Interpretable and Lightweight Machine Learning Approach for Autism Classification Using Biomarkers Derived from Multi-trial Resting EEG

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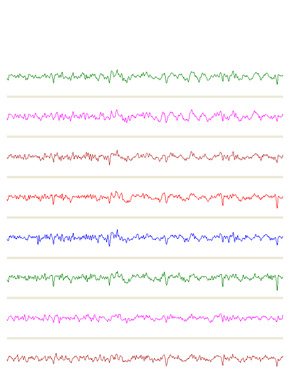
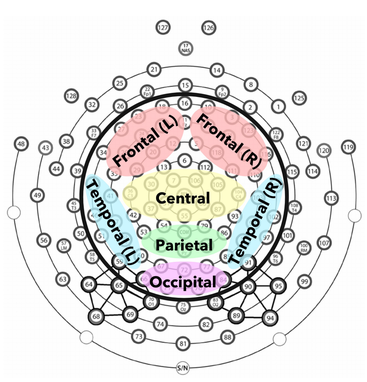
INTRODUCTION

- Autism Spectrum Disorder (ASD): heterogenous, hard to identify biomarkers for diagnosis
- Electroencephalography (EEG): valuable tool for biomarker identification—non-invasive, high temporal resolution, affordable



Subset of EEG signals
(Figure from Biopac)



EEG head map
(Template from Neuhaus *et. al.*[1])

GOALS

- Predict ASD from EEG using machine learning tools
- Explore distributional features across EEG trials
- Identify important features for ASD diagnosis

METHODS

1) DATA[1]

Group	Size	Male/Female	Age (years)
Autism (ASD)	94	55/39	12.5±2.9
Control (CON)	96	49/47	12.9±2.8

3) FEATURE EXTRACTION

- Get Power Spectral Density (PSD) at each electrode and frequency band using Welch's estimate {hamming, 512 point}

Two Feature Aggregation Types

Mean-EEG	Across-trial
PSD of Mean EEG (conventional)	PSD of EEG for each trial
Mean, std. deviation, skew, & kurtosis of PSD in each frequency band	Mean, std. deviation, skew, & kurtosis of PSD in each frequency band
# Electrodes × # Within-band features × # Frequency bands = 128 x 5 x 4 = 2560 features	Mean and std. deviation of band features <u>across trials</u>
	2 x 2560 = 5210 features

2) PREPROCESSING

- Low pass (<100 Hz) and Notch (60Hz) filters
- Wavelet threshold and bad segment rejection
- ICA and bad channel rejection[1]

4) TRAINING AND TESTING

- Four classifiers trained on the two standardized feature types separately
  1. Logistic regression (LR)
  2. Random forest without bootstrap (RF)
  3. Kernel-support vector machine (SVM)
  4. An artificial neural network (ANN)
- Stratified 5-fold cross-validation
  - Repeated 5x
- Evaluation: accuracy, F1 score, precision, recall, specificity, AUROC, AUPRC metrics
- Feature importance: determined by magnitude of mean feature weights in cross-validation across-trial LR models

RESULTS

REPEATED 5-FOLD CROSS-VALIDATION MODEL PERFORMANCE

Model	Features	Accuracy	F1 score	Precision	Recall	Specificity	AUROC	AUPRC
LR	Across-trial	**0.678±0.083**	**0.678±0.083**	**0.674±0.101**	0.693±0.108	0.664±0.123	**0.748±0.073**	**0.751±0.086**
	Mean-EEG	0.608±0.060	0.597±0.088	0.601±0.082	0.604±0.117	0.61±0.085	0.648±0.070	0.678±0.084
RF	Across-trial	0.660±0.085	0.646±0.102	0.665±0.112	0.649±0.147	**0.681±0.121**	0.742±0.082	0.744±0.089
	Mean-EEG	0.614±0.068	0.589±0.076	0.626±0.095	0.571±0.109	0.662±0.115	0.672±0.092	0.693±0.088
SVM	Across-trial	0.659±0.079	0.656±0.089	0.659±0.101	0.679±0.146	0.654±0.106	0.734±0.087	0.743±0.093
	Mean-EEG	0.577±0.064	0.532±0.087	0.608±0.136	0.509±0.161	0.669±0.146	0.608±0.146	0.619±0.102
ANN	Across-trial	0.654±0.088	0.682±0.099	0.650±0.108	**0.751±0.156**	0.590±0.160	0.721±0.095	0.709±0.084
	Mean-EEG	0.622±0.079	0.616±0.112	0.600±0.112	0.661±0.160	0.564±0.158	0.651±0.108	0.683±0.098

Table 1: Metrics from all experiments. Significant differences ($p<0.05$) from two-sample t-tests between the two feature types are highlighted in green. (No significant differences between model choices found.)

