

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

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Introduction

The Data

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Introduction

Background

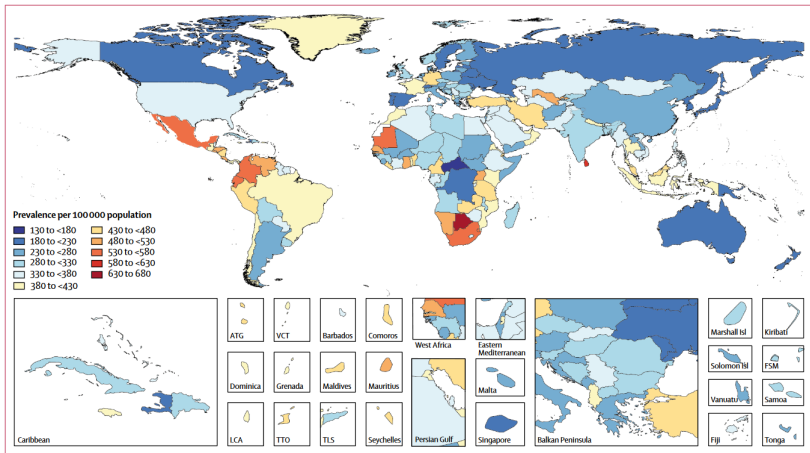


Figure 1: Epilepsy Epidemiology

Aims

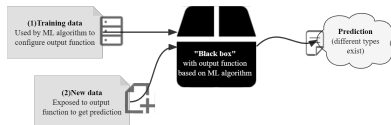


Figure 2: Black-box of AI

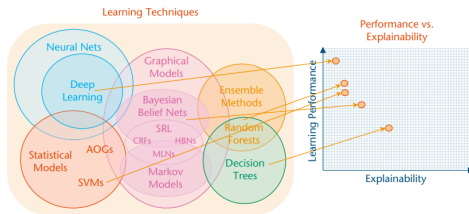


Figure 3: Learning Performance Versus Explainability Trade-Off of AI

Scheme

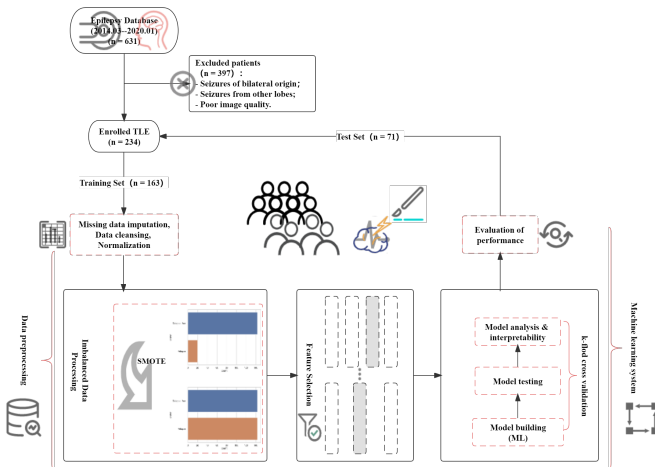


Figure 4: Flowchart of TLE Postsurgical IML

The Data

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 image. This is followed by **Preprocessing** of the anatomical image, which includes segmentation into regions of interest (ROIs) and generation of a binary mask.

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

- Shape:** Features derived from the 3D volume, including **Volume**, **Surface Area**, **Perimeter**, **Compactness**, **Convexity**, **Roundness**, **Sphericity**, **Ellipsoidness**, **Convexity**, **Roundness**, **Sphericity**, **Ellipsoidness**, **Convexity**, **Roundness**, **Sphericity**, **Ellipsoidness**.
- First-order statistics:** Features derived from the histogram of the PET signal, including **Mean**, **Standard Deviation**, **Variance**, **Skewness**, **Kurtosis**, **Entropy**, **Energy**, **Information**, **Correlation**, **Contrast**, **Haralick**, **Texture**, **Entropy**, **Energy**, **Information**, **Correlation**, **Contrast**, **Haralick**, **Texture**.
- Second-order statistics:** Features derived from the co-occurrence matrix of the PET signal, including **Mean**, **Standard Deviation**, **Variance**, **Skewness**, **Kurtosis**, **Entropy**, **Energy**, **Information**, **Correlation**, **Contrast**, **Haralick**, **Texture**, **Entropy**, **Energy**, **Information**, **Correlation**, **Contrast**, **Haralick**, **Texture**.

Feature Selection: The extracted features are then subjected to **Feature selection** using the **Lasso** method. This step identifies the most relevant features for the model. The selected features are then combined with **Clinical features** to form the **Clinical-PET features**.

The final output of the model is the **PET Rad-Score**, which is a quantitative measure of the PET signal, derived from the combination of the selected radiomics and clinical features.



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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

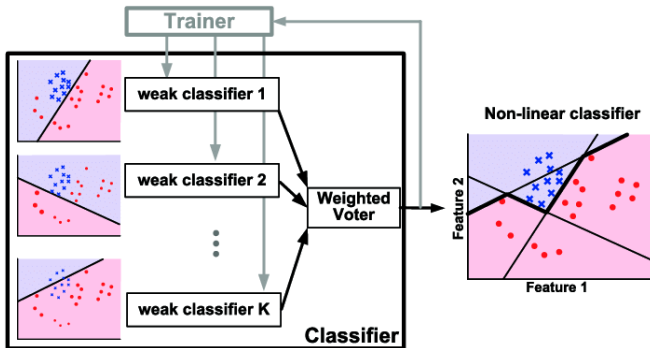


Figure 7: Illustration of AdaBoost Algorithm

- `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

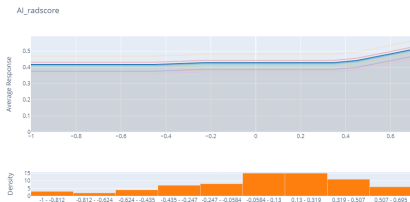
PDP plots:

Partial Dependence Plot

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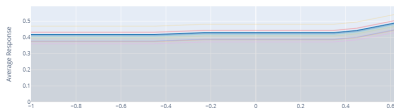


Partial Dependence Plot

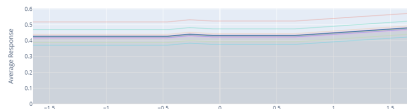
PDP plots:



AI_radscore



Lat_radscore



Conclusion

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- 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

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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

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.