A Machine Learning Approach for Classification of Spike-Wave Discharges in Absence Epilepsy

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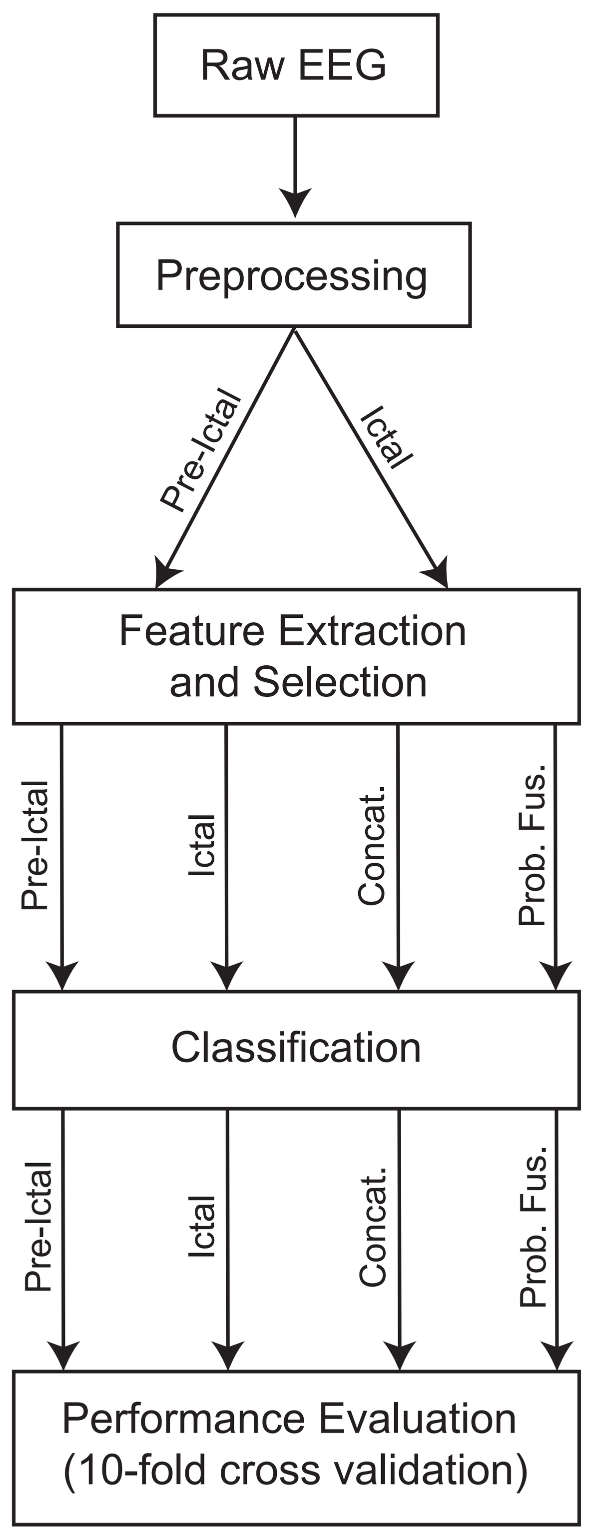
1. Introduction

In examining electroencephalography (EEG) recordings of childhood absence epilepsy (CAE), the most apparent marker is spike-wave discharges (SWDs) **[1]**. SWDs are characterized by the spike-wave rhythms with frequencies > 2.5 Hz and are often induced clinically via hyperventilation, photic stimulation, or sleep deprivation. It is widely believed that the SWD complexes arise out of thalamocortical oscillations which yield the episodes of impaired consciousness seen in absence epilepsy **[2,3]**. These discharges, which cannot be examined effectively in clinic, pose a great challenge to clinicians in evaluating the patient's ability to drive or other such activities which greatly impact quality of life **[4]**. Although they may not be perceived by the individual, epileptiform discharges may result in sudden and transient lapses in cognitive function and as a result affect the individual in a way that brings about a public safety concern **[5]**.

