Discover Our Brain Potential: Personalized Brain-Computer Interfaces with Machine Learning

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Outline

Brain-Computer Interfaces (BCI)

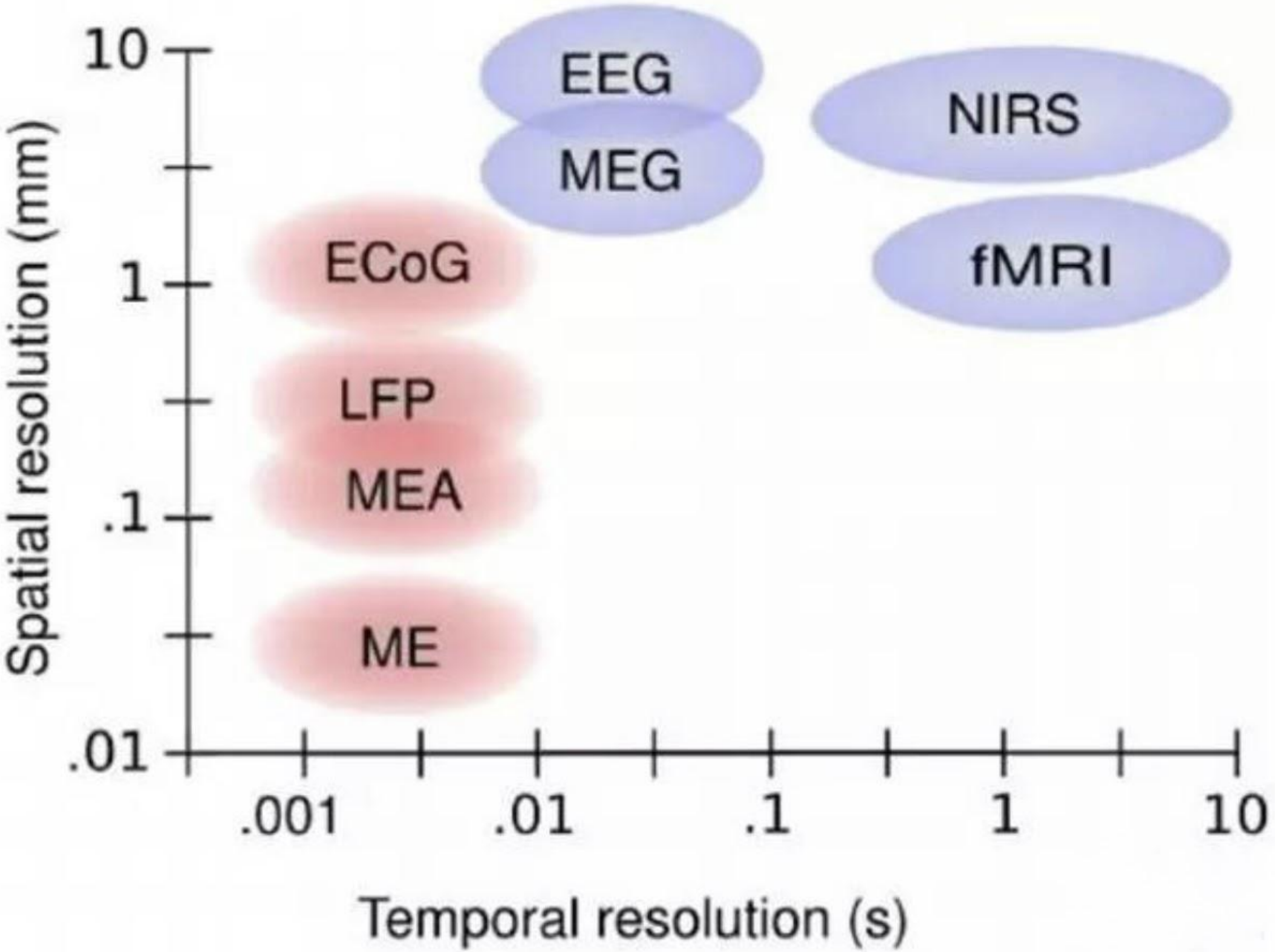
Clinical

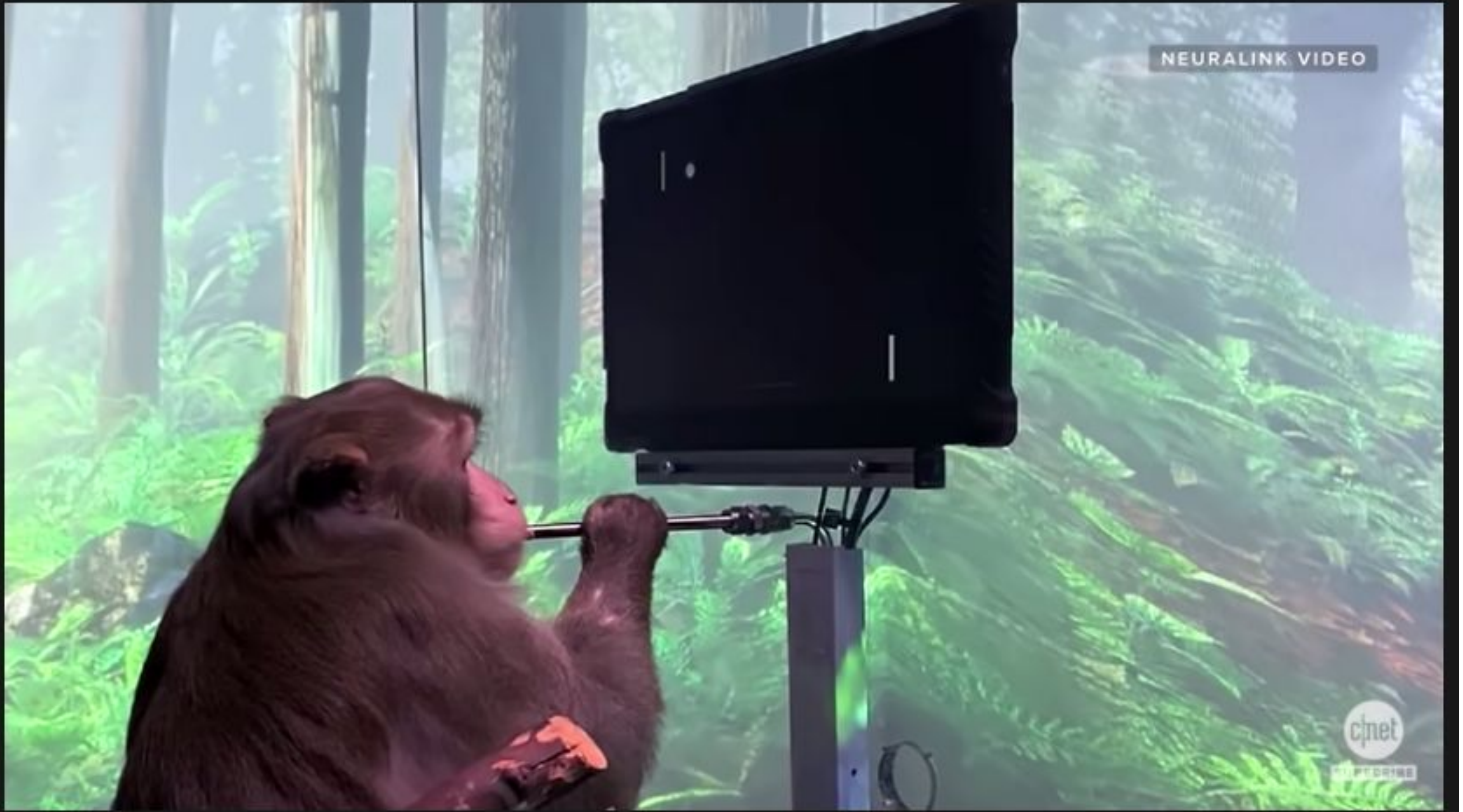
Clustering: First Episode Psychosis (FEP) patients vs healthy controls

Non-Clinical

New algorithms for electroencephalogram (EEG) Classification


A STEVEN SPIELBERG FILM
READY
PLAYER
ONE


EEG
MEG
NIRS
fMRI
ECoG
LFP
MEA
ME
Spatial resolution (mm)
10
1
.1
.01
.001
.01
.1
1
10
Temporal resolution (s)



Elon Musk's Neuralink monkey brain demo explained

283,116 views • Apr 9, 2021 4.6K 135 SHARE SAVE ...

Clinical

Clustering: FEP patients vs health controls

Clinical, non-invasive, wired

Electroencephalography (EEG)

