

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

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# Introduction

## The Data

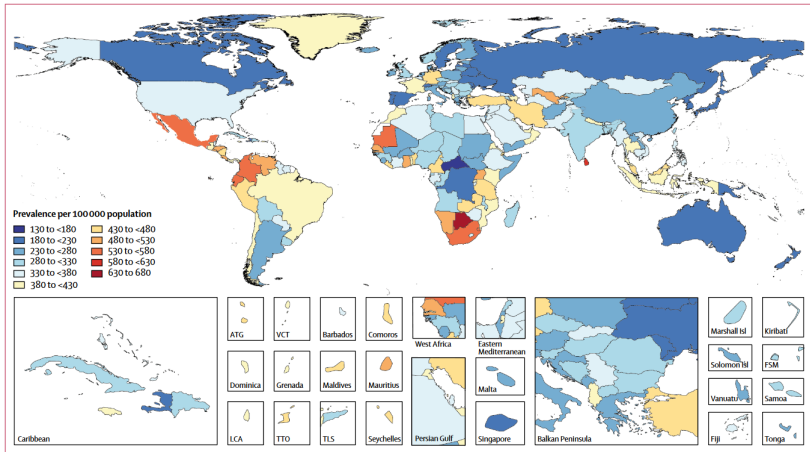
## The Model

## The Explanation

## Conclusion

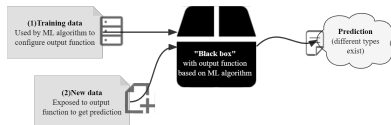
# Introduction

# Background

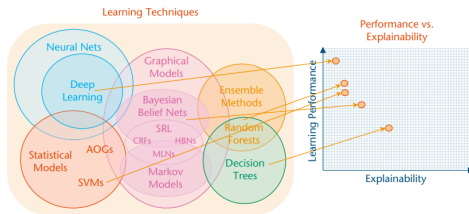


**Figure 1: Epilepsy Epidemiology**

# Aims

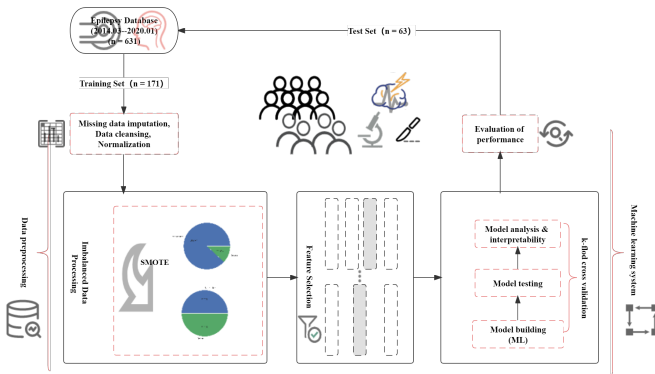


**Figure 2:** Black-box of AI



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

# Scheme



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

# The Data

The flowchart illustrates the architecture of the PET-Rad-Score model, which integrates radiomics and clinical data for PET image analysis. The process is divided into three main stages: Preprocessing, Feature Extraction, and Feature Selection.

**Preprocessing:** The initial step involves bias field correction and signal normalisation of the PET images, as shown by the brain scan visualization.

**Feature Extraction:** The extracted features are categorized into three groups:

- Shape:** Visualized by a 3D brain model showing segmented regions.
- First-order statistics:** Represented by two histograms showing the distribution of pixel intensities.
- Second-order statistics:** Represented by two heatmaps showing the spatial relationships between pixels.

**Feature Selection:** The extracted features are processed through a selection step, which includes:

- Radiomics features:** A large set of features derived from the PET images.
- Feature selection:** Utilizing Lasso regression to select the most relevant features.
- Clinical features:** Additional clinical data is integrated with the selected radiomics features (indicated by a plus sign).

The final output is the **Clinical-PET features**, which are used for the final model training and evaluation.

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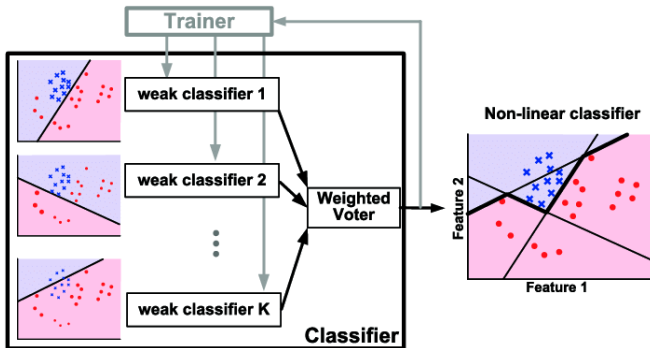
# The Model

# 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:

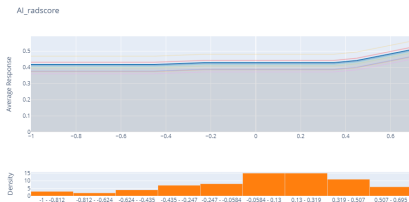


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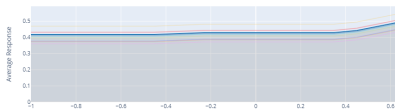


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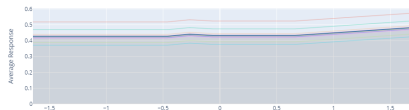
PDP plots:



AI\_radscore



Lat\_radscore



# Conclusion

# Key Points

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

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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

# Limitations

- More data, especially external validation cohort;



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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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# References I

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