Primary Inquiry

To introduce an EEG-based machine learning approach to predict with a minimum false discovery rate whether or not generalized 3-4Hz SWDs produce impaired behavioral responsiveness.

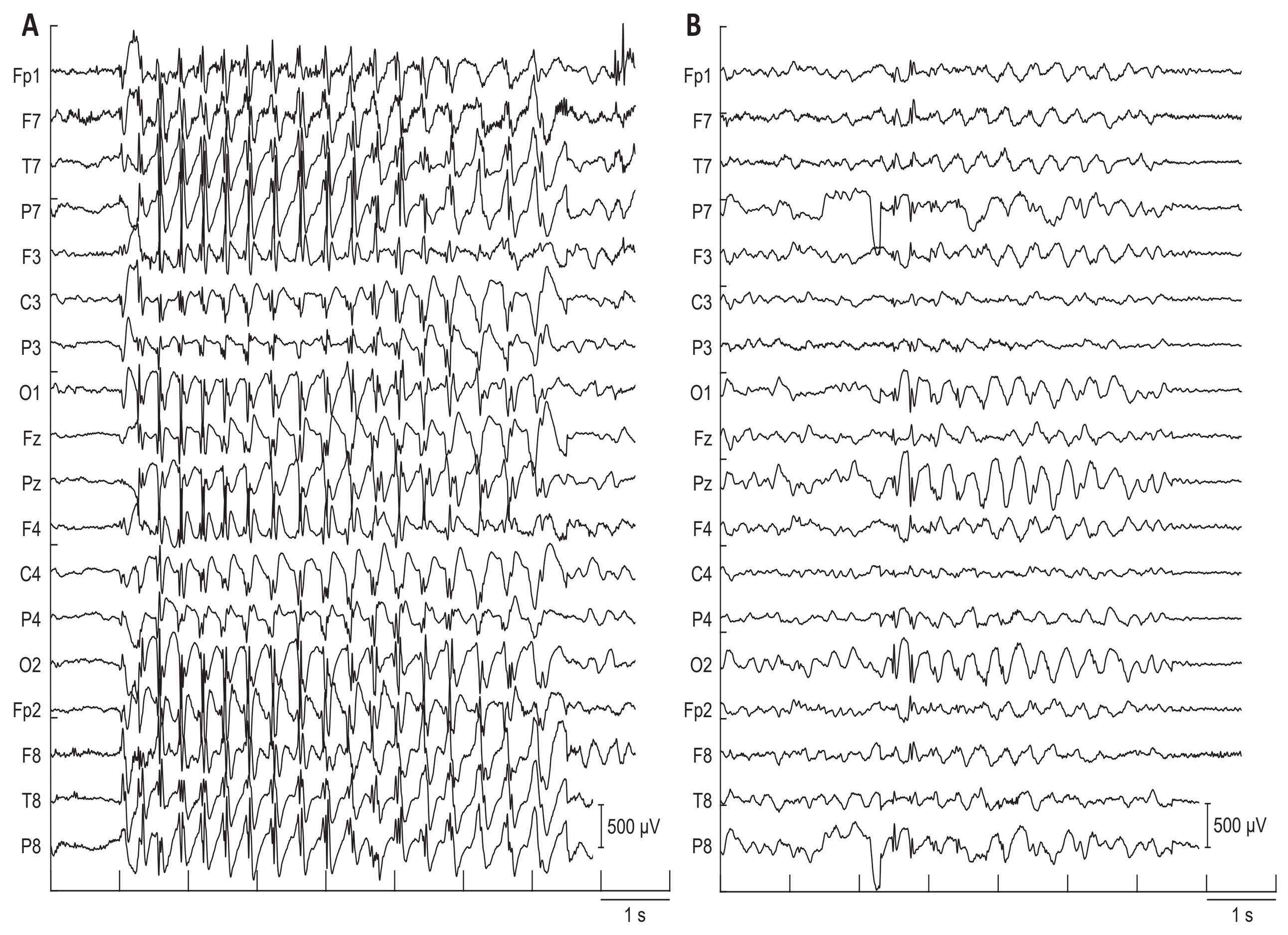
2. Summary Methods



Using features extracted from the pre-ictal and ictal periods, support vector machines (SVM) and linear discriminant analysis (LDA) were employed to classify seizures as spared or impaired according to behavioral testing.