Biomarkers, machine learning

Human cognitive tasks and mental states

Brandeis University

Harvard Medical School

McLean
Harvard Medical School Affiliate

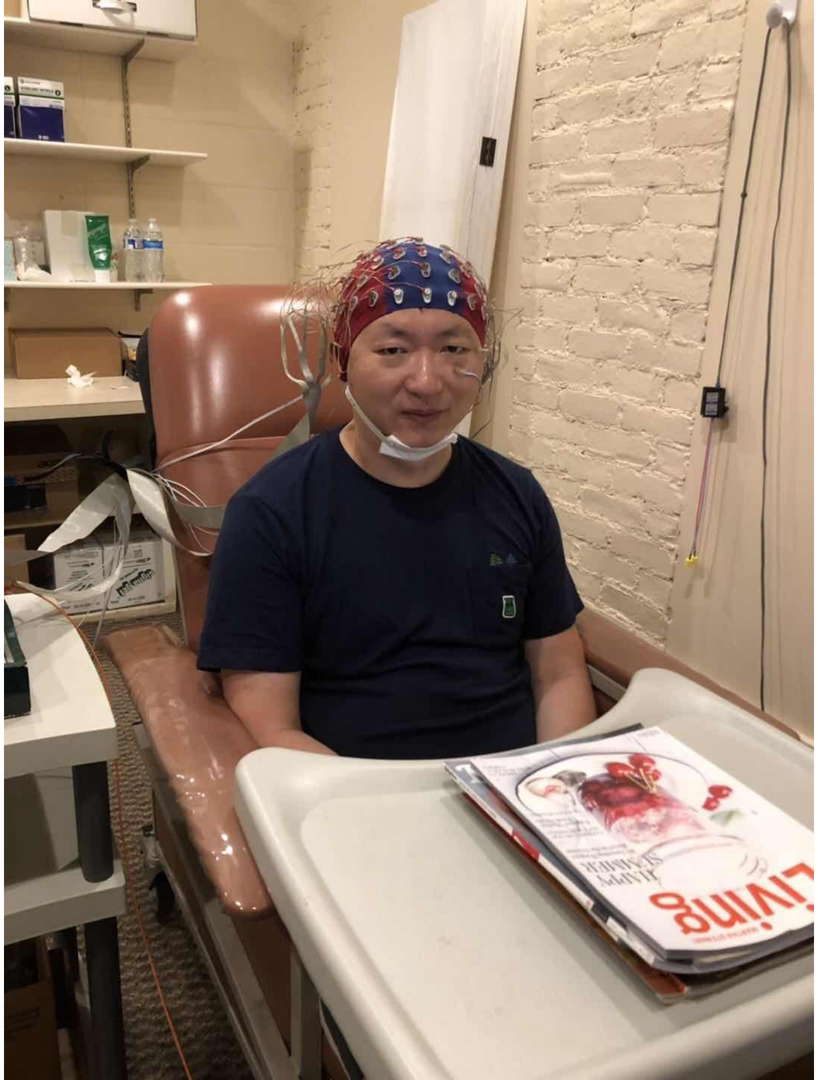
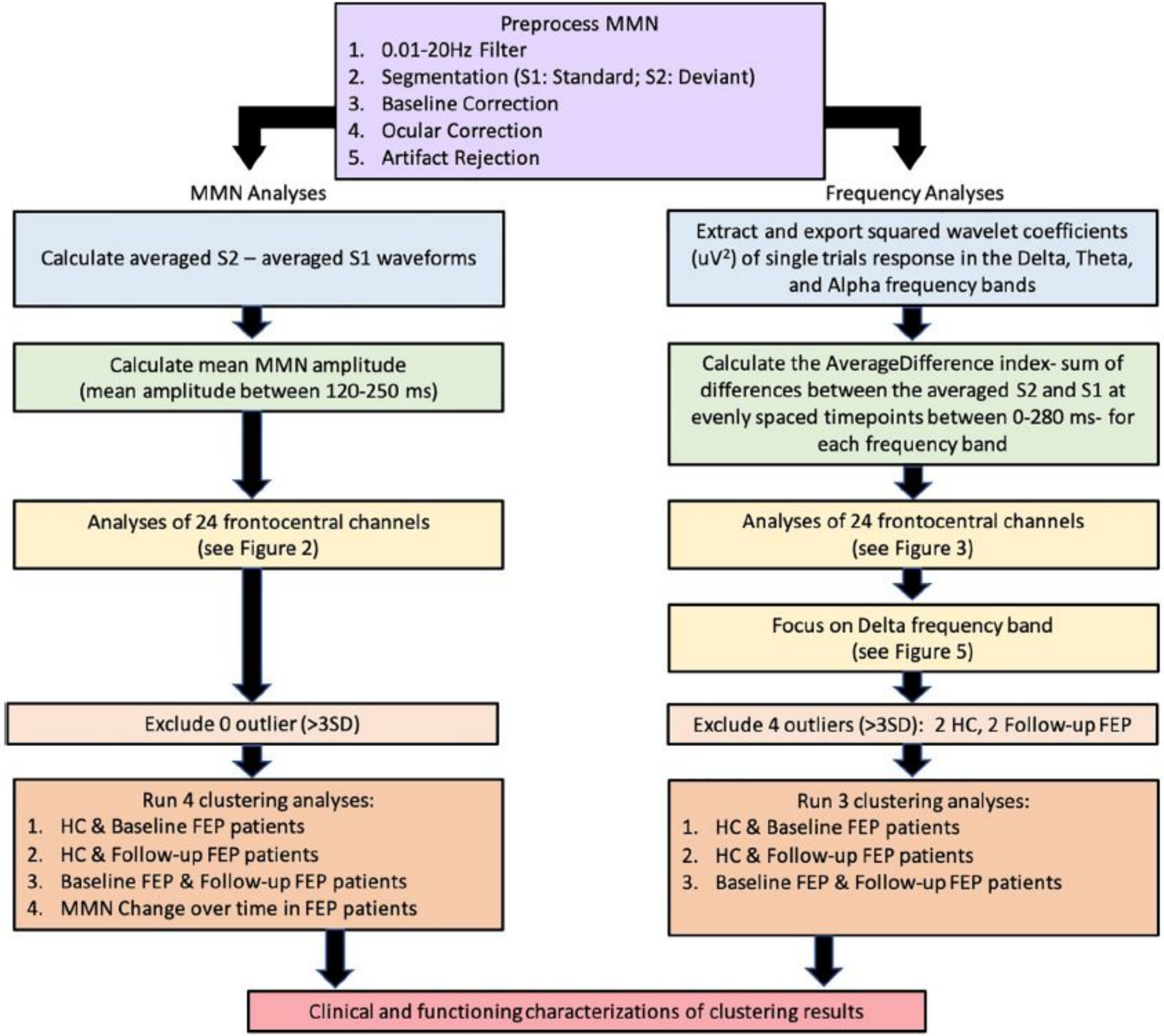
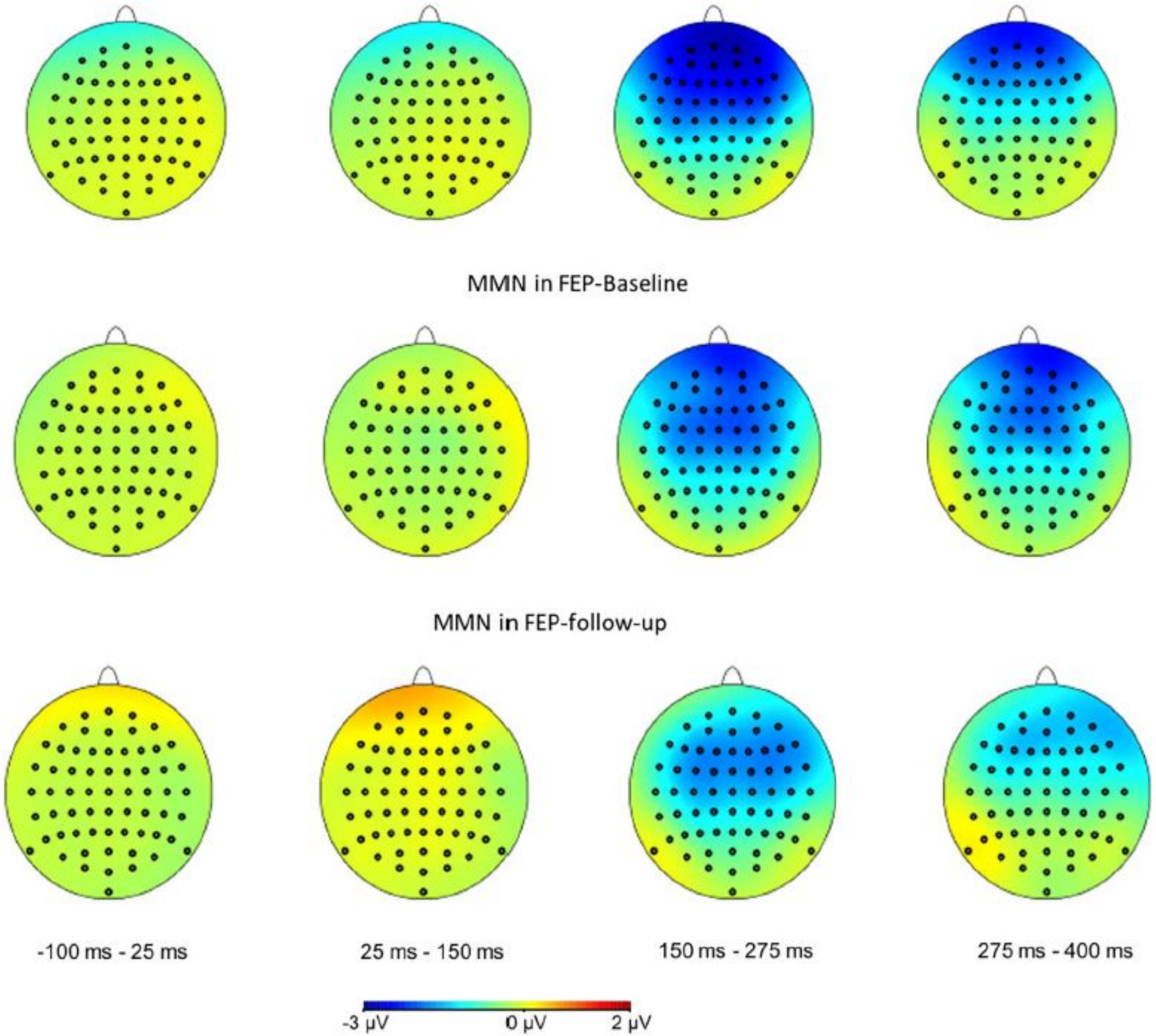

Living
HAPPY SUMMER

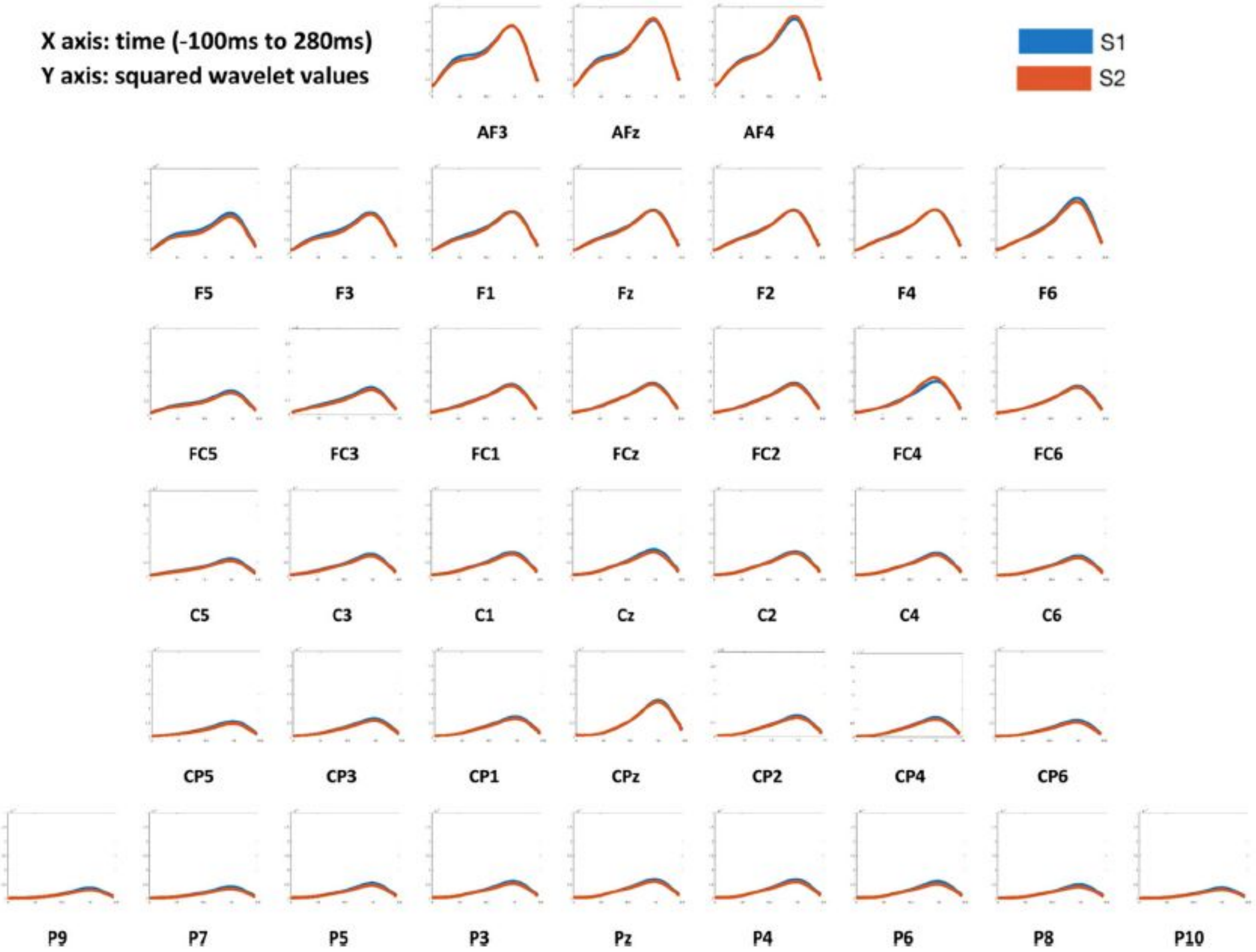
TABLE 1 | Comparisons between controls, baseline patients, and 6-month follow-up patients.

