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Development of an EEG-based Impulsivity-related CPT Score Prediction System in children with ADHD

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Outline

01 Introduction

02 Development of an EEG-based Impulsivity-related CPT Score Prediction System

03 Experiment and Equipment

04 Results

05 Conclusion

Attention Deficit Hyperactivity Disorder (ADHD)

- A neurodevelopmental condition primarily defined by persistent patterns of inattention, hyperactivity, and **impulsivity**.
- Affects approximately **5%** of the population in Taiwan and ranges from **5%** to **7.2%** globally[1,2] .
- Clinical diagnostic methods
  - consultation and observation by clinician (Diagnostic and Statistical Manual of Mental Disorders, DSM-5)
  - primary observer fill out rating scales (Disruptive Behavior Disorder Rating Scale, DBDRS)
  - psychological test
  - intelligence test
  - attention test (ex: Continuous Performance Test, CPT)

Clinical diagnostic deficiency

1. Subjective diagnostic method
2. Complicated diagnostic process

[1] Y.M. Tai and H.W. Chiu, *International journal of medical informatics*, vol. 78, 2009.
[2] L.J. Wang et al, *Epidemiology and psychiatric sciences*, vol. 26, no. 6, 2017.

Related literature review

- By combining resting-state EEG with machine learning to classify impulses, an accuracy of **95%** was achieved .
- Through the comparison of power spectra, with frontal alpha power identified as a key indicator.
- Uses a 4s short time window to identify emotions, with an accuracy up to **85%**.

Study	Age	Subjects	Task	EEG Feature	Feature Selection	ML Model	Validation	Accuracy / Main Finding
Hüpen et al., 2023[19]	Adults (18–35)	60 healthy adults	Resting-state EEG + Self-report (impulsivity questionnaire)	Power spectral density (δ, θ, α, β, γ)	SHAP used for feature importance	Random Forest (RF)	10-fold cross-validation	RF with α-band power achieved 95.18% accuracy
Lee et al., 2017[20]	Adults (~20–40)	109 gambling disorder patients (high/medium/low impulsivity by BIS-11)	Resting-state EEG	Power spectral density (θ, α, β)	None	None (statistical comparison only)	Group comparison via ANOVA	Frontal-central α power negatively correlated with impulsivity
Yu et al., 2023[21]	Adults (Mean age: 22.4 years)	32 healthy participants	Real-time emotion recognition	Power spectral density (δ, θ, α, β, γ)	None	LSTM with Additive Attention Mechanism	10-fold cross-validation	SEED & SEED-IV: Achieved 85.40% and 74.26% accuracy.

[19] Hüpen, P., Kumar, H., Shymanskaya, A., Swaminathan, R., & Habel, U. (2023). *Impulsivity Classification Using EEG Power and Explainable Machine Learning*. *International Journal of Neural Systems*
[20] Lee, J. Y., Park, S. M., Kim, Y. J., Kim, D. J., Choi, S. W., Kwon, J. S., & Choi, J. S. (2017). *Resting-state EEG activity related to impulsivity in gambling disorder*. *Journal of Behavioral Addictions*
[21] S. Yu, L. He, C. Jiao, S. Sun, D. Chen, and L. Wang, "Real-time EEG-based emotion recognition using LSTM with additive attention mechanism," Sensors, vol. 23, no. 20, p. 8520, Oct. 2023.

Motivations of this study

1.Can individual impulsive performance be predicted through specific EEG features?

➡ Behavioral data only show outward actions, making it essential to bypass these surface-level behaviors and capture the brainwaves associated with impulsivity directly.

2. Does EEG activity exhibit identifiable neurophysiological markers associated with impulsive behaviors or high-trait impulsivity?

