

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

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References

Introduction

Background

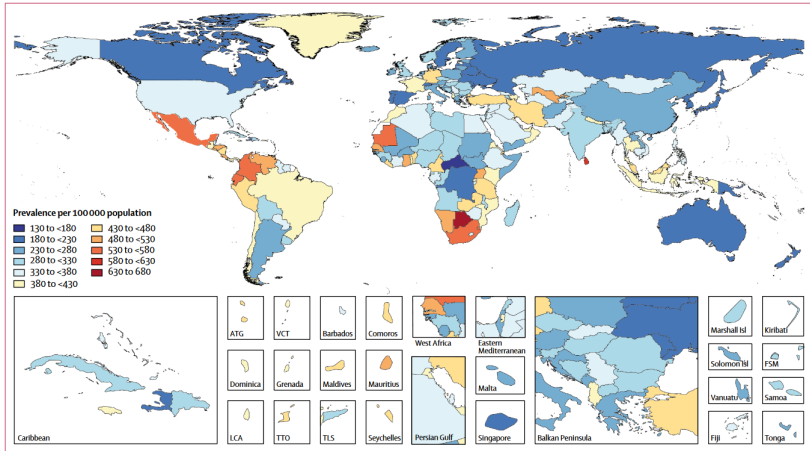


Figure 1: Epilepsy Epidemiology

Aims

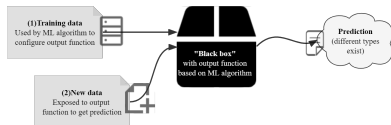


Figure 2: Black-box of AI

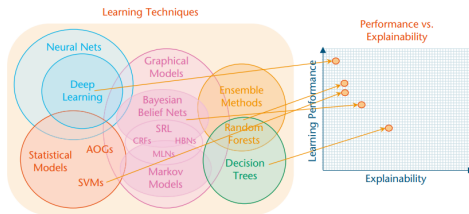


Figure 3: Learning Performance Versus Explainability Trade-Off of AI

Scheme

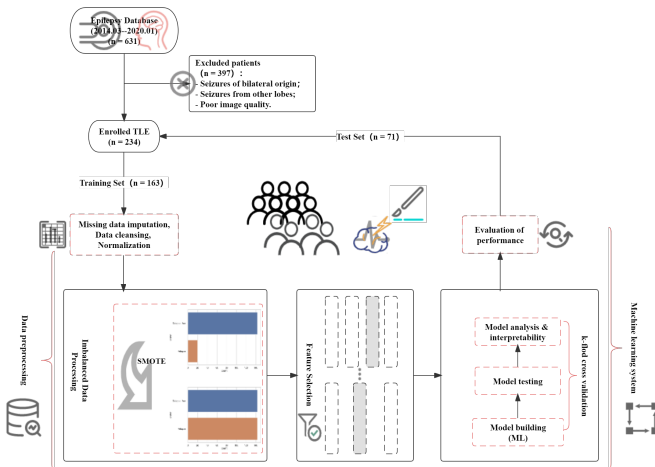


Figure 4: Flowchart of TLE Postsurgical IML

The Data

Combined of PET Radiomics and Clinical Features

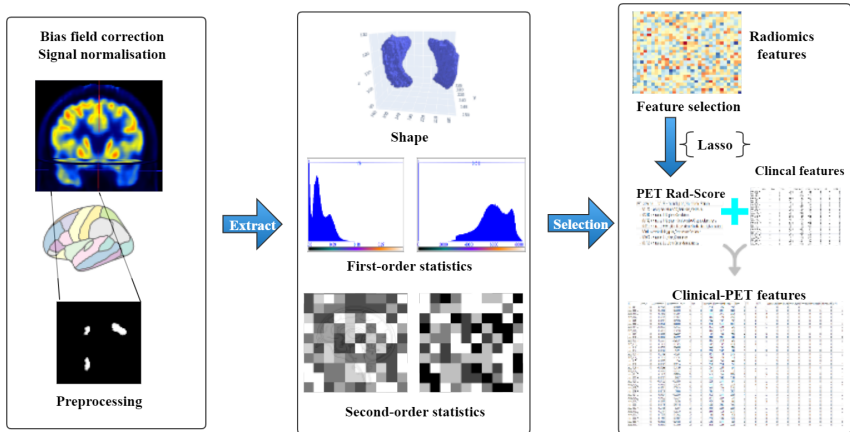


Figure 5: PET Radiomics Score and Clinical-PET Features

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

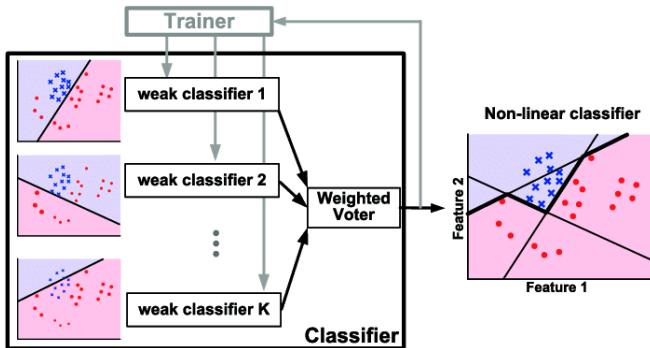


Figure 7: Illustration of AdaBoost Algorithm

- `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

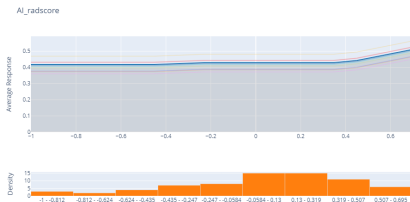
PDP plots:

Partial Dependence Plot

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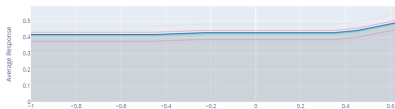


Partial Dependence Plot

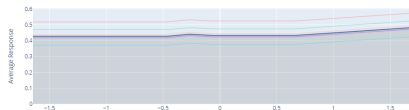
PDP plots:



AI_radscore



Lat_radscore



Conclusion

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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- 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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