Scope and Arbitration in Machine Learning Clinical EEG Classification

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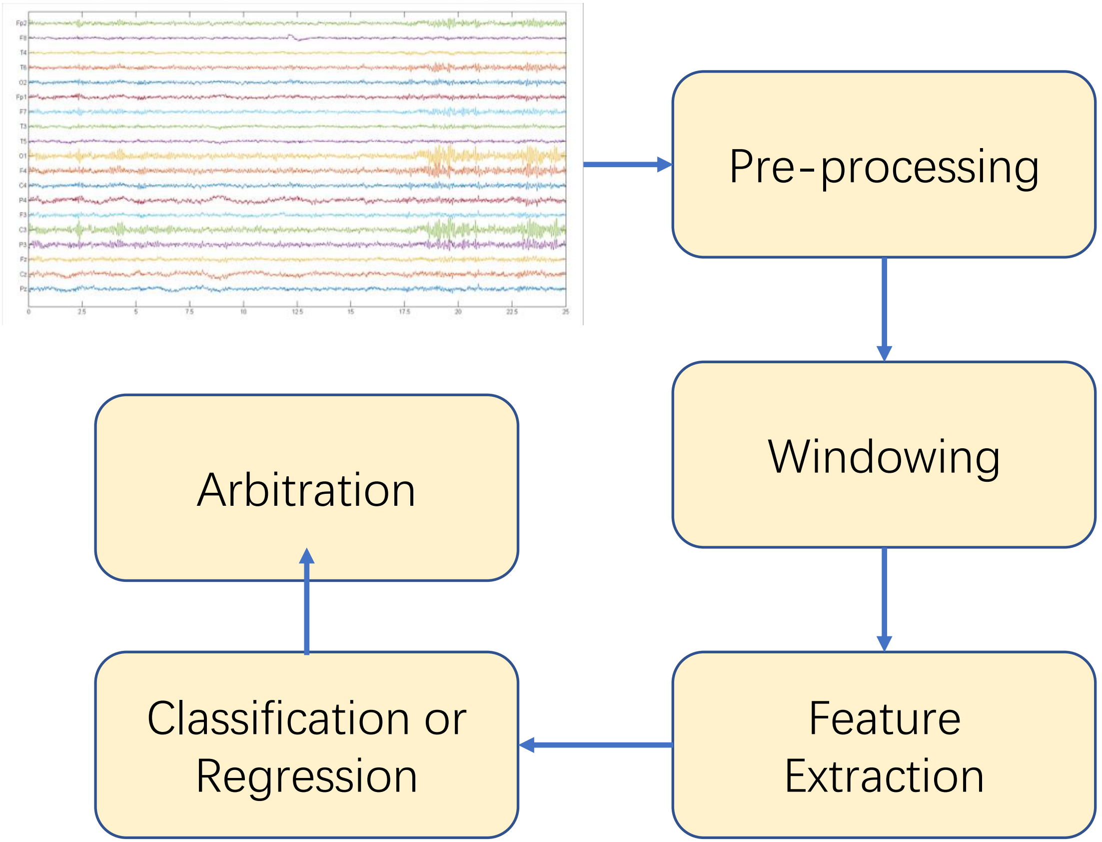
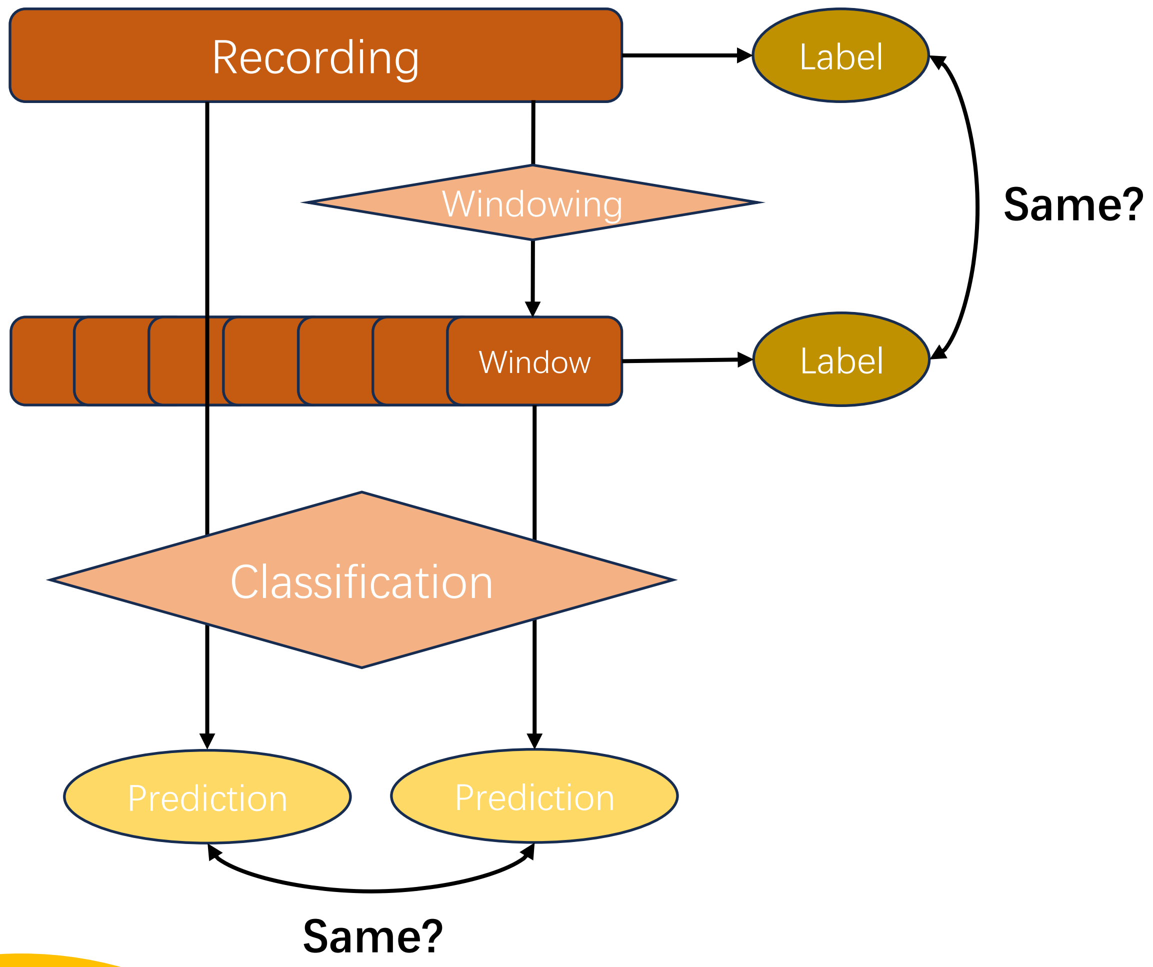
Introduction