REPEATED 5-FOLD CROSS-VALIDATION ACCURACY

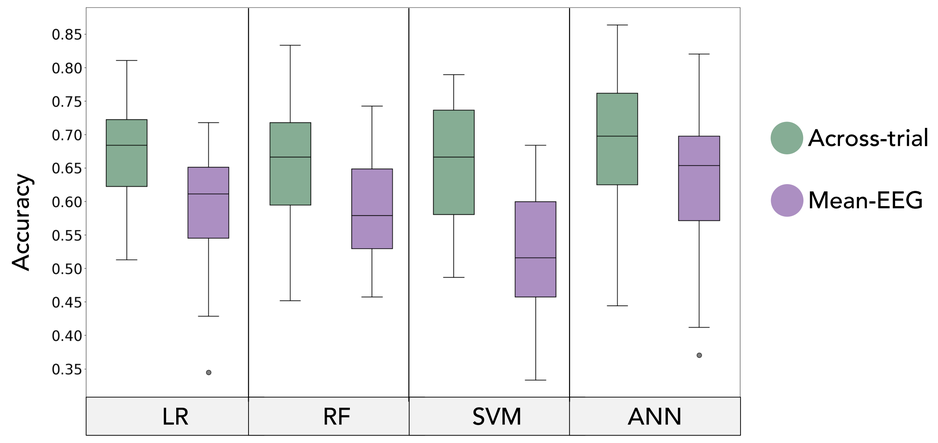
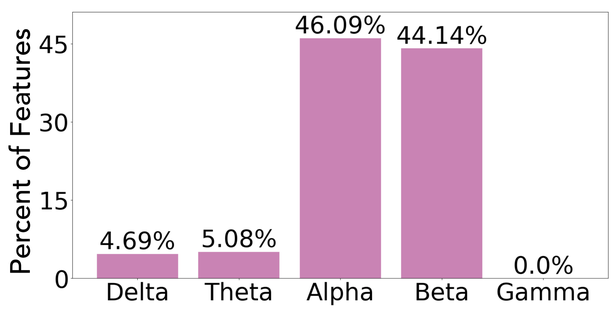


Fig 1: Accuracy of all models using the two feature types. Across-trial feature models show higher accuracy.

DISTRIBUTION OF TOP 5% MOST IMPORTANT FEATURES



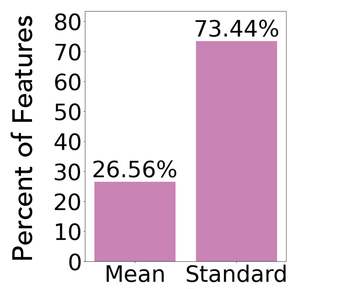


Fig 2: Frequency band distribution (left) and across-trial feature distribution (right) of the top 5% most important features. P-values from chi-square goodness-of-fit tests with the null hypothesis of a uniform distribution.

SIGNIFICANTLY DIFFERENT BRAIN REGIONS BETWEEN GROUPS

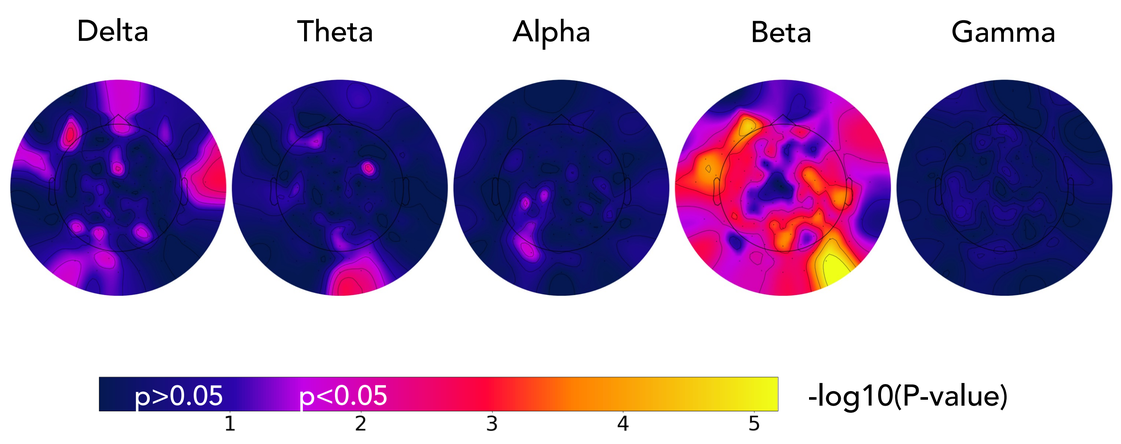


Fig 3: Topological head plots of significant regions based on two-sample t-tests for the difference between ASD and CON in the mean of summed across-trial features adjusted by LR model weights.

DISCUSSION AND CONCLUSION

- Features recording variability across trials are more important
  - Trial-to-trial variability differs between ASD and CON groups[2]
- The choice of machine learning model is not significant
- Beta frequency: highest diagnostic value in all brain regions
- Occipital and frontal temporal regions: higher diagnostic value across multiple frequency bands
- Future work:
  - Incorporate features from task-EEG data
  - Use deep learning for feature extraction

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