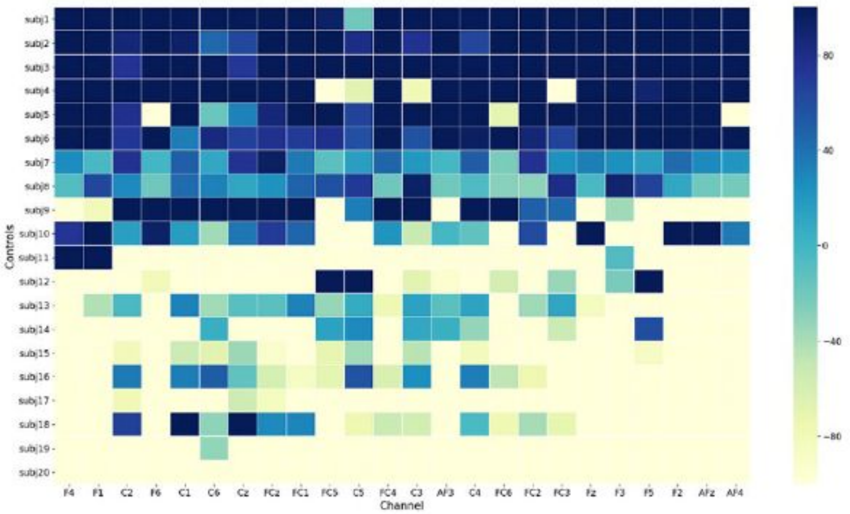
Variables	Controls (N=33)	Baseline Patients (N=20)	6m Follow-up Patients (N=18)	Statistics P value
	Mean (Std Errors)	Mean (Std Errors)	Mean (Std Errors)	
Age	22.91 (3.9)	22.7 (3.2)	23.39 (3.3)	F = 0.19 p = 0.83
Females (count, %)	12 (36.36%)	7 (35.00%)	6 (33.33%)	χ = 0.05 p = 0.98
Education (years)	15.55 (1.7)	14.95 (1.6)	15.06 (1.6)	F = 0.97 p = 0.388
UPSA total score	83.45 (8.3)	79.99 (10.9)	82.52 (12.0)	F = 0.58 p = 0.56
MCAS total score	54.75 (0.6)	48.1 (5.8)	48.0 (6.2)	F = 17.38 p <0.0001
MATRICS Neurocognitive Composite Score	50.45 (5.2)	46.21 (6.4)	48.63 (8.1)	F = 2.70 p = 0.07
MATRICS Social Subscore	54.52 (6.6)	53.58 (11.5)	55.33 (13.8)	F = 0.13 p = 0.88
TASIT	55.77 (4.5)	53.69 (6.4)	54.67 (5.2)	F = 0.579 p = 0.46
PANSS positive	N/A	14.45 (6.8)	13.18 (5.4)	t = 0.62 p = 0.27
PANSS negative	N/A	12.5 (3.8)	10.41 (3.5)	t = 1.70 p = 0.048
PANSS general	N/A	30.6 (7.9)	26.70 (8.4)	t = 1.45 p = 0.08
PANSS total	N/A	57.55 (16.7)	50.29 (16.1)	t = 1.33 p = 0.09
Chlorpromazine equivalents	N/A	226.51 (234.3)	292.45 (241.6)	t = -0.74 p = 0.77

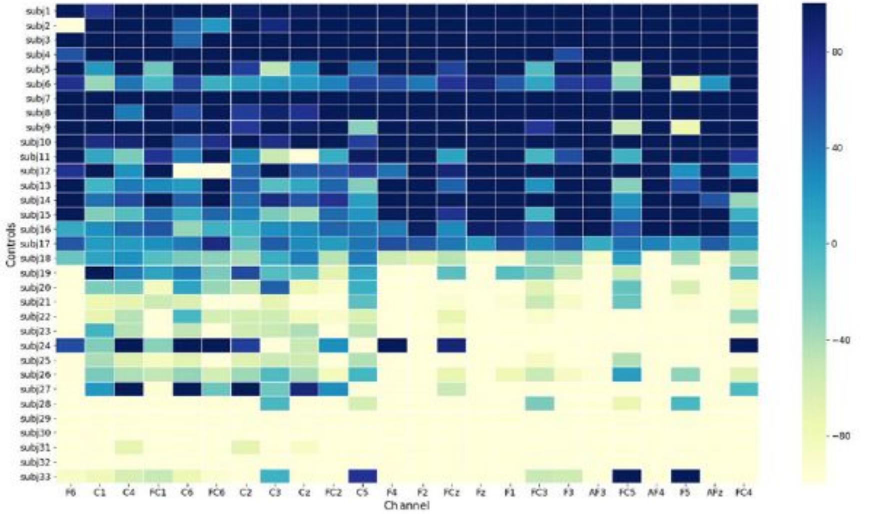
Means with standard deviations in parentheses unless specified otherwise; UPSA, UCSD Performance-based Skills Assessment; MCAS, Multnomah Community Ability Scale; MATRICS, Measurement and Treatment Research to Improve Cognition in Schizophrenia; TASIT, The Awareness of Social Inference Test; PANSS, Positive and Negative Syndrome Scale; CPZ, chlorpromazine equivalents.

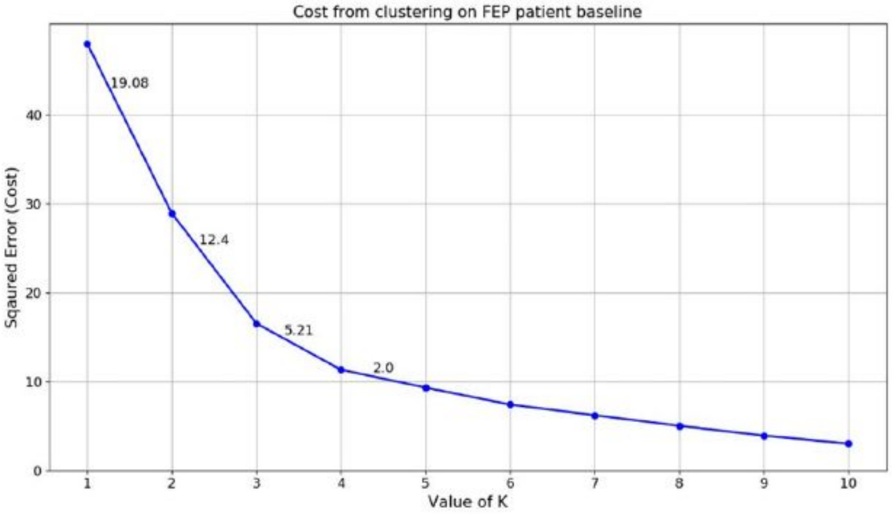

Preprocess MMN
1. 0.01-20Hz Filter
2. Segmentation (S1: Standard; S2: Deviant)
3. Baseline Correction
4. Ocular Correction
5. Artifact Rejection
MMN Analyses
Frequency Analyses
Calculate averaged S2 – averaged S1 waveforms
Extract and export squared wavelet coefficients (uV²) of single trials response in the Delta, Theta, and Alpha frequency bands
Calculate mean MMN amplitude (mean amplitude between 120-250 ms)
Calculate the AverageDifference index- sum of differences between the averaged S2 and S1 at evenly spaced timepoints between 0-280 ms- for each frequency band
Analyses of 24 frontocentral channels (see Figure 2)
Analyses of 24 frontocentral channels (see Figure 3)
Focus on Delta frequency band (see Figure 5)
Exclude 0 outlier (>3SD)
Exclude 4 outliers (>3SD): 2 HC, 2 Follow-up FEP
Run 4 clustering analyses:
1. HC & Baseline FEP patients
2. HC & Follow-up FEP patients
3. Baseline FEP & Follow-up FEP patients
4. MMN Change over time in FEP patients
Run 3 clustering analyses:
1. HC & Baseline FEP patients
2. HC & Follow-up FEP patients
3. Baseline FEP & Follow-up FEP patients
Clinical and functioning characterizations of clustering results

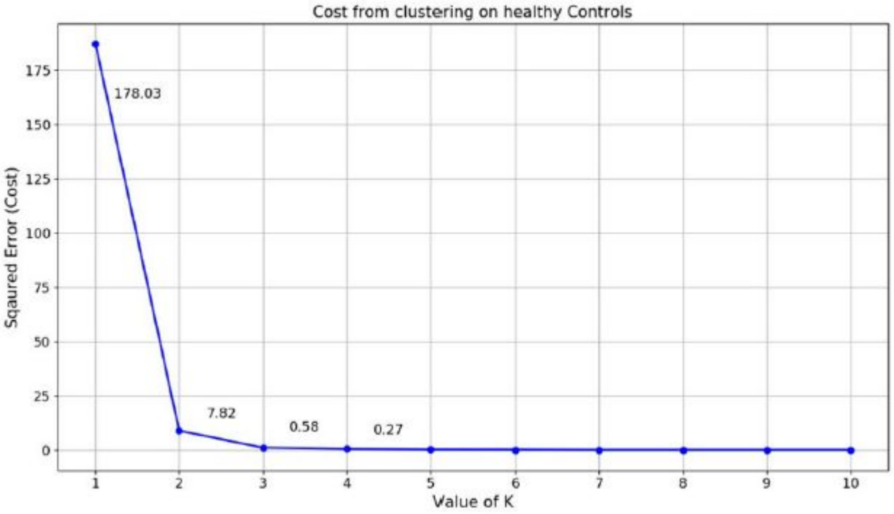

MMN in FEP-Baseline
MMN in FEP-follow-up
-100 ms - 25 ms
25 ms - 150 ms
150 ms - 275 ms
275 ms - 400 ms
-3 µV
0 µV
2 µV


X axis: time (-100ms to 280ms)
Y axis: squared wavelet values
S1
S2
AF3
AFz
AF4
F5
F3
F1
Fz
F2
F4
F6
FC5
FC3
FC1
FCz
FC2
FC4
FC6
C5
C3
C1
Cz
C2
C4
C6
CP5
CP3
CP1
CPz
CP2
CP4
CP6
P9
P7
P5
P3
Pz
P4
P6
P8
P10


subj1
subj2
subj3
subj4
subj5
subj6
subj7
subj8
subj9
subj10
subj11
subj12
subj13
subj14
subj15
subj16
subj17
subj18
subj19
subj20
Controls
F4
F1
C2
F6
C1
C6
Cz
FC2
FC1
FC5
C5
FC4
C3
AF3
C4
FC6
FC2
FC3
Fz
F3
F5
F2
AFz
AF4
Channel
80
40
0
-40
-80


subj1
subj2
subj3
subj4
subj5
subj6
subj7
subj8
subj9
subj10
subj11
subj12
subj13
subj14
subj15
subj16
subj17
subj18
subj19
subj20
subj21
subj22
subj23
subj24
subj25
subj26
subj27
subj28
subj29
subj30
subj31
subj32
subj33
Controls
F6
C1
C4
FC1
C6
FC6
C2
C3
Cz
FC2
C5
F4
F2
FCz
Fz
F1
FC3
F3
AF3
FC5
AF4
F5
AFz
FC4
Channel
80
40
0
-40
-80


Cost from clustering on FEP patient baseline
Sqaured Error (Cost)
Value of K
19.08
12.4
5.21
2.0
0
10
20
30
40
1
2
3
4
5
6
7
8
9
10


Cost from clustering on healthy Controls
Sqaured Error (Cost)
Value of K
178.03
7.82
0.58
0.27
0
25
50
75
100
125
150
175
1
2
3
4
5
6
7
8
9
10