A typical EEG classification task workflow based on machine learning.

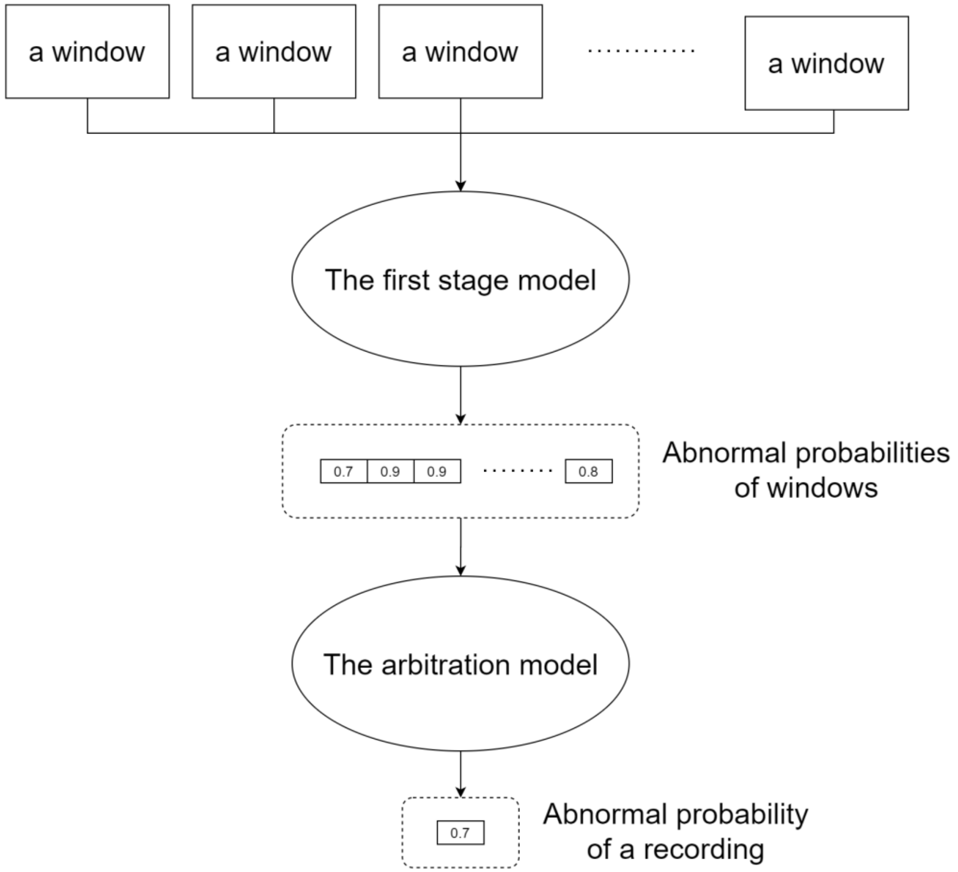




The Windowing Conundrum in EEG Classification

- **Labeling Dilemma:** One label per session may not reflect the true nature of each window, leading to potential misclassification.
- **Result Aggregation:** Determining the overall recording status from windowed results is uncertain—abnormal recordings could contain normal windows.

Method



Integrating EEG Data with an Arbitration Model

Model Design: We created a model to synthesize window results in an EEG.
Window-Level Learning: It captures window interrelationships.
Bias Correction: It corrects label bias for accurate EEG interpretation.
Arbitration Innovation: First to emphasize and utilize machine learning in arbitration, marking a significant advancement in the field.

