

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

Huanhua Wu  
Prof. Hao Xu\*

The First Affiliated Hospital of Jinan University

2023-02-06



# Introduction

## The Data

## The Model

## The Explanation

## Conclusion

Introduction  
○○○

The Data  
○○

The Model  
○○○

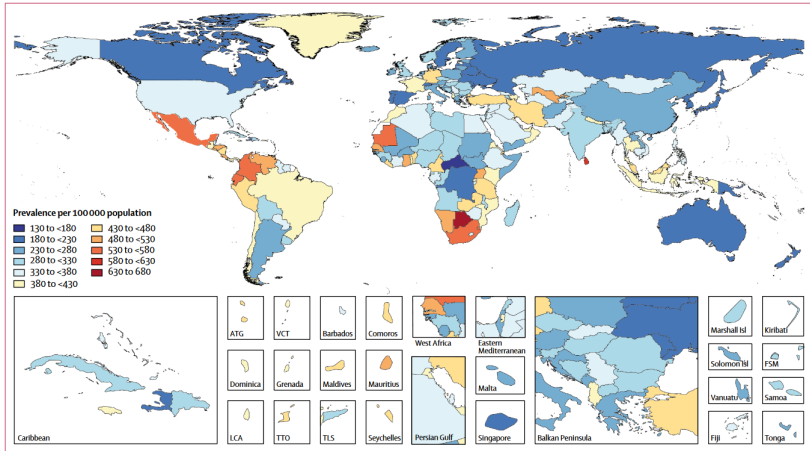
The Explanation  
○○

Conclusion  
○○○○

References

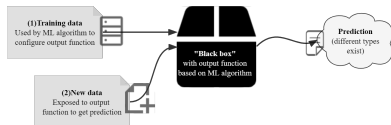
# Introduction

# Background

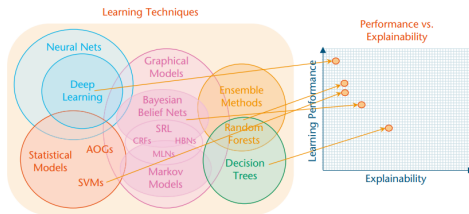


**Figure 1: Epilepsy Epidemiology**

# Aims

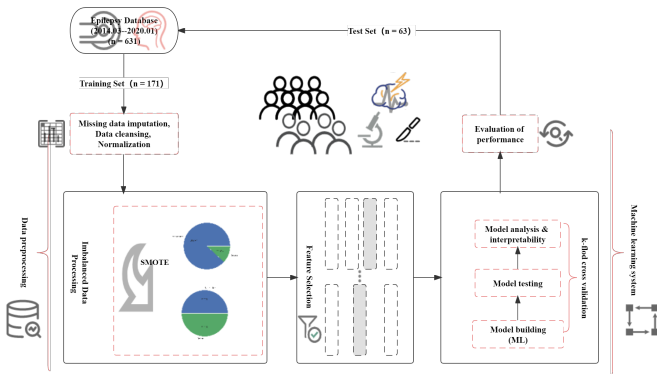


**Figure 2:** Black-box of AI



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

# Scheme

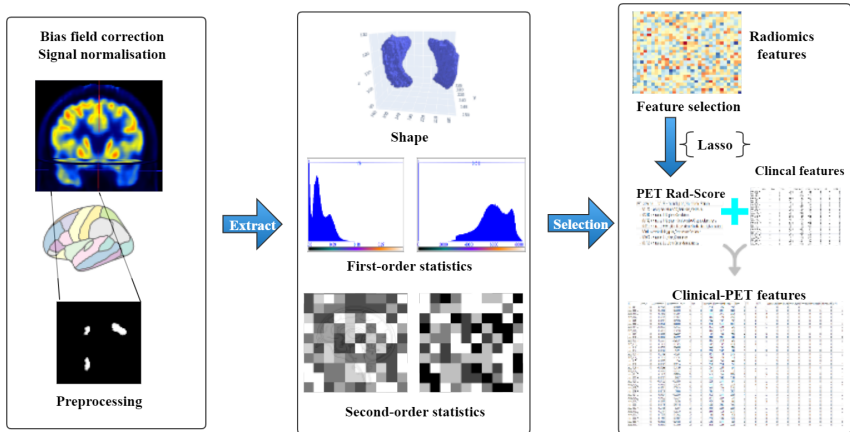


**Figure 4:** Flowchart of TLE Postsurgical IML

# The Data



# Combined of PET Radiomics and Clinical Features



**Figure 5:** PET Radiomics Score and Clinical-PET Features

# Exploratory Data Analysis

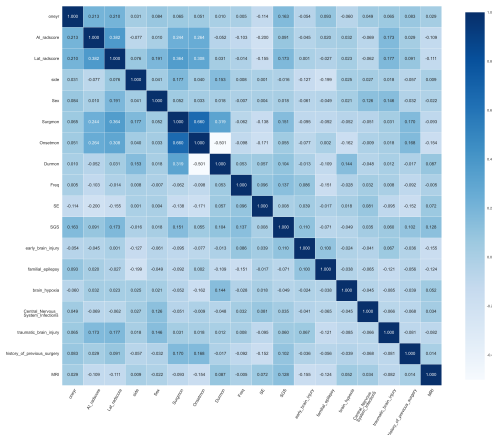


Figure 6: Heatmap of Clinical-PET Features

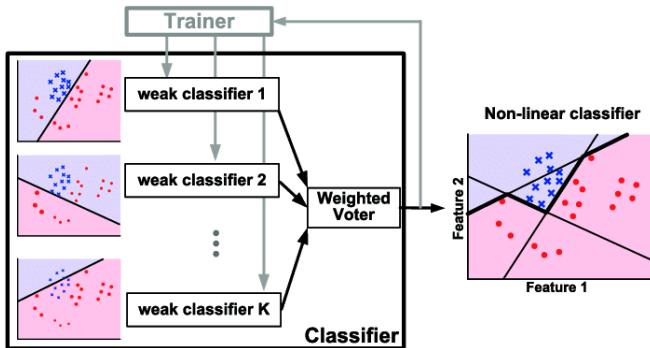
# The Model

# 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

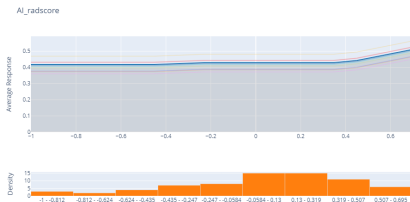
PDP plots:

# Partial Dependence Plot

PDP plots:

# Partial Dependence Plot

PDP plots:

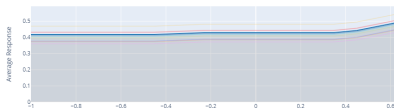


# Partial Dependence Plot

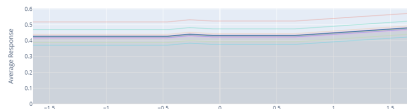
PDP plots:



AI\_radscore



Lat\_radscore



# Conclusion

# Key Points

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

# Key Points

- Metabolic radiomics are helpful to predict the postsurgical seizure outcomes;
- Combination of PET Radiomics and Clinical Features are more robust;

# 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;

# Limitations

- More data, especially external validation cohort;
- Fusion of PET/MRI multimodal imaging;

# 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 [\(Beghi et al., 2019\)](#), [\(Rajpurkar, 2021\)](#), [\(Marc Becker, 2022\)](#), [\(Molnar, 2022\)](#).

**Email:** [wane199@outlook.com](mailto:wane199@outlook.com)



# References I

Beghi, E., Giussani, G., Nichols, E., Abd-Allah, F., Abdela, J., Abdelalim, A., Abraha, H. N., Adib, M. G., Agrawal, S., Alahdab, F., et al. (2019). Global, regional, and national burden of epilepsy, 1990–2016: a systematic analysis for the global burden of disease study 2016. *The Lancet Neurology*, 18(4):357–375.

Marc Becker, e. a. (2022). *mlr3book*.

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

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