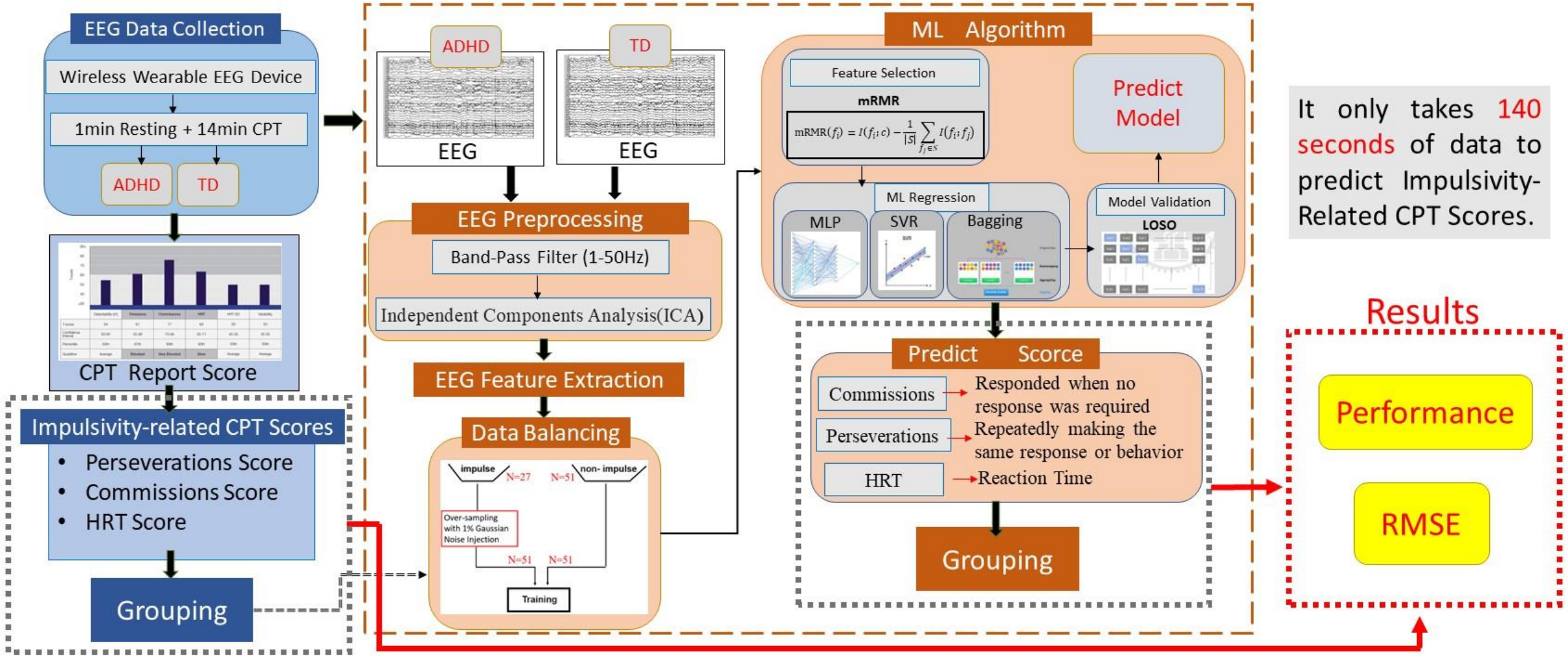
➡ Do these impulsive states have their own unique patterns?

3. Can the rapid detection of impulsive tendencies serve as a technical foundation for real-time alerts and early intervention?

➡ Early identification of impulsive urges provides the awareness needed to empower individuals to regulate their responses before being overwhelmed by emotional triggers.

The aim of this study is to develop an EEG-based impulsivity-related CPT score prediction system. To this end, this work investigates the features of impulsiveness to achieve real-time detection and restraint.

EEG-based Impulsivity-Related CPT Score Prediction System



It only takes 140 seconds of data to predict Impulsivity-Related CPT Scores.