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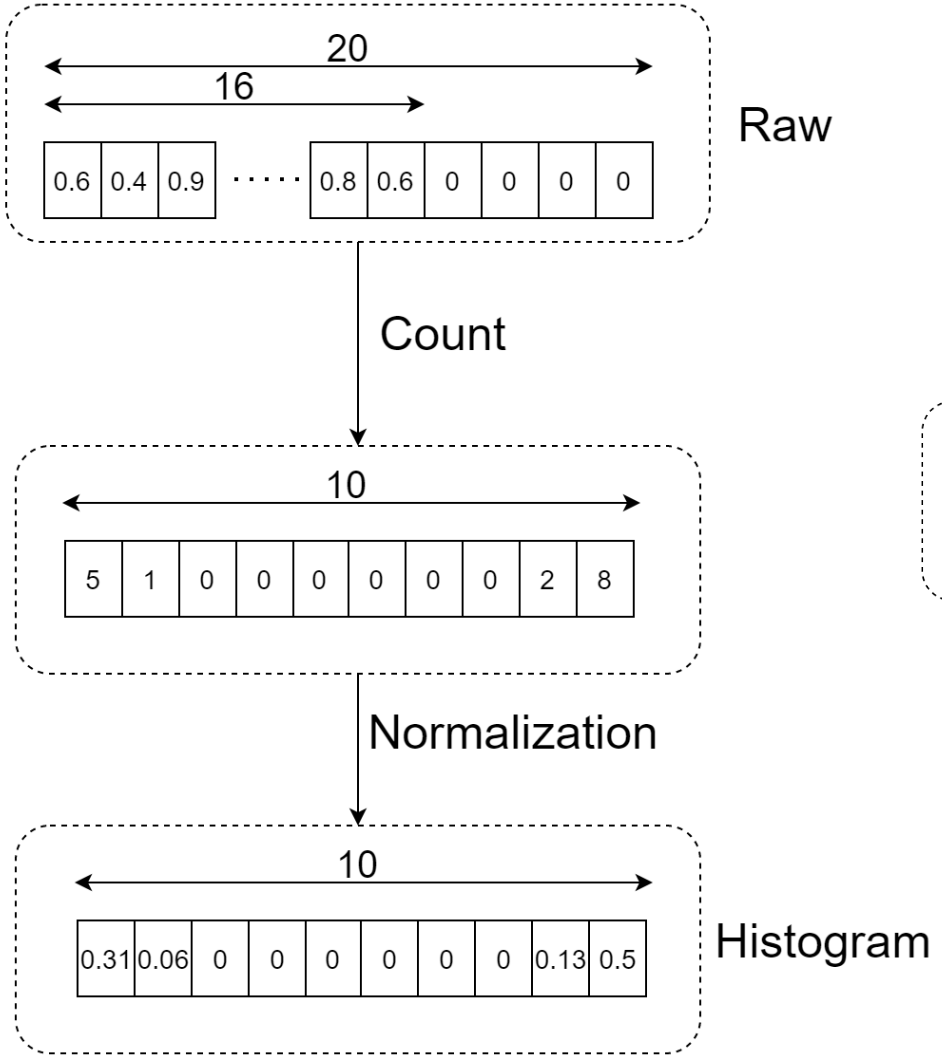
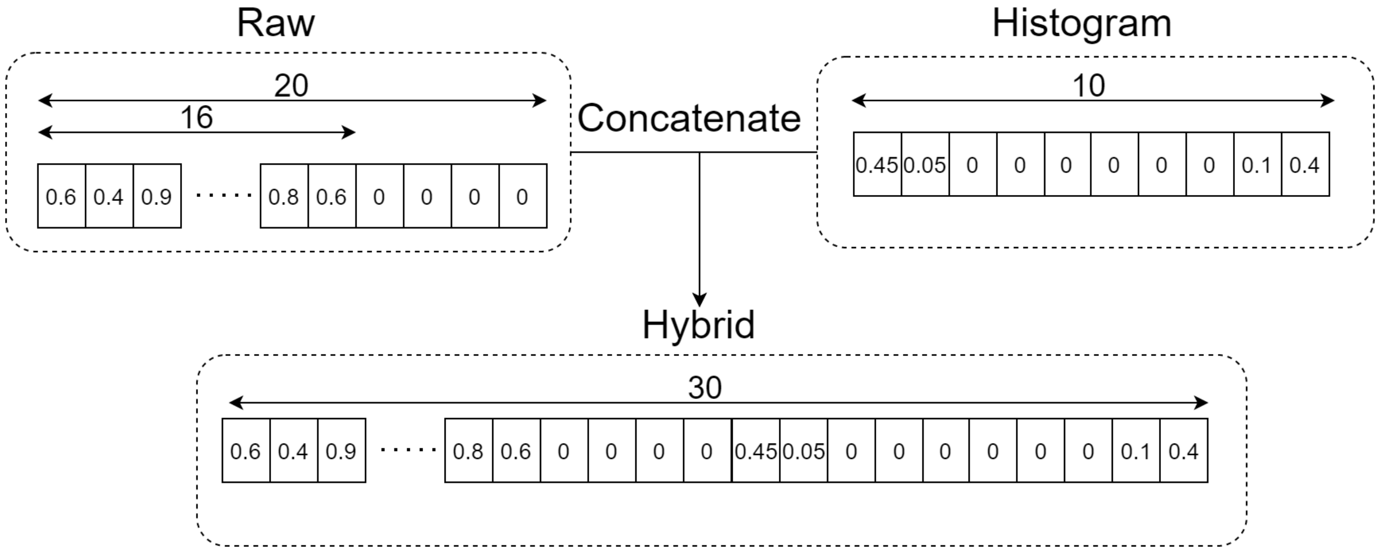
Diverse Input Strategies for EEG Data Analysis





