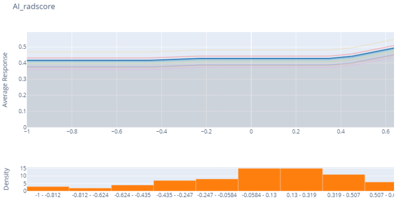
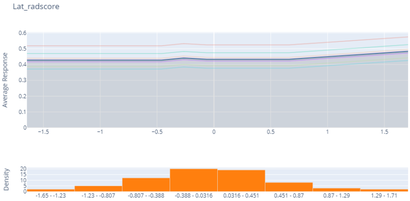


Partial Dependence Plot

PDP plots:





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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- 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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