Non-clinical

Multi-Class Time Continuity Voting for EEG Classification

Non-Clinical, Non-invasive, wireless

Everyone can use it everyday

Human-In-The-Loop Machine Learning

Interpretable results

MUSE headband by InteraXon

Tasks

From Neuroscience:

learning, memory, behavior, perception, and consciousness

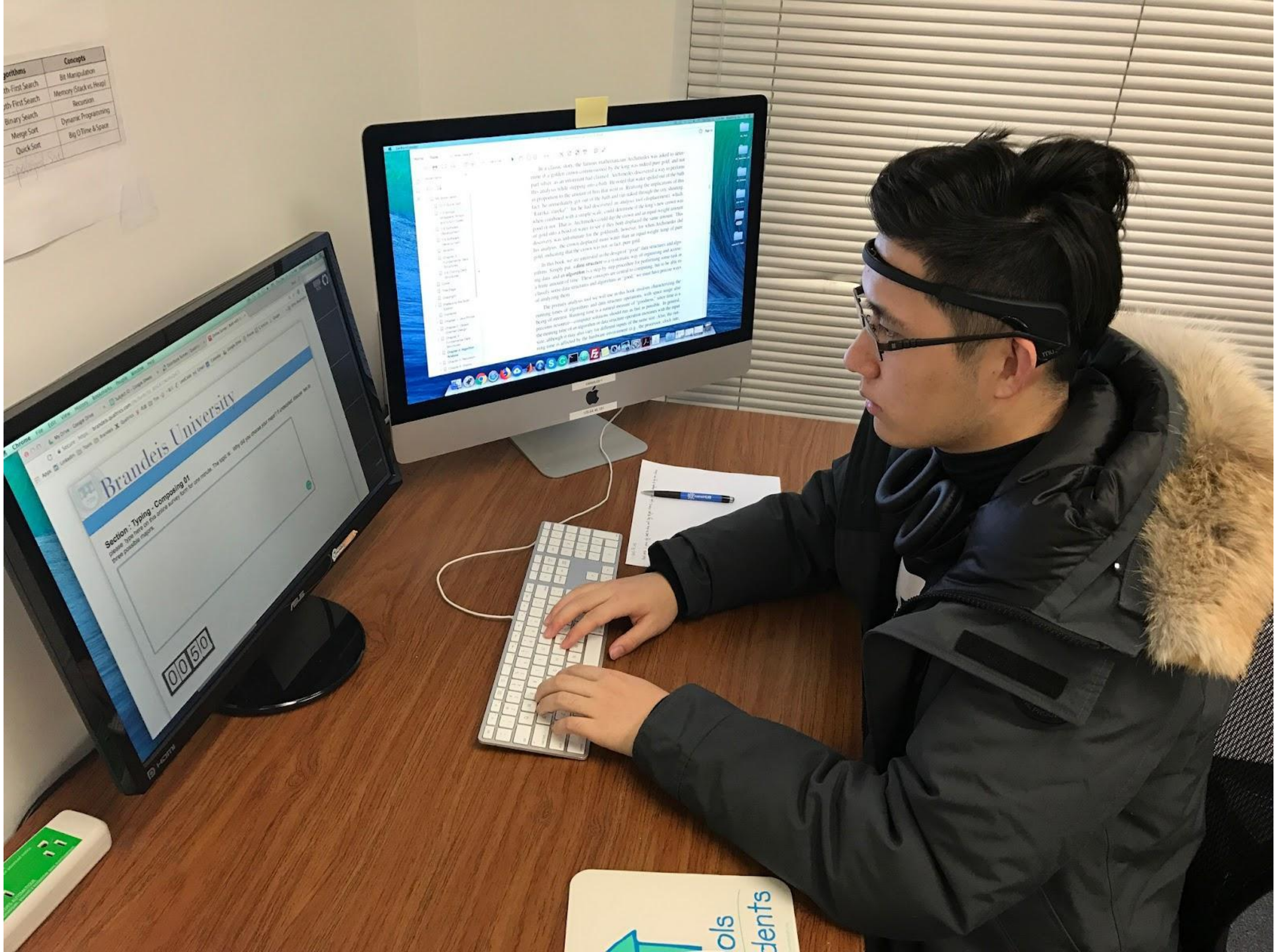
From four basic language skills:

listening, speaking, reading, and writing; [speaking -> noise]

What we have done:

reading, writing, typing, thinking, recalling, counting, drawing, solving math problems, and programming


PROBABILISTIC GRAPHICAL MODELS
PRINCIPLES AND TECHNIQUES
muse


Brandeis University
Section : Typing : Composing 01
0050

S/T	1	2	3	4	5
1	T	C	R	B	D
2	B	T	C	R	D
3	T	B	R	D	C
4	T	C	R	B	D
5	C	T	R	D	B
6	T	C	B	R	D

Fig. 2. Session (S) with Task (T) order shuffled

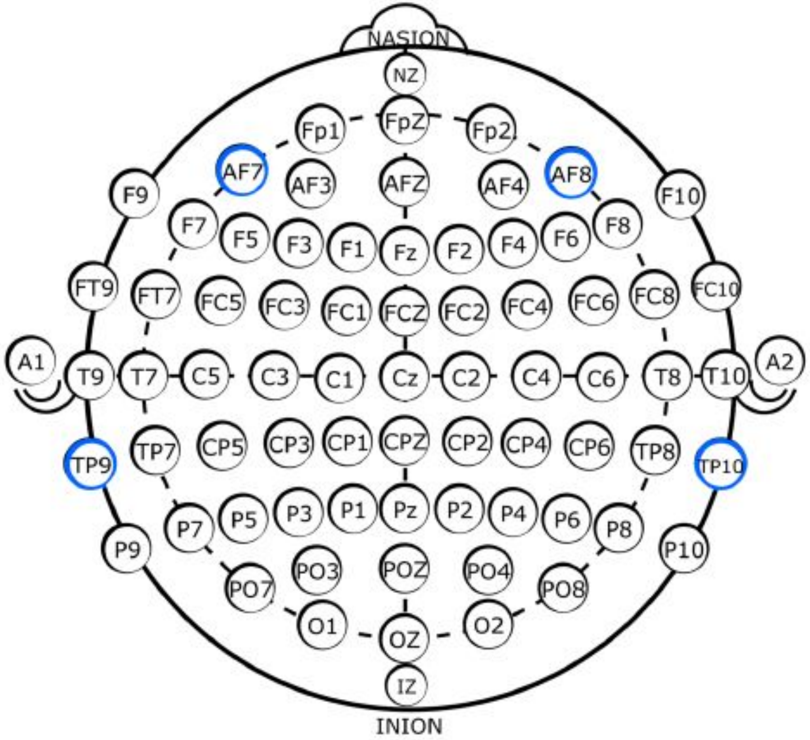
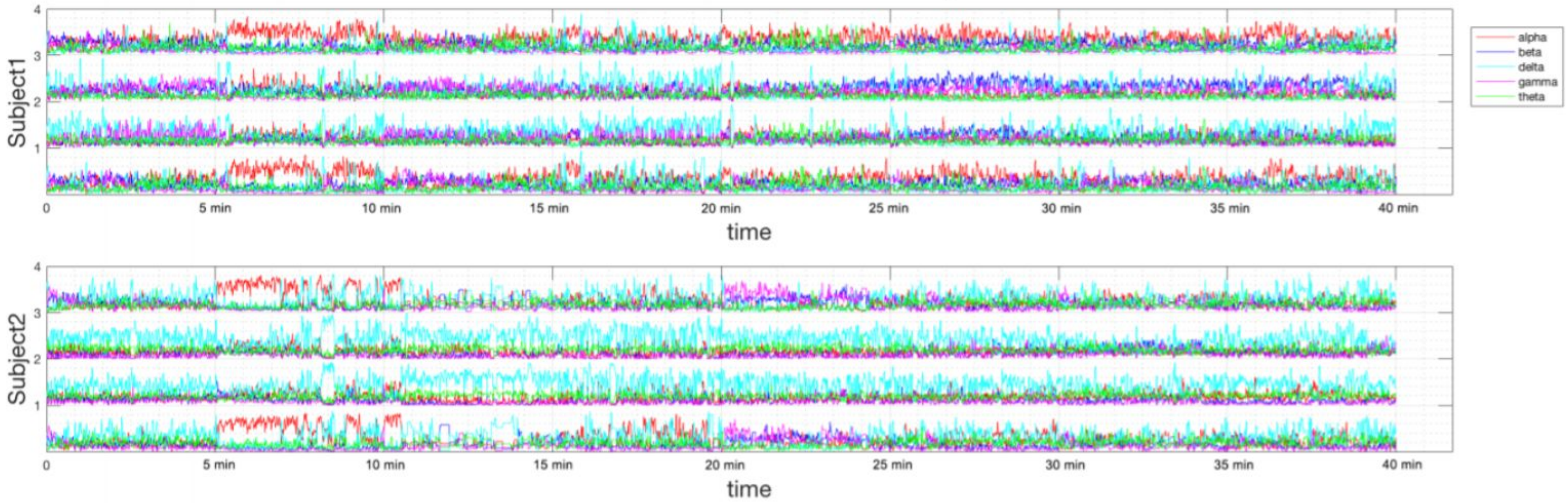
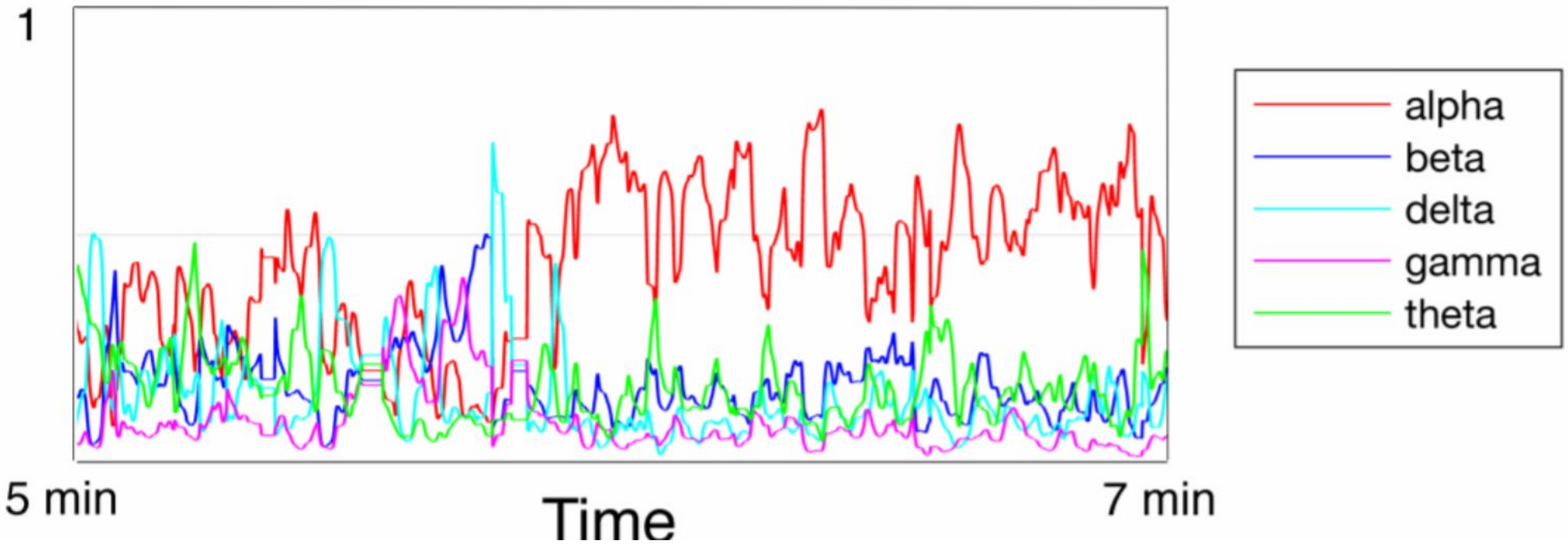