In constructing our classifier, we prioritized the minimization of the false discovery rate, with the goal of avoiding at all costs classifying patients as potentially able to drive (spared) when in fact they are not. We used the labelled data sets to fine tune the model parameters. Subsequently, the optimized classifiers were validated on a novel unlabeled dataset of patients with absence epilepsy on medication treatment which simply classified patients overall as having clinical seizures or not.

3. Example EEG of Impaired vs. Spared SWDs



Behaviorally impaired SWD   Behaviorally spared SWD

4. EEG Features of Impaired vs. Spared SWDs

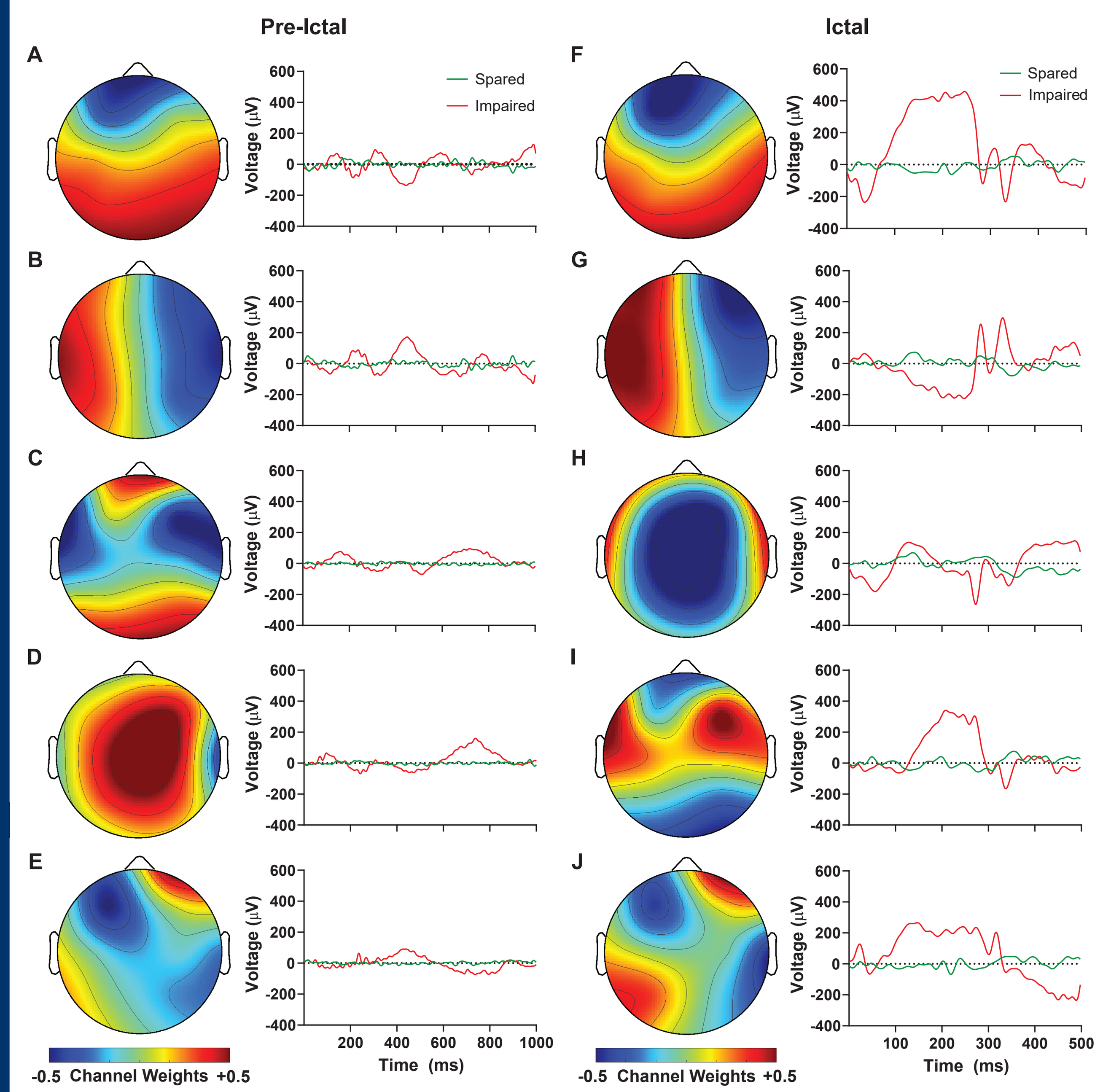
	Pre-Ictal		
Feature	Spared (Mean ± SEM)	Impaired (Mean ± SEM)	Rank-Sum P-Value
Wave Power	27.5 ± 2.6	90.8 ± 15.7	< 0.001
Hjorth Mobility	0.14 ± 0.01	0.08 ± 0.00	< 0.001
Hjorth Complexity	3.31 ± 0.14	4.08 ± 0.15	< 0.001
Delta Power	66.1 ± 6.3	254 ± 44	< 0.001