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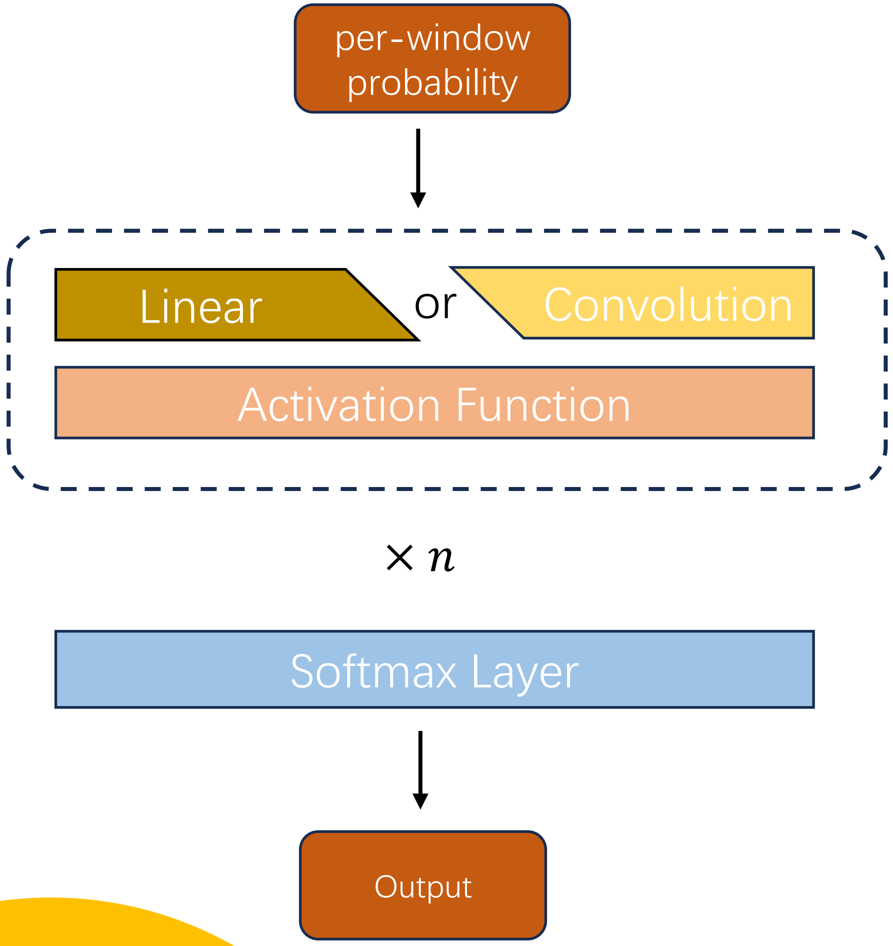
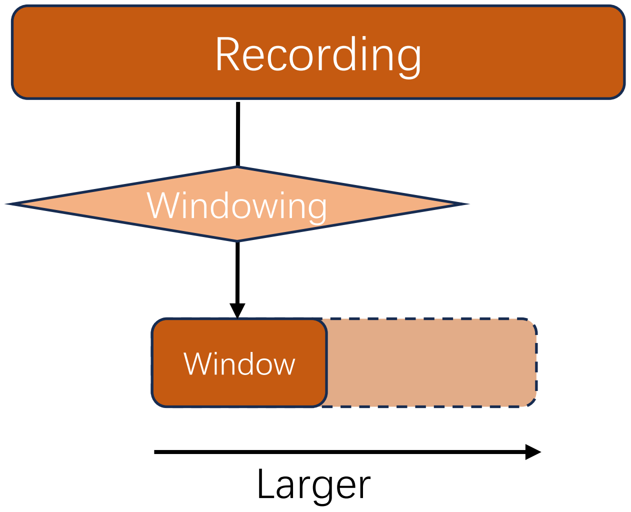


Arbitration Model Architecture (Artificial Neural Network)

- **Final Architecture:** The proposed models consist of a fully-connected layer followed by a softmax layer for final classification.
- **Depth and Size Variations:** We tested multi-layer perceptrons with 1 to 4 layers and hidden layers ranging from 5 to 20 units in size.
- **Alternatives to Fully-Connected Layers:** We also experimented with convolutional layers as an alternative to fully-connected ones.
- **Activation Functions:** Different activation functions were trialed, including RELU, ELU, and GELU.

The Scope Issue and Window Length



Scope Limitation: Traditional models may miss the full EEG context.
Global Info: Bigger windows provide a broader view.
Solution: Longer windows for better EEG capture.
Note: This complements machine learning arbitration.