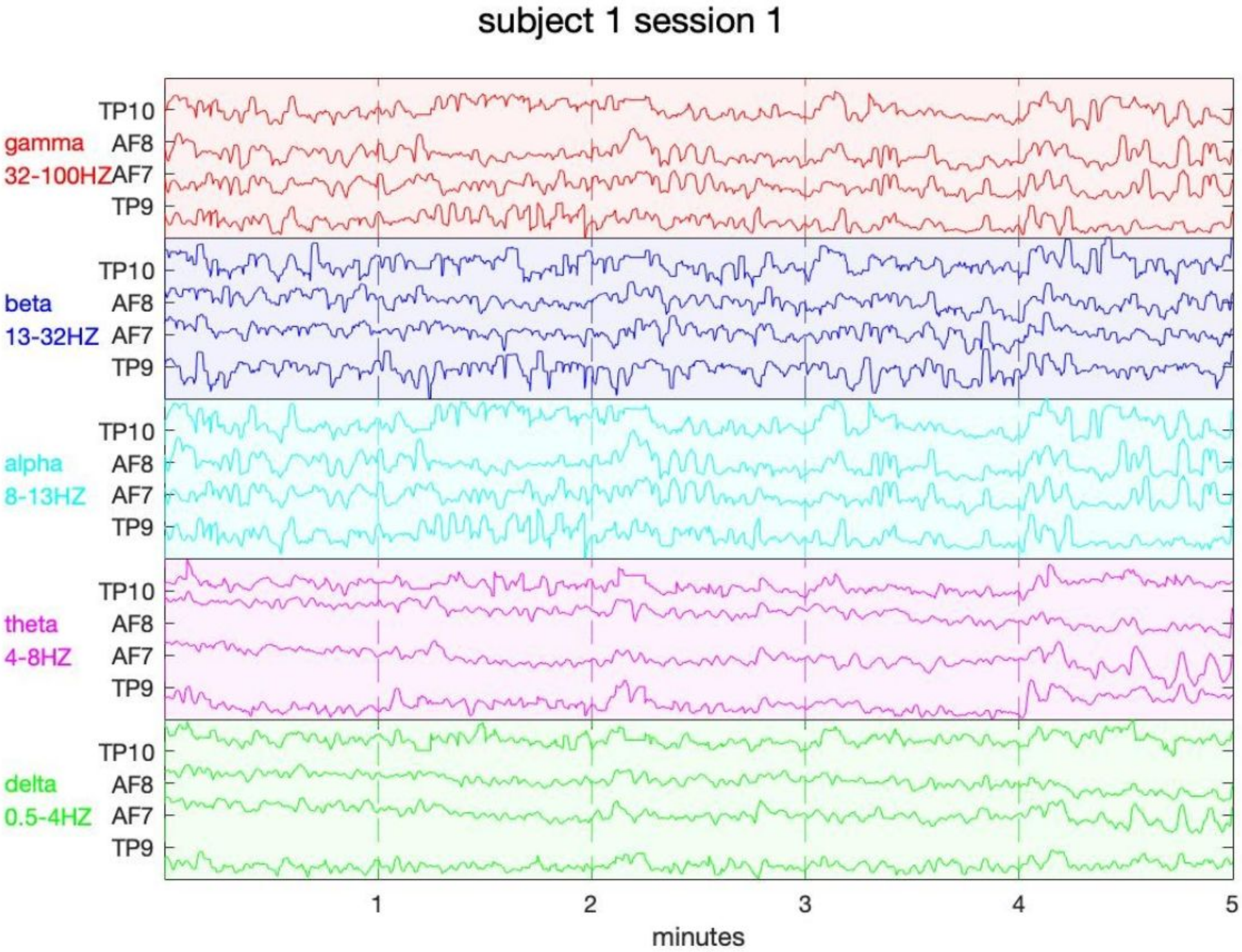
Fig. 3. 10-20 System, four electrodes used on Muse Headset were highlighted

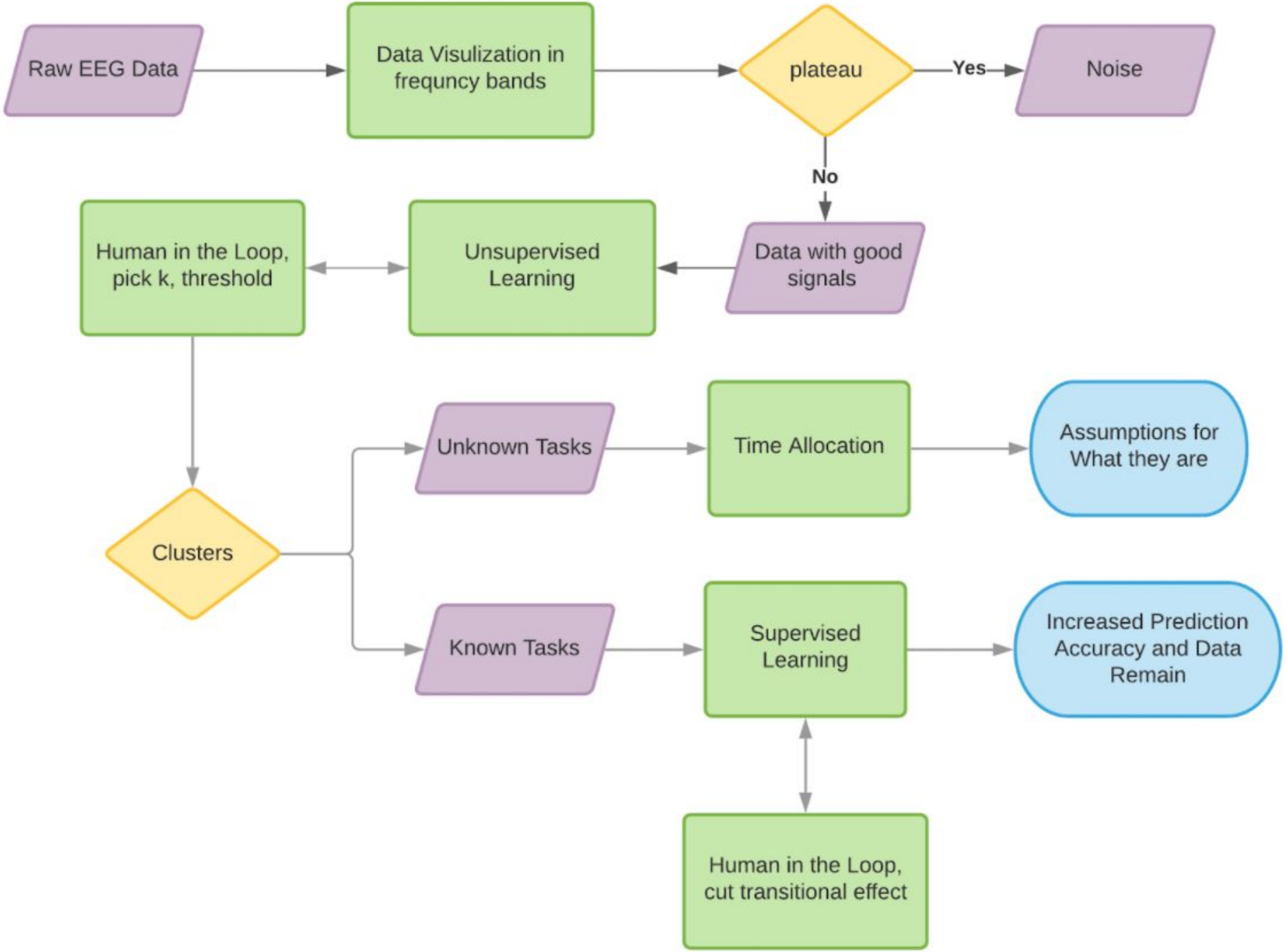
Relative EEG bands for Subjects 1 and 2



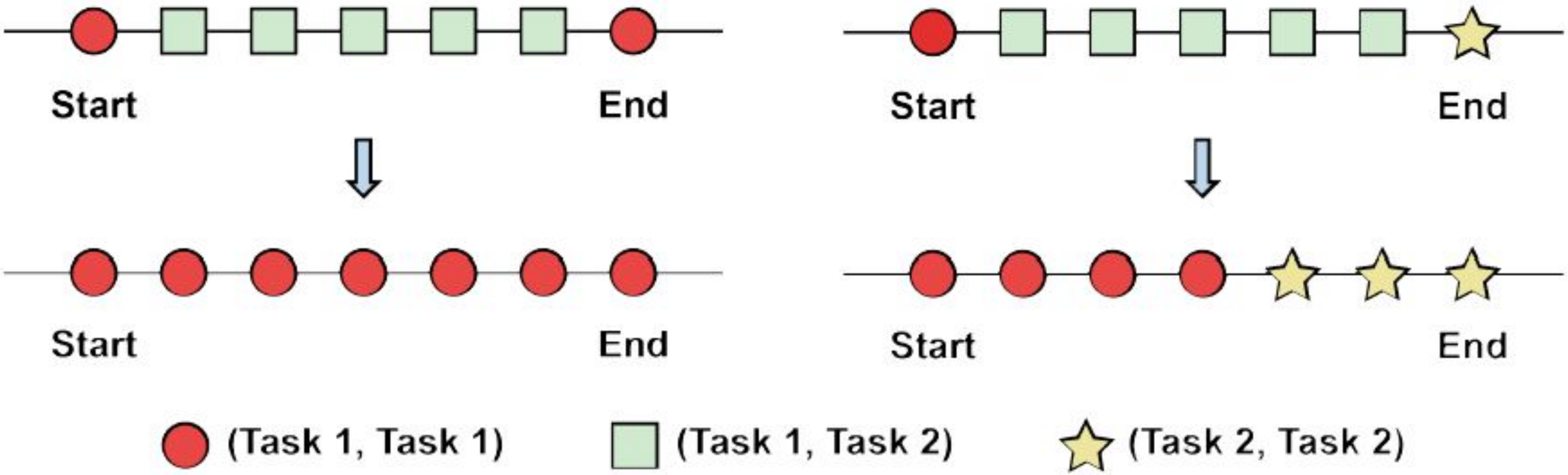
Relative EEG bands for Subject 1



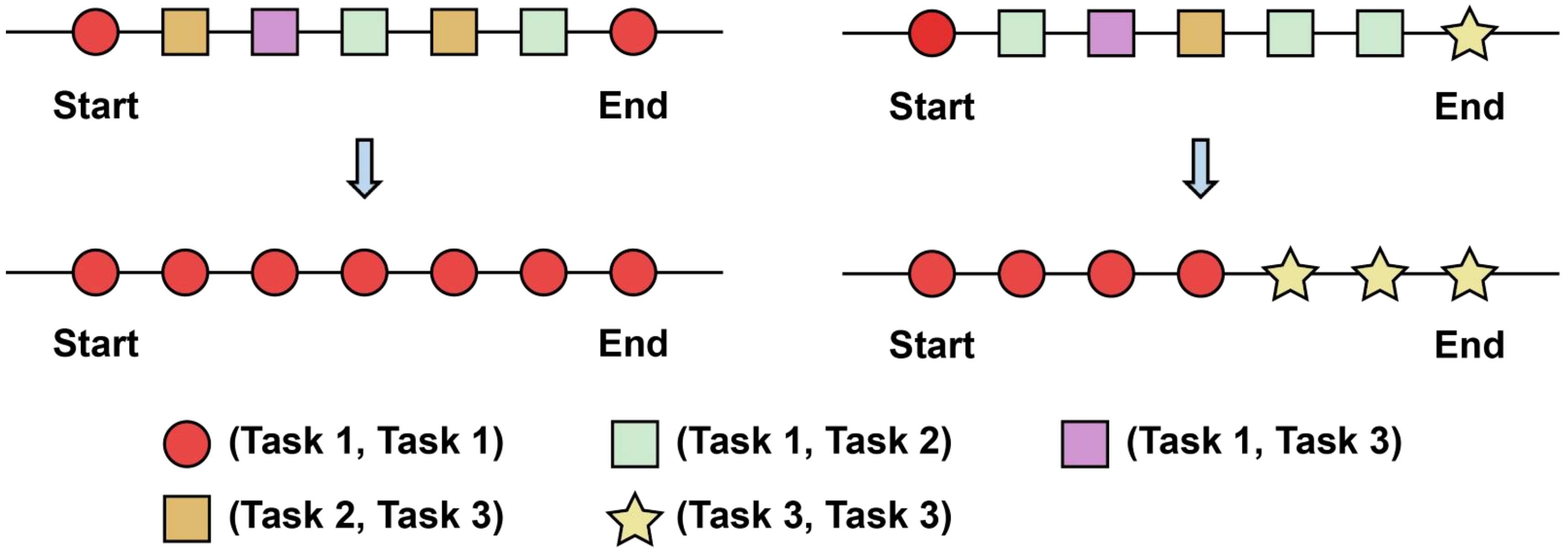

subject 1 session 1
gamma
32-100HZ
beta
13-32HZ
alpha
8-13HZ
theta
4-8HZ
delta
0.5-4HZ
TP10
AF8
AF7
TP9
1
2
3
4
5
minutes