EEG data collection

school-age children (8-12)

Number	ADHD:TD	Boys:Girls	Average age
107	78:29	86:21	9.05

Participants



Wearable and Wireless EEG device
- 32 Channel
- Sample rate : 500Hz

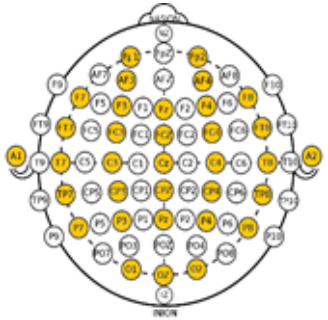
《Wireless EEG device》



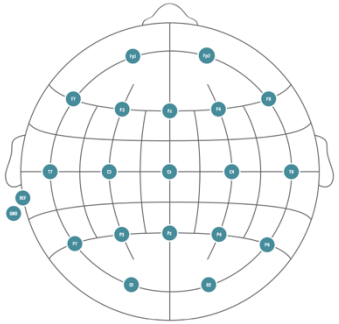
Wearable and Wireless EEG device
- 20 Channel
- Sample rate : 500Hz

《Wireless EEG device》

EEG channel location



《10-20 System》



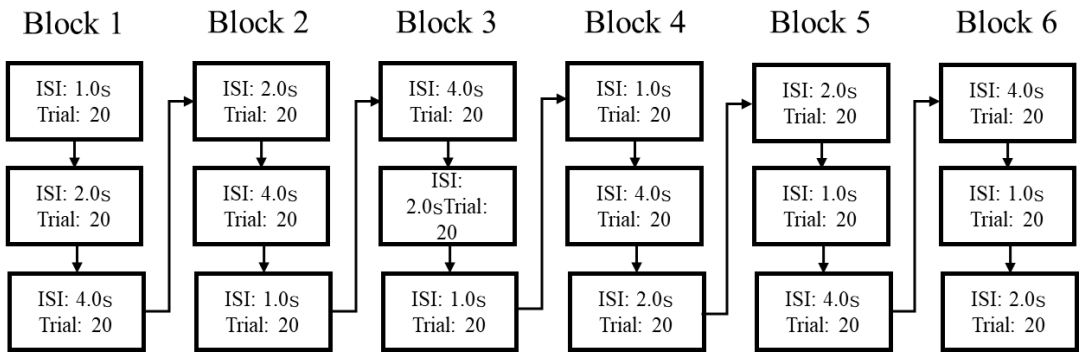
《10-20 System》

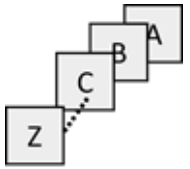
Conners CPT

Continuous Test

CPT3 (Age:>8 yr)

Total : 14 min.





Description and category of CPT indexes

Variable Type	Index	Description	Category
Detectability	d'	differentiating targets from nontargets	Attention
Error Type	Omissions	rate of missed targets	Attention
	Commissions	rate of incorrect responses to non-targets	Attention/Hyperactivity
	Perseverations	rate of random, repetitive, or anticipatory responses	Hyperactivity
Reaction Time Statistics	**HRT**	mean response speed	Attention/Hyperactivity
	HRT SD	consistency in reaction times	Attention
	Variability	variability in reaction time consistency	Attention
	HRT Block Change	sustain or increase response speed in later blocks	N/A
	HRT ISI Change	change in response speed at longer ISIs	N/A