	Ictal		
Feature	Spared (Mean ± SEM)	Impaired (Mean ± SEM)	Rank-Sum P-Value
Wave Power	661 ± 79	2624 ± 403	< 0.001
Seizure Duration	947 ± 46	4336 ± 467	< 0.001
Hjorth Activity	924 ± 97	4307 ± 622	< 0.001
Hjorth Mobility	0.09 ± 0.00	0.07 ± 0.00	< 0.001
Mean Vrms	31.6 ± 1.83	57.7 ± 4.83	< 0.001
Delta Power	859 ± 102	2911 ± 432	< 0.001
Theta Power	435 ± 46	1720 ± 239	< 0.001
Alpha Power	144 ± 14	336 ± 60	< 0.001
Voltage Variance	924 ± 97	4307 ± 622	< 0.001
Power Skewness	1.95 ± 0.06	1.42 ± 0.05	< 0.001
Power Kurtosis	7.91 ± 0.35	5.23 ± 0.25	< 0.001
Multiscale Permutation Entropy	2.39 ± 0.03	2.14 ± 0.04	< 0.001

At a p-value of 0.001, 16 of 24 features were significant and, therefore, selected for classification.

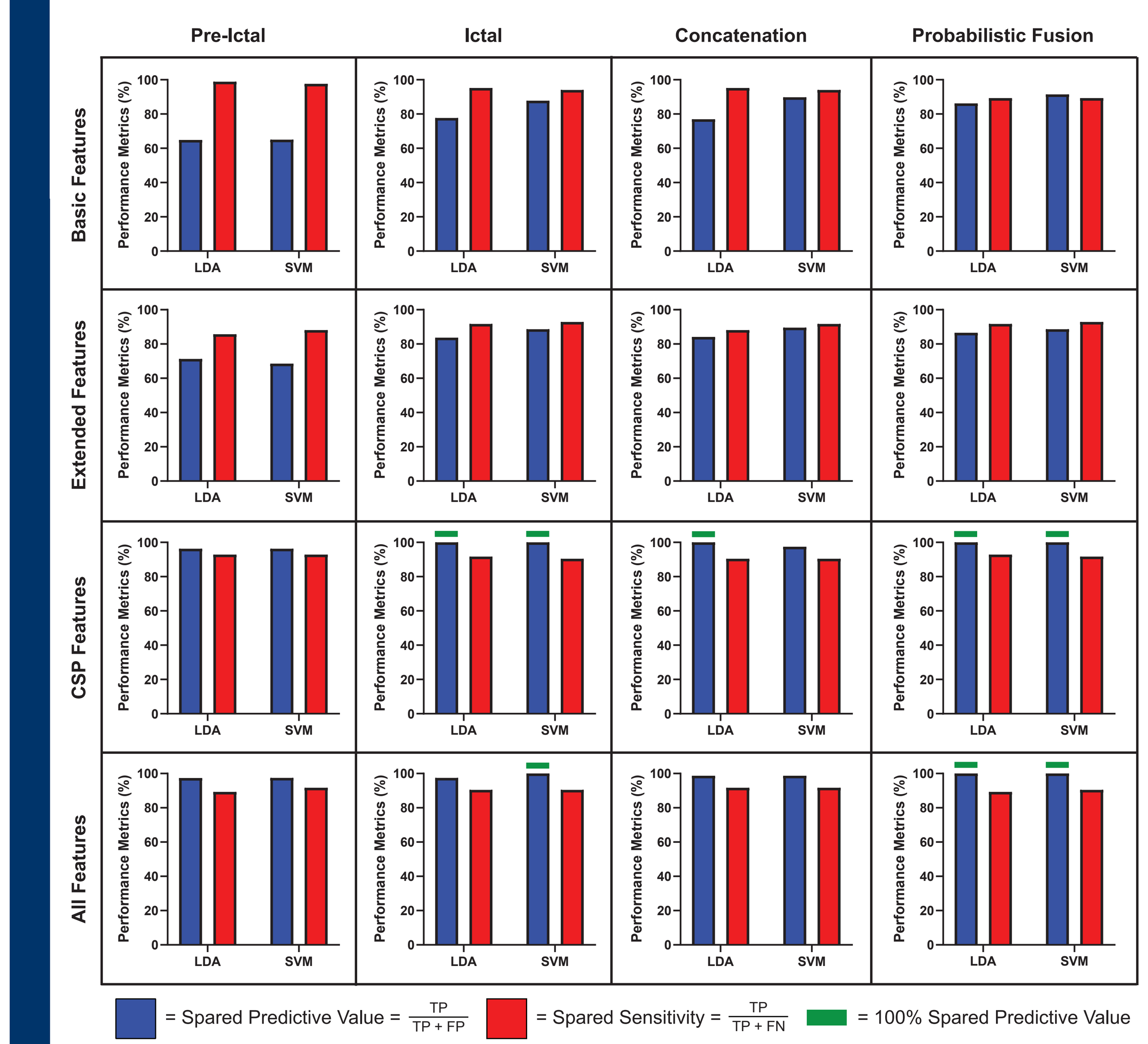
Seizure duration is reported in miliseconds. All voltage is in µV.

