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

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Introduction

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Introduction



Background

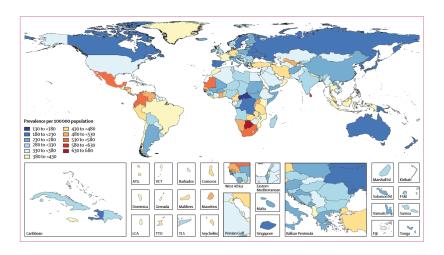


Figure 1: Epilepsy Epidemiology



Aims

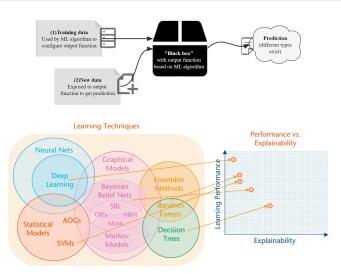


Figure 2: Focus on Interpretability of ML



Scheme

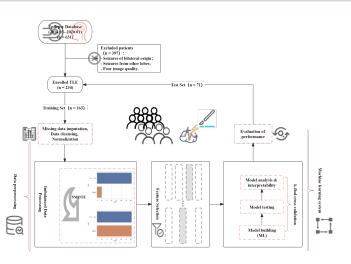


Figure 3: Flowchart of TLE Postsurgical IML



The Data



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Combined of PET Radiomics and Clinical Features

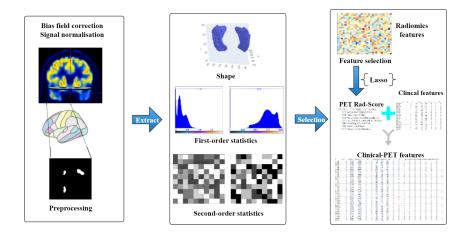


Figure 4: PET Radiomics Score and Clinical-PET Features



Exploratory Data Analysis

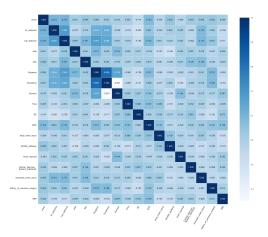


Figure 5: Heatmap of Clinical-PET Features



The Model



Benchmark

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

								Folds\Tuned_A	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
Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Ada Boost Classifier	0.883	0.789	0.400	0.433	0.393	0.345	0.357	4								
Extreme Gradient Boosting	0.884	0.777	0.300	0.400	0.333	0.287	0.295	3	0.824	0.550	0.000	0.000	0.000	-0.085	-0.091	0.183
Random Forest Classifier	0.884	0.763	0.200	0.350	0.250	0.217	0.230	4	0.875	0.893	0.000	0.000	0.000	0.000	0.000	0.500
Gradient Boosting Classifier	0.890	0.762	0.350	0.483	0.390	0.346	0.360	5	0.938	0.929	0.500	1.000	0.667	0.636	0.683	0.750
Light Gradient Boosting Machine		0.749	0.250	0.325	0.267	0.211	0.221	6	0.938	0.964	0.500	1.000	0.667	0.636	0.683	0.833
Logistic Regression	0.878	0.669	0.050	0.100	0.067	0.055	0.059	U								
Extra Trees Classifier	0.884	0.662	0.100	0.200	0.133	0.118	0.127	7	0.875	0.554	0.000	0.000	0.000	0.000	0.000	0.321
K Neighbors Classifier	0.865	0.646	0.200	0.200	0.183	0.140	0.149	8	0.938	0.964	0.500	1.000	0.667	0.636	0.683	0.833
Linear Discriminant Analysis	0.884	0.642	0.100	0.200	0.133	0.119	0.128	9	0.938	1.000	0.500	1.000	0.667	0.636	0.683	1.000
Naive Bayes	0.251	0.586	0.900	0.129	0.226	0.014	0.072	10		0.679	0.500	1.000	0.667	0.636	0.683	0.591
Decision Tree Classifier	0.798	0.584	0.300	0.264	0.259	0.158	0.167									
								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



AdaBoost Algorithm

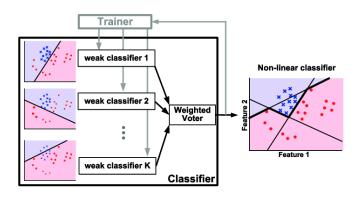


Figure 6: Illustration of AdaBoost Algorithm

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



The Explanation



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Permutation Importance

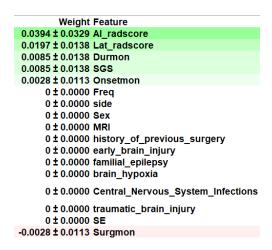
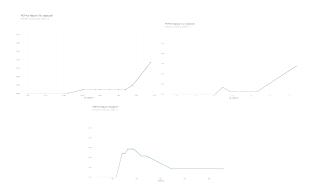


Figure 7: Permutation Importance of AdaBoost



Partial Dependence Plot





Conclusion



Key Points

- 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



Limitations

- 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!



References I

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