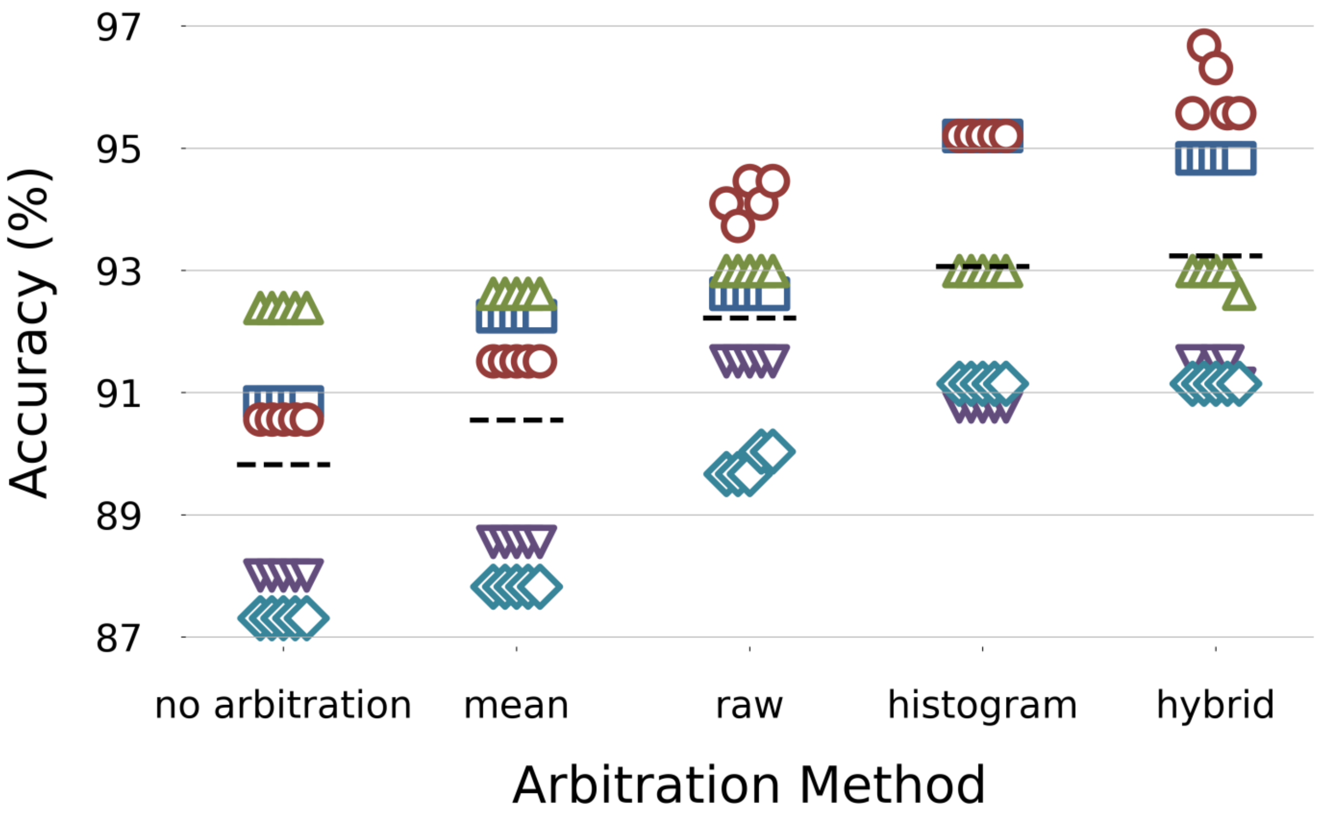
Results

Results

Table 1. Summary of state-of-the-art performance metrics for different models applied to abnormal EEG classification

Model	Accuracy	Sensitivity	Specificity
1D-CNN (T5-O1 channel)[12]	79.3 %	71.4 %	86.0 %
1D-CNN (F4-C4 channel)[12]	74.4 %	55.6 %	90.7 %
Deep4 [1]	85.4 %	75.1 %	94.1 %
TCN [5]	86.2 %		
ChronoNet [9]	86.6 %		
Alexnet[2]	87.3 %	78.6 %	94.7 %
VGG-16 [2]	86.6 %	77.8 %	94.0 %
Fusion Alexnet[8]	89.1 %	80.2 %	96.7 %
[6]	89.8 %	81.3 %	**96.9 %**
Proposed	**93.3 %**	**92.0 %**	92.9 %

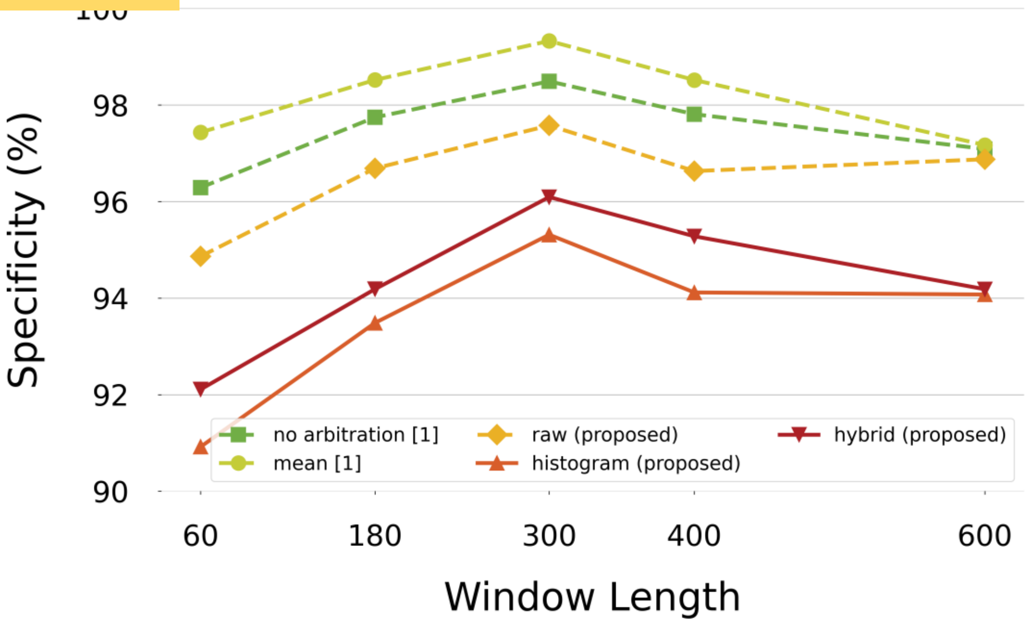
Arbitration Model Results on BD-Deep4 [1]