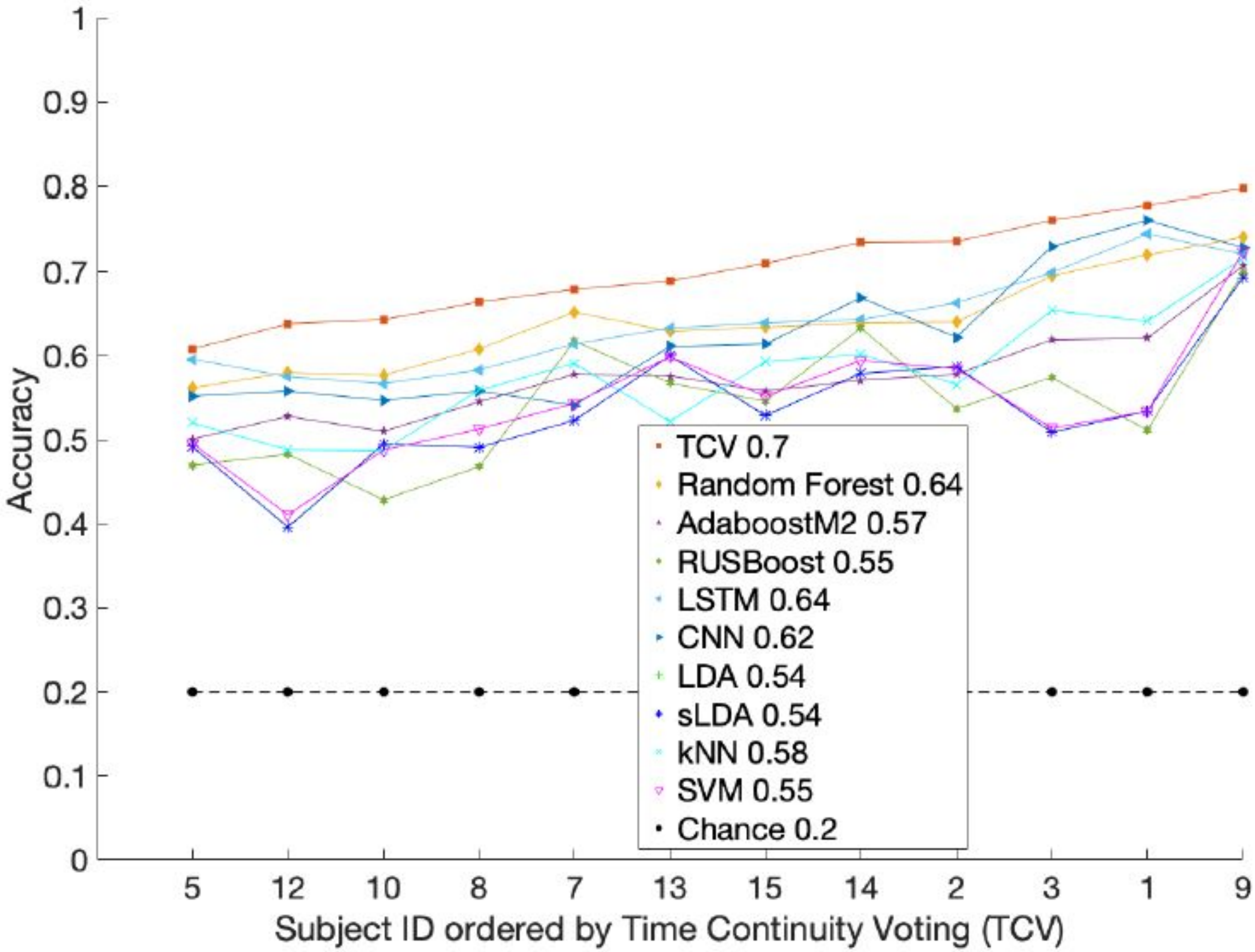

Raw EEG Data
Data Visulization in frequncy bands
plateau
Yes
Noise
No
Data with good signals
Unsupervised Learning
Human in the Loop, pick k, threshold
Clusters
Unknown Tasks
Time Allocation
Assumptions for What they are
Known Tasks
Supervised Learning
Increased Prediction Accuracy and Data Remain
Human in the Loop, cut transitional effect

Time-Series, Time Continuity Voting (TCV)



Time-Series, Time Continuity Voting (TCV)





Accuracy
Subject ID ordered by Time Continuity Voting (TCV)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
5
12
10
8
7
13
15
14
2
3
1
9
TCV 0.7
Random Forest 0.64
AdaboostM2 0.57
RUSBoost 0.55
LSTM 0.64
CNN 0.62
LDA 0.54
sLDA 0.54
kNN 0.58
SVM 0.55
Chance 0.2

Compare

Machine Learning (**Single Algorithms**)

LDA, SVM, KNN etc. - Adequate Accuracy - Runtime low (Fast)

Machine Learning (**Ensemble Methods**)

Random Forest, Adaboost, XGBoost, etc - Better Accuracy - Runtime increased

Machine Learning (**Deep Learning)**

CNN, RNN, Transformer, etc. - higher Accuracy - Require Big Data & GPU (Slow)

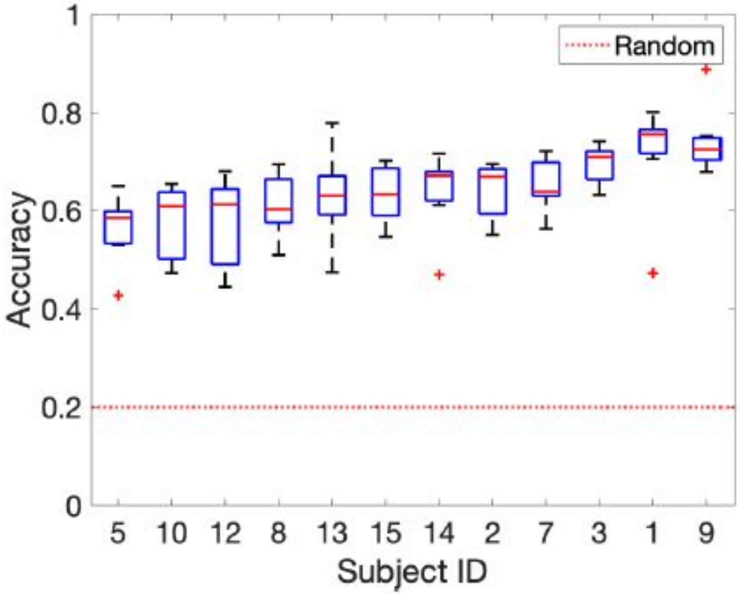


Fig. 7. Subject Difference

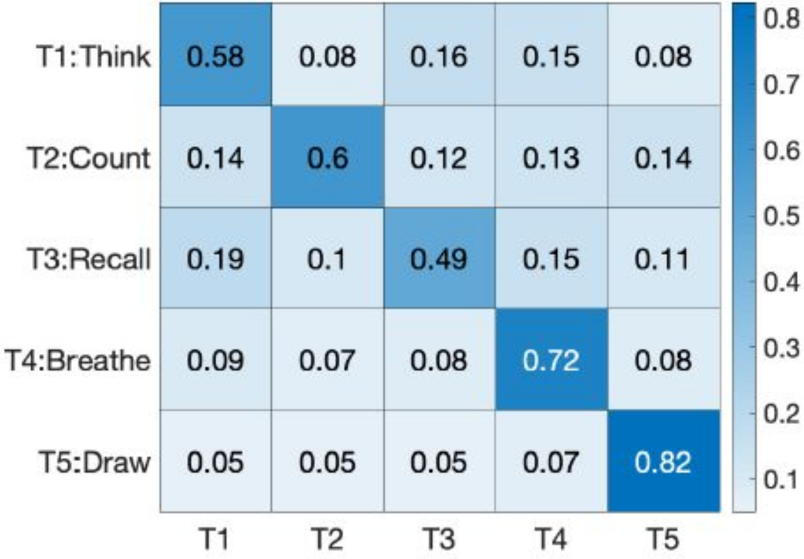


Fig. 8. Task Prediction Accuracy, average of all twelve subjects.

Time-Series

Time Majority Voting (TMV)

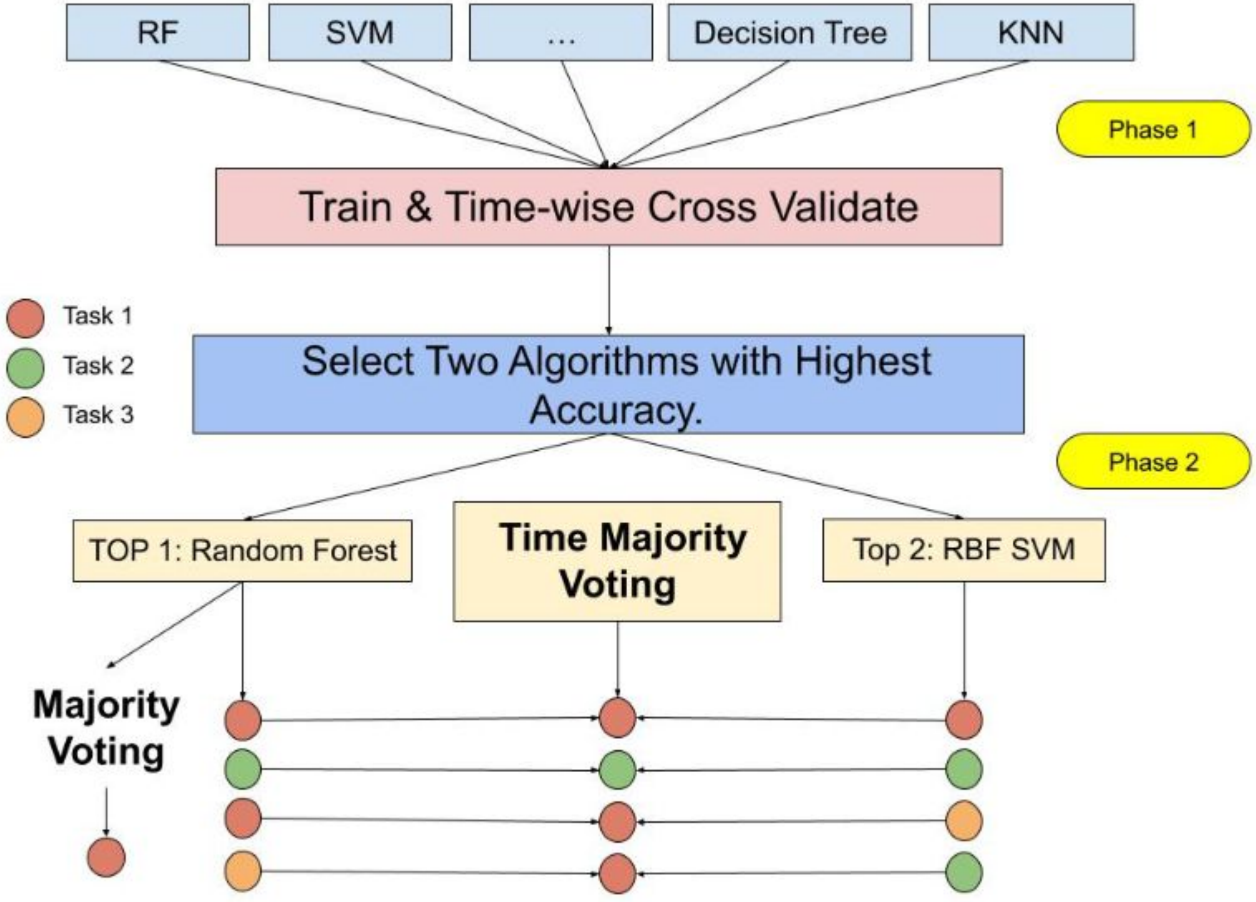


Fig. 1. Our New Algorithm: Time Majority Voting

Time-Series

Time Majority Voting (TMV)