1 min EO resting

Instruction and 1 min practice

Task EEG data

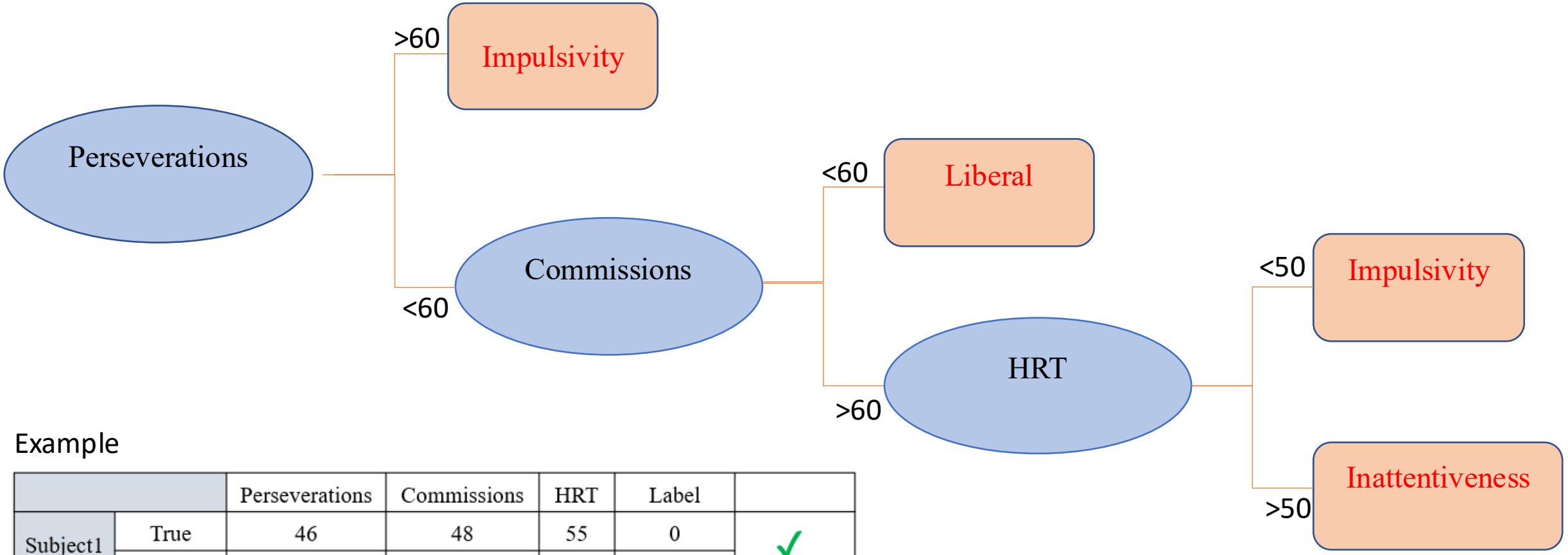
Children(8-12 years):14 mins CPT3





Label Rule

- The classification is determined as Impulsivity, Liberal, or Inattentiveness according to the following rules.
- The classification accuracy was calculated based on the applied classification.



Example

		Perseverations	Commissions	HRT	Label	
Subject1	True	46	48	55	0	✓
	predicted	44	46	62	0	
Subject2	True	67	57	56	1	✗
	predicted	58	45	61	0	

Experimental Results

Choose data block--- Task-ADHD (1/2)

- The Bagging model outperformed others in Block 1, yielding the lowest RMSE across behavioral indicators along with superior classification accuracy and stability.

Performance Comparison of ML Classifiers on CPT3 EEG Data across Different Blocks(Task-ADHD)

EEG data Block of CPT3	ML classifier	Accuracy		RMSE_Perseverations		RMSE_Commission		RMSE_HRT	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std
Block 1	Bagging	72%^{a}	45%	13.57^{a}	9.03	9.40	5.16	12.01^{a}	7.43
	SVR	71%^{a}	46%	14.19^{a}	9.88	10.15	5.69	12.53^{ab}	7.50
	MLP	59%^{b}	50%	19.67^{b}	13.09	11.46	6.47	15.85^{b}	10.29
Block 6	Bagging	65%^{ab}	48%	14.99^{a}	9.88	9.95^{ab}	5.46	12.69^{a}	7.56
	SVR	76%^{a}	43%	15.22^{a}	10.53	9.90^{a}	5.52	13.16^{ab}	8.05
	MLP	60%^{b}	49%	21.69^{b}	13.77	12.28^{b}	7.23	17.18^{b}	11.91
Block 1~6	Bagging	63%^{a}	31%	15.25^{a}	10.21	10.21	6.02	13.22	6.95
	SVR	56%^{a}	39%	17.16^{a}	10.05	10.11	6.08	13.38	8.69
	MLP	54%^{b}	36%	18.83^{b}	13.02	11.05	7.02	14.98	9.15