5. CSP Features of Impaired vs. Spared SWDs



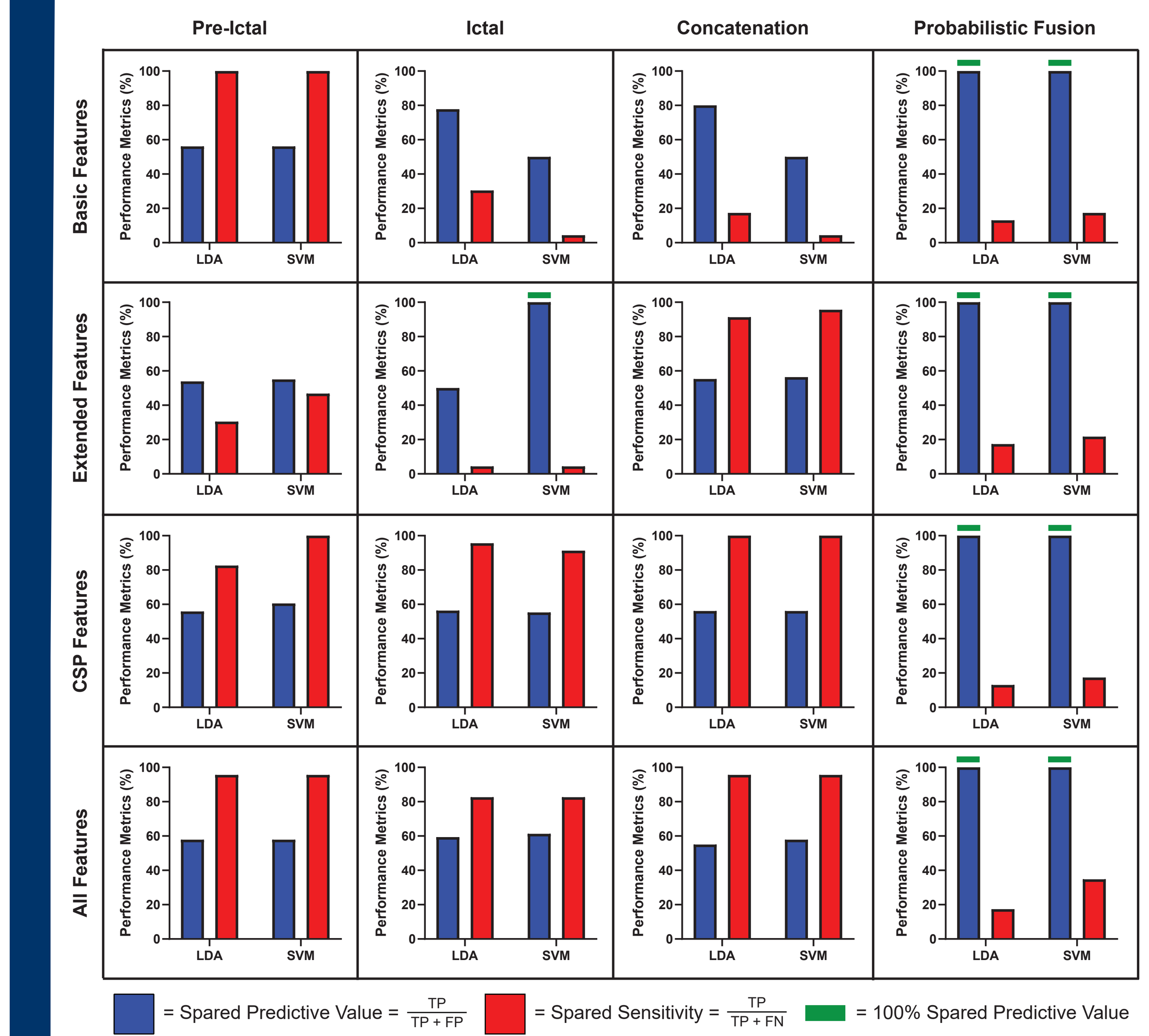
Top spatial filters obtained by applying the common spatial pattern (CSP) algorithm on the 1000ms prior to seizure onset (A-E) and the 500ms following seizure onset (F-J). The headmaps on the left of each subplot visualize the channel weights in defining each spatial filter. The line plots on the right show projected spared and impaired seizures onto the corresponding filters.

6. 10-Fold Cross Validation Results



* Spared (n=84) and Impaired (n=49)

7. Validation on Unlabeled Dataset



* Spared (n=24) and Impaired (n=18)

8. Conclusions

- The proposed approach demonstrates the feasibility and reliability of machine learning-based systems in clinical practice for the purposes of more finely evaluating patients with absence epilepsy.

- With further validation, this method could lead to significant improvements in quality of life by helping assess a patient's ability to drive.

- The synthesis of time, frequency, and spatial domain features is highly accurate in assessing subclinical SWDs.

9. Future Directions

- Validate this method with larger cohorts for generalizablility to more novel datasets.

- Incorporate fMRI data to develop a more precise machine learning model.

- Generalize the proposed approach to more broad diagnoses outside of childhood and juvenile absence epilepsy by including additional EEG markers.

10. References

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