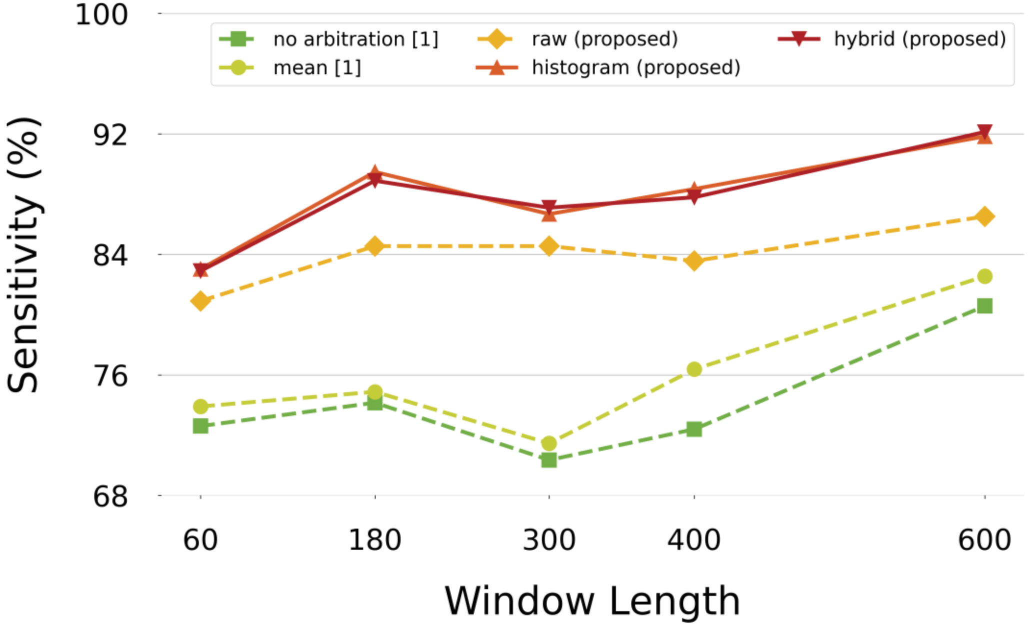


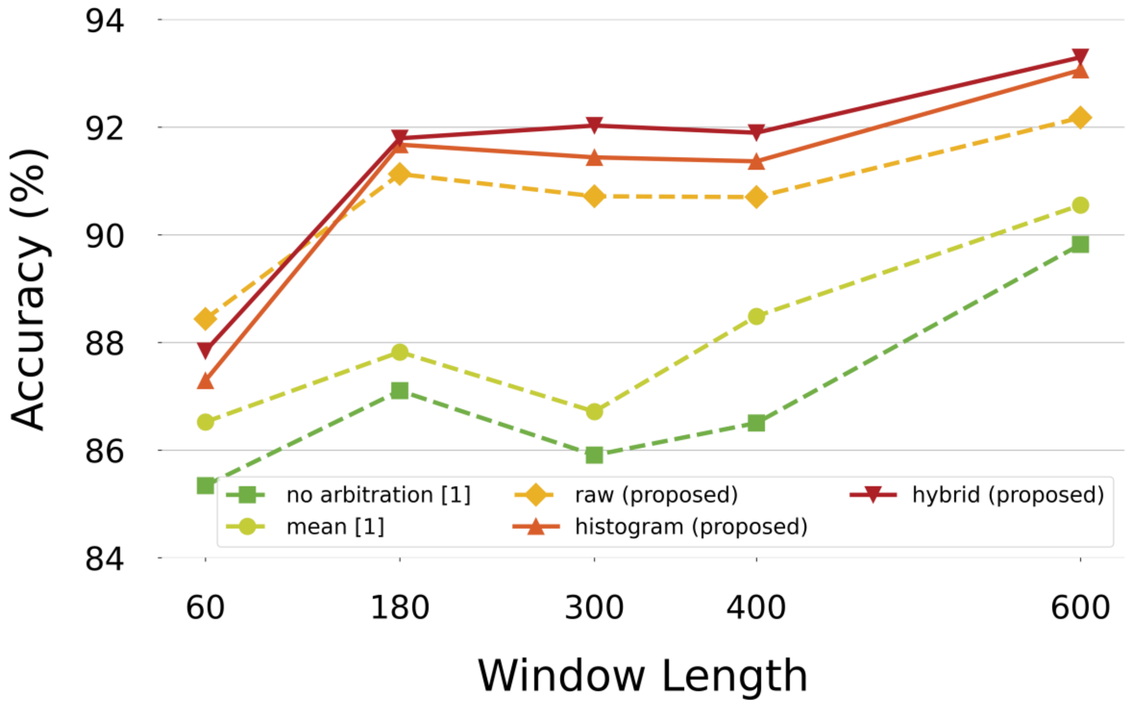
Performance of different arbitration models using window lengths of 60 s. Points with the same marker shape come from the same instance of the first-stage model (BD-Deep4). The dashed lines represent the mean for each arbitration method.