Choose data block Task-TD (2/2)

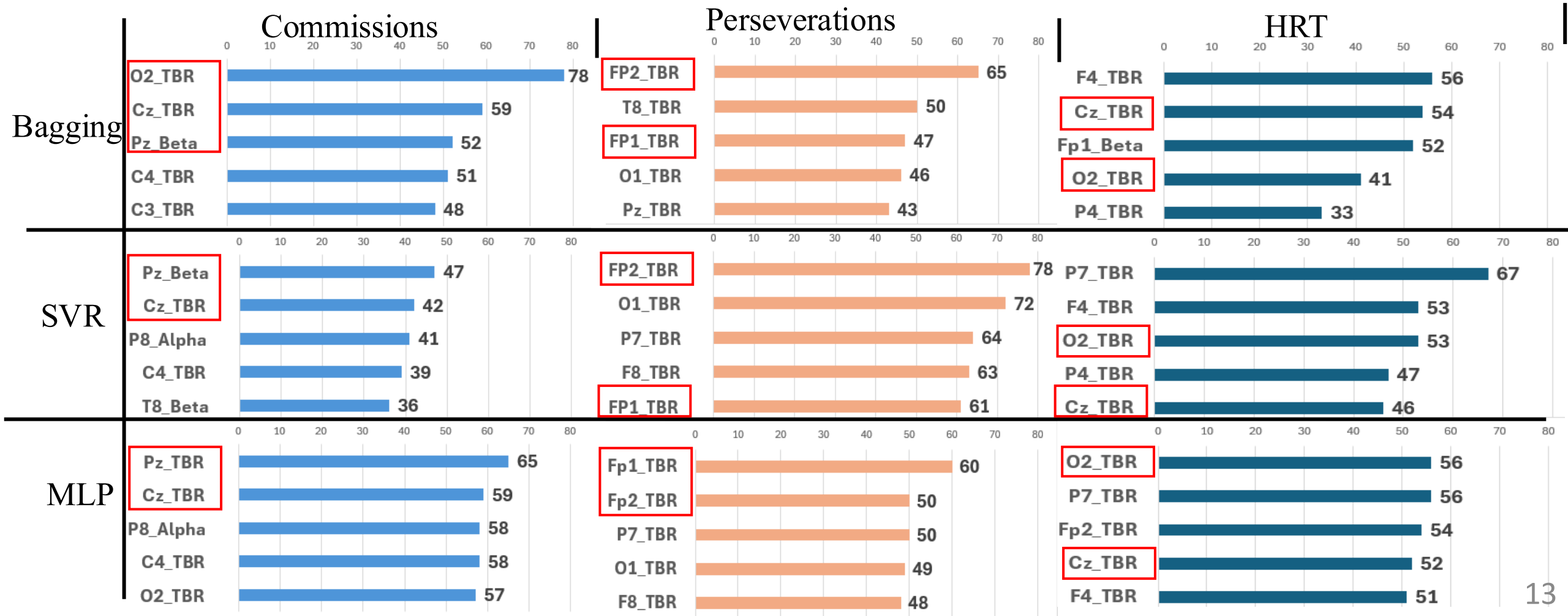
- The Bagging model in Block 6 outperformed others with the highest accuracy, greatest stability, and the lowest predictive error across all RMSE metrics.

Performance Comparison of ML Classifiers on CPT3 EEG Data across Different Blocks(Task-TD)

EEG data Block of CPT3	ML classifier	Accuracy		RMSE_Perseverations		RMSE_Commission		RMSE_