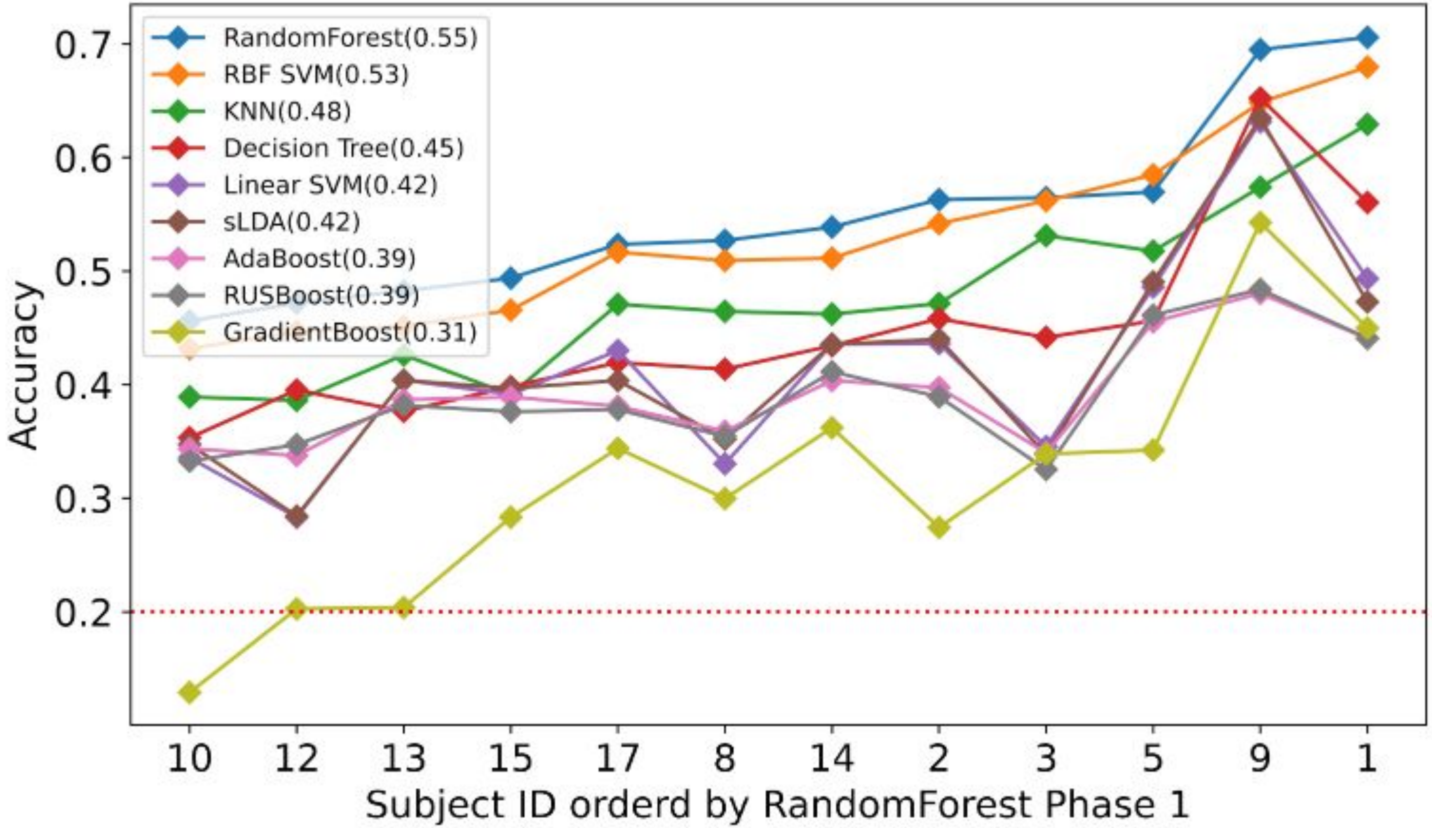


Fig. 2. Accuracy for Different Algorithms

Time-Series

Time Majority Voting (TMV)

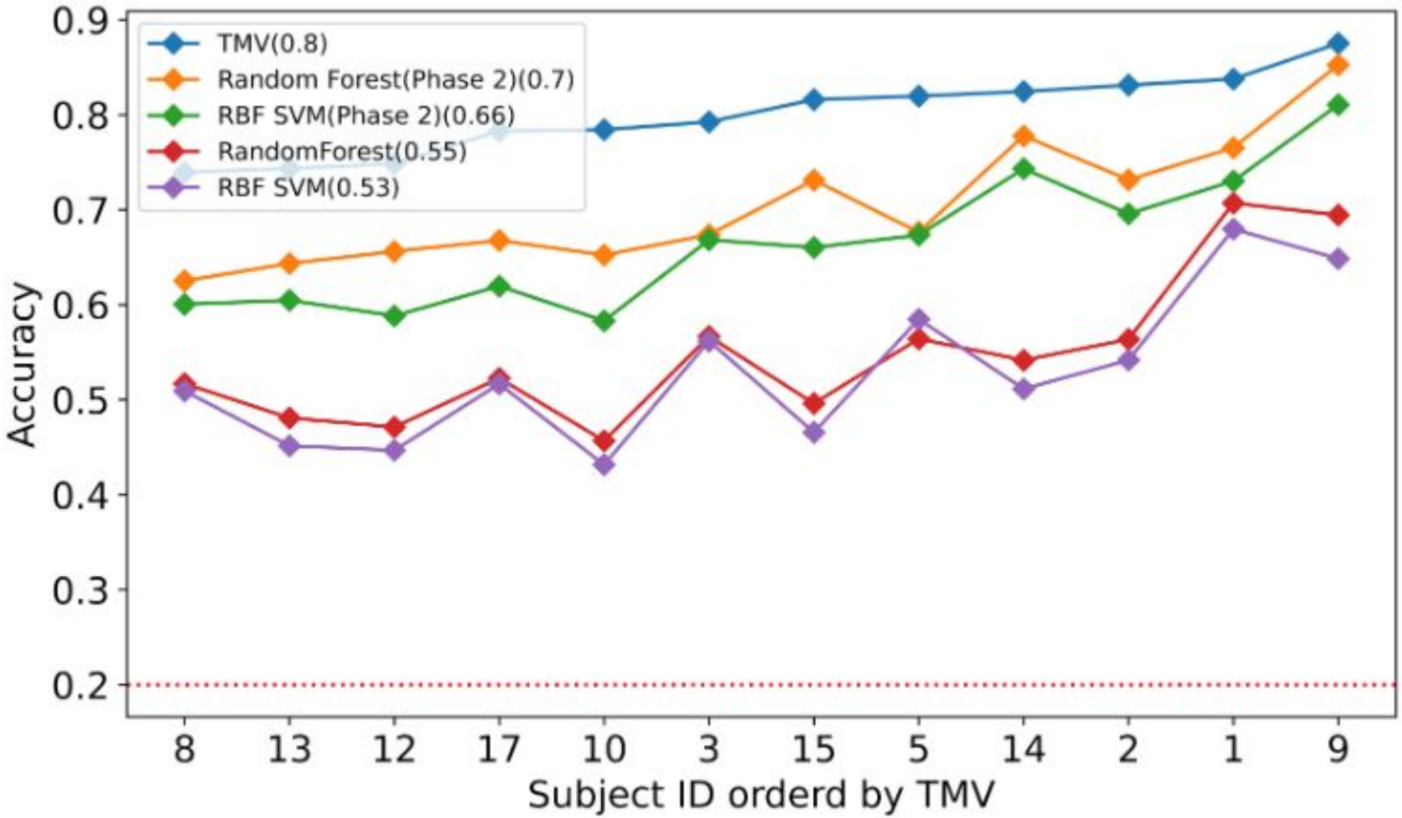


Fig. 5. TMV, RF Phase 2, RBF SVM Phase 2, RF phase 1, and RBF SVM Phase 1

Transformer

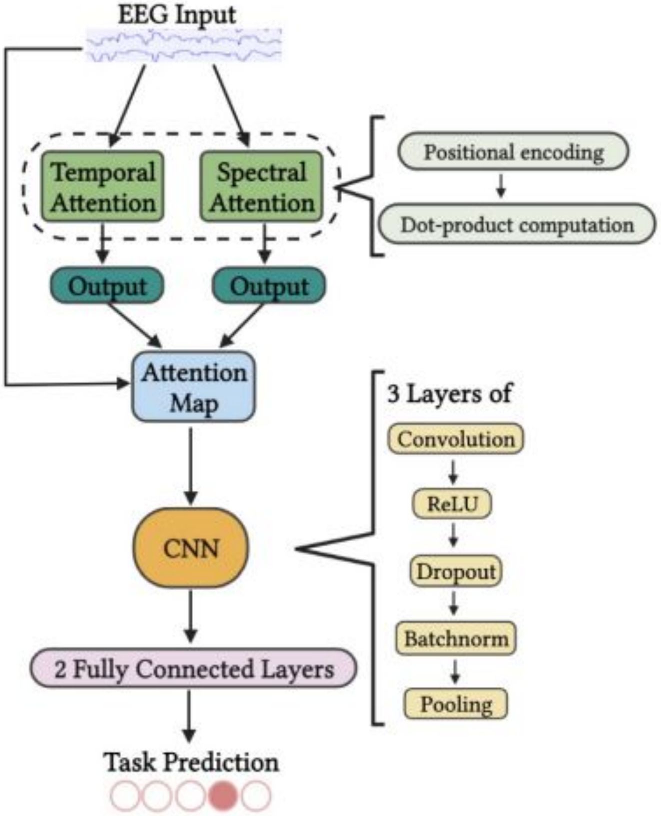


Fig. 1: Model architecture. Every EEG input is fed into the Temporal and Spectral Attention modules. The two outputs of the self-attention modules are added to the original input with weights and produce an attention map, which is then sent into the three-layers CNN. Two fully connected layers form the end of the CNN and make the task prediction (one of three classes for the BCI III dataset or one of five classes for the RWT dataset).

Transformer

Table 2: Ablation Experiment

	Accuracy on RWT (%)	Accuracy on BCI III (%)
Full Model	46	79
CNN	36	73
Temporal Attention	33	69
Spectral Attention	38	70
Temporal Attention + CNN	39	75
Spectral Attention + CNN	41	77

Transformer

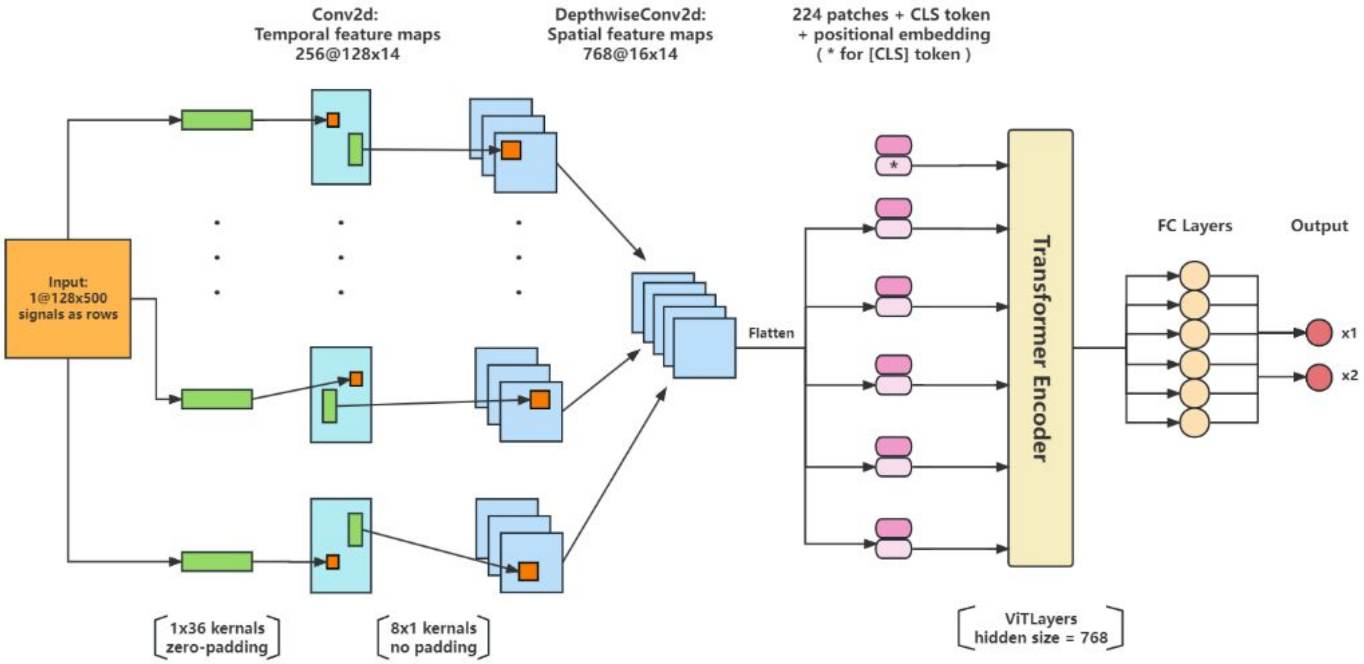


Figure 2: Proposed EEGViT, a hybrid ViT (Vision Transformer) architecture designed specifically for EEG raw signal as input. A two-step convolution operation is applied to generate patch embeddings. Then we add positional embeddings and pass the resulting sequence into ViT layers. The illustration of positional embedding and ViT layer is based on [10].