Effect of Window Length

Increasing window length improves accuracy by increasing sensitivity, with relatively little effect on specificity







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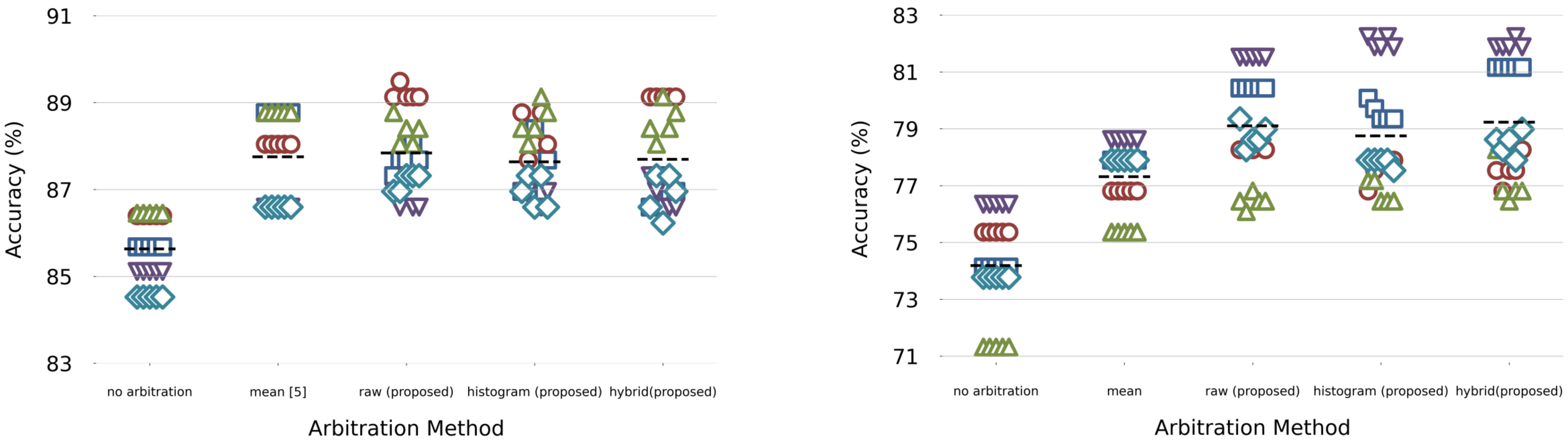
Arbitration Model Results on TCN [5,14] and ViT [15]



(a) TCN (b) ViT

Performance of different arbitration methods using (a) TCN and (b) ViT as the first-stage architecture with a window length of 60 s.

Conclusion

Conclusion

- **Approach Benefits:** Our method surpasses prior EEG classification benchmarks.
- **Enhanced Sensitivity:** More accurate window-label alignment boosts model sensitivity.
- **Clinical Relevance:** This could streamline EEG analysis for healthcare providers.
- **Broader Impact:** The method may be applicable to other time-series tasks.
- **Note:** The inter-rater agreement ceiling is not a constraint for TUAB.

Thank You!

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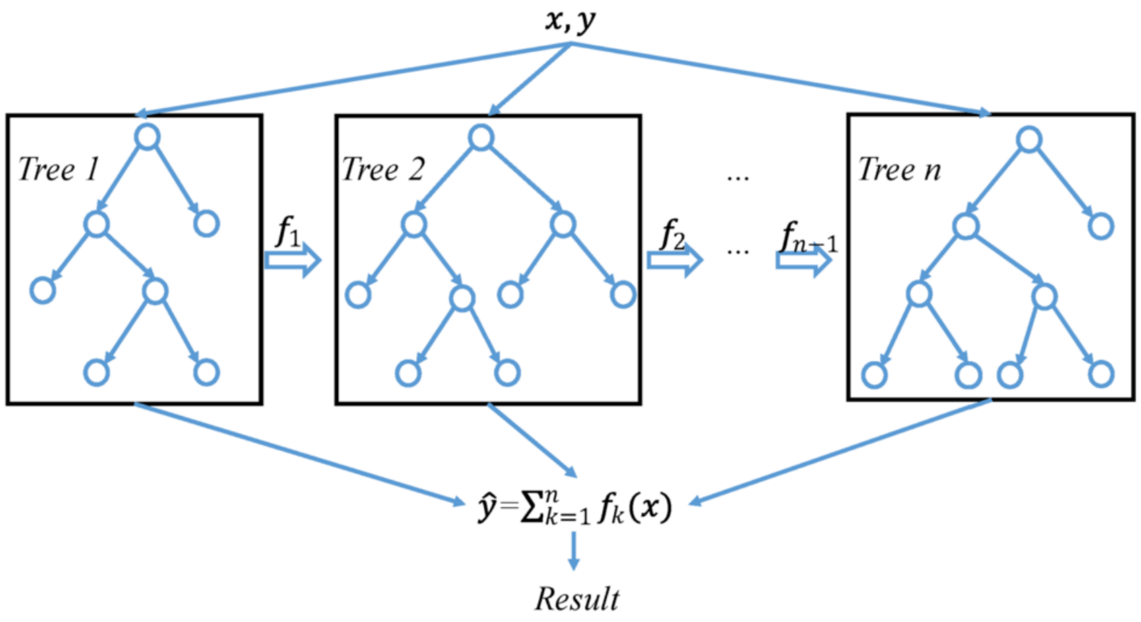
Appendix

Arbitration Model Architecture (XGBoost)

- **Tabular Data Perspective:** We treated the outputs of the first-stage model as tabular data, which led us to evaluate XGBoost, known for its strong performance on such datasets.
- **Hyperparameter Optimization:** A grid search was utilized during each training run to find the optimal 'maximum depth' from {5, 10, 15, 20, 25}, using three-fold cross-validation for selection.



Comparison of performance between models

Model	Accuracy	Sensitivity	Specificity
1D-CNN (T5-O1 channel) (Yıldırım et al., 2020)	79.3 %	71.4 %	86.0 %
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Deep4 (Schirrmeister et al., 2017)	85.4 %	75.1 %	94.1 %
TCN (Gemein et al., 2020)	86.2 %		
ChronoNet (Roy et al., 2019)	86.6 %		
Alexnet (Amin et al., 2019)	87.3 %	78.6 %	94.7 %
VGG-16 (Amin et al., 2019)	86.6 %	77.8 %	94.0 %
Fusion Alexnet (Alhussein et al., 2019)	89.1 %	80.2 %	96.7 %
Fusion CNN (Muhammad et al., 2020)	89.8 %	81.3 %	96.9 %
Scope and Arbitration (Deep4-ANN-Hybrid) Zhu et al. (2023)	93.3 %	92.0 %	92.9 %
Window Stacking Meta-Model (TCN-XGBoost-Raw)	**99.0 %**	**98.1 %**	**100 %**

Table 1: Summary of state-of-the-art performance metrics for different models applied to abnormal EEG classication on the TUAB dataset

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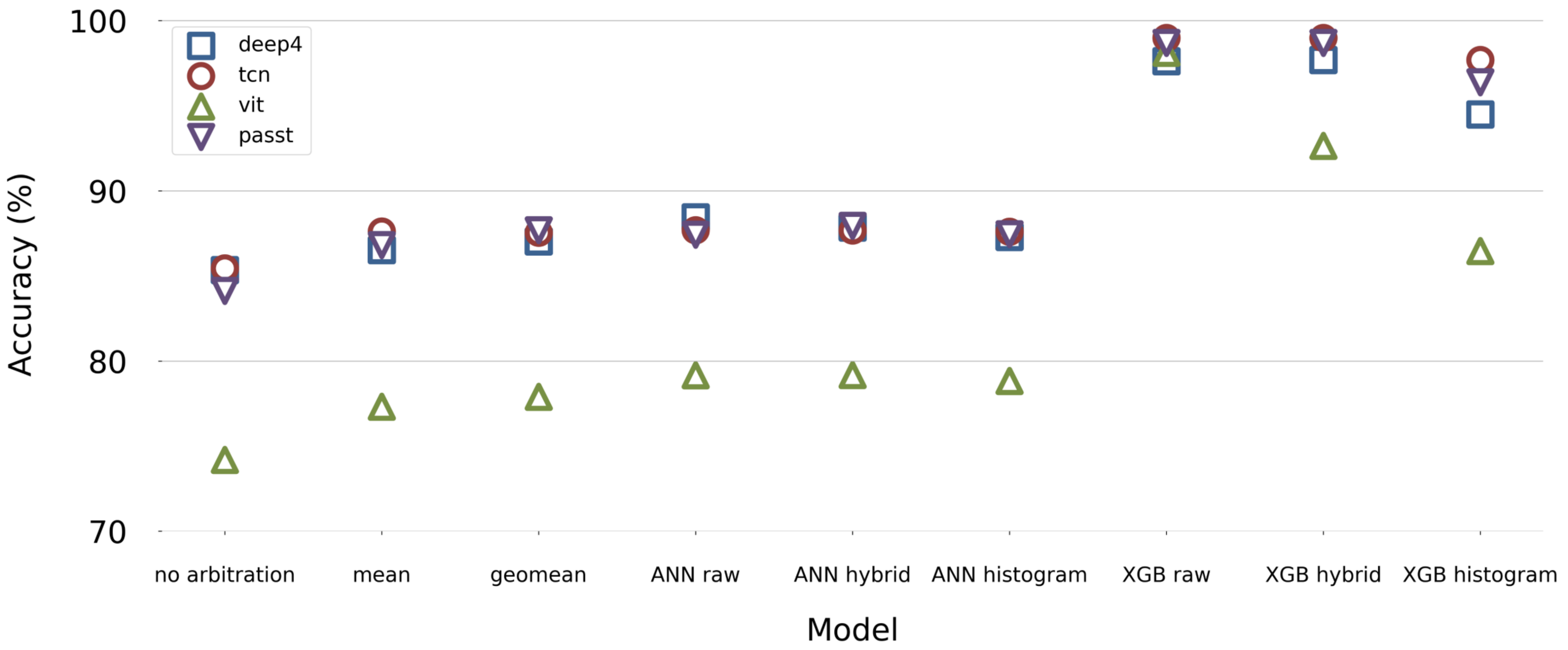
Second-Stage Model Results



Performance comparison of single-stage and various two-stage architectures, all with a window length of 60s, using the TUAB dataset. Each column represents a different arbitration method. Each marker type represents a different first-stage architecture. Each data point is the average accuracy across twenty-five experiments.

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