Transformer

Model	Absolute Position RMSE (mm)
Naive Guessing	123.3 ± 0.0
KNN	119.7 ± 0
RBF SVR	123 ± 0
Linear Regression	118.3 ± 0
Ridge Regression	118.2 ± 0
Lasso Regression	118 ± 0
Elastic Net	118.1 ± 0
Random Forest	116.7 ± 0.1
Gradient Boost	117 ± 0.1
AdaBoost	119.4 ± 0.1
XGBoost	118 ± 0
CNN	70.4 ± 1.1
PyramidalCNN	73.9 ± 1.9
EEGNet	81.3 ± 1.0
InceptionTime	70.7 ± 0.8
Xception	78.7 ± 1.6
ViT-Base	61.5 ± 0.6
ViT-Base Pre-trained	58.1 ± 0.6
EEGViT	61.7 ± 0.6
EEGViT Pre-trained	**55.4 ± 0.2**

t,

Table 4: Comparison of Root Mean Squared Error (RMSE) loss in millimeters for different models on the Absolute Position Task. Original error is in pixels, and we convert it into millimeters by 2 pixels/mm for better interpretation. Lower RMSE values indicate better performance as they represent closer estimations to the actual values. The values represent the mean and standard deviation of 5 runs.

Algorithms

Abbreviation	Definition
AE	Autoencoder
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
CV	Computer Vision
DBN	Deep Belief Network
DNN	Deep Neural Network
GAN	Generative Adversarial Network
KNN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machine
ViT	Vision Transformer

Table 1: List of Algorithm Acronyms

Algorithms

Algorithm	Paper Count	MI	Seizure	Emotion
CNN	22	16	1	1
RNN	14	3	1	2
Transformer	14	3	2	0
ANN	5	0	0	0
SVM	4	1	0	1
KNN	4	0	1	1
RF	3	0	0	0
AE	2	0	0	0

Table 3: Algorithm Breakdown for Non-Review Papers

Datasets

Dataset	Task	Year	Cited
DEAP [17]	Emotion	2011	3439
PhysioNet [28]	MI	2000	3140
BCI Competition IV [34]	MI	2012	783
Dreamer [15]	Emotion	2016	517
SEED [6]	Emotion	2013	358
Bonn [20]	Seizure	2013	316
CHB-MIT [24]	Seizure	2021	21
EEGEyeNet [13]	MI	2021	16

Table 4: Dataset Breakdown for Non-Review Papers

Outline

Brain-Computer
Interfaces
(BCI)

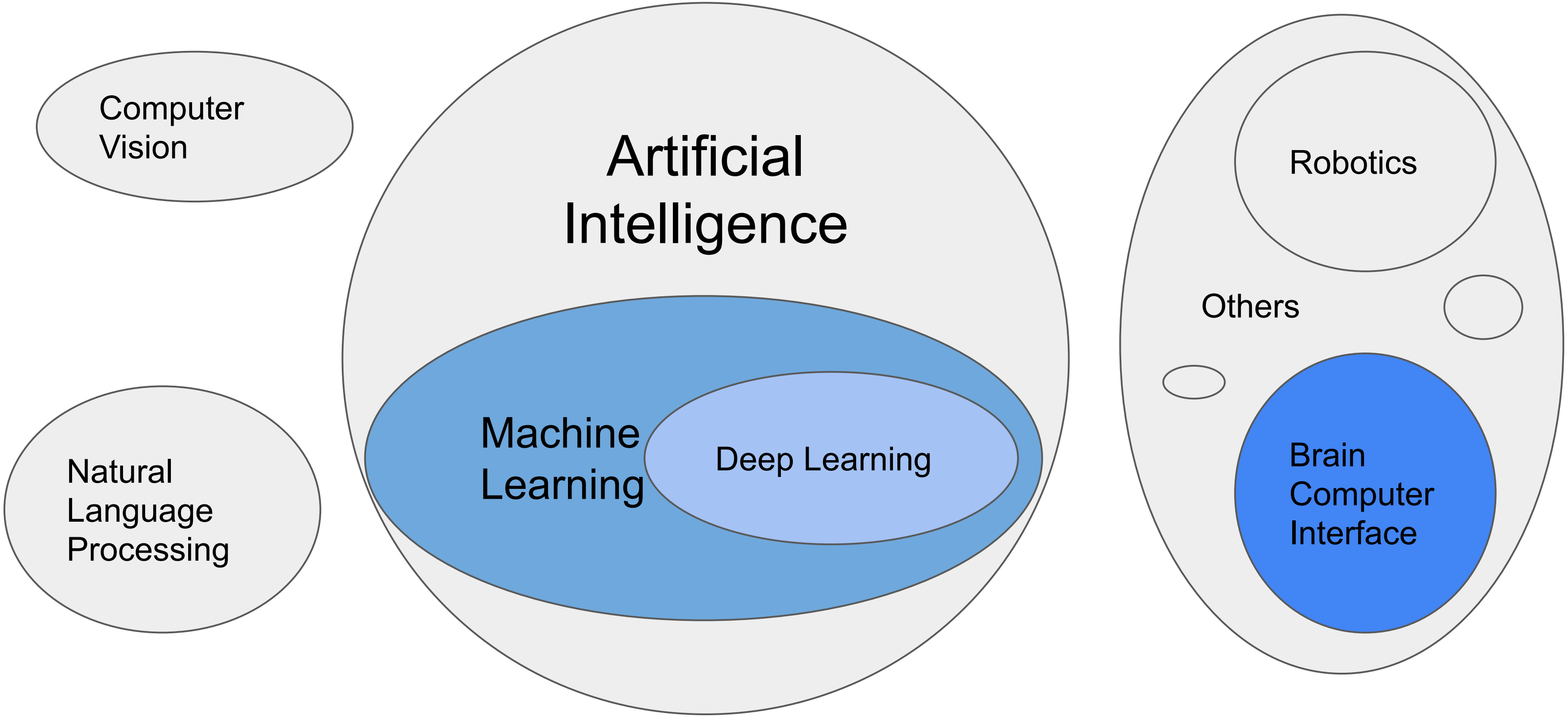
Clinical

Non-Clinical

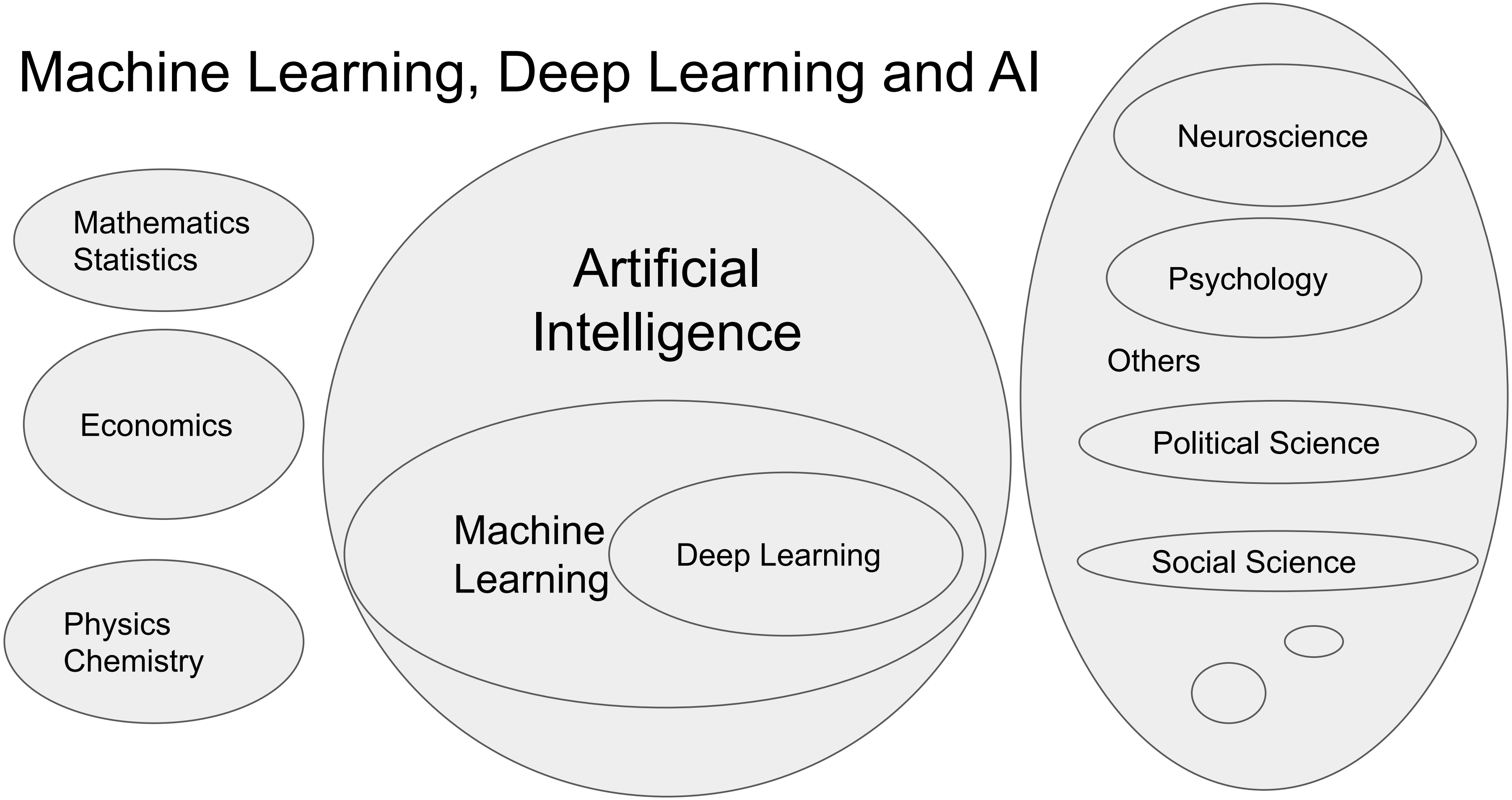
Clustering:
FEP patients vs
health controls

New algorithms for
EEG Classification

Machine Learning, Deep Learning and AI



Machine Learning, Deep Learning and AI



Thank you so much!

Questions?

More Details on my profile:
[go.gwu.edu/xqu]

Not Active for this presentation

Slides more for possible Q and A

Research Lab Overview

Current Composition

- **15 students**: 9 undergraduate + 6 graduate
- Weekly meetings (remote/in-person)

Research Goals

- 1-2 years: **Pipeline from learning to publishing**
- **Summer-to-summer** research milestones

Research Lab Overview

Conferences and Achievements

- Attendance at **top CS conferences** (virtual/hybrid)
- Focus on **home conferences** with previous publications

What We Offer

- **Structured research training** for new members
- Opportunities to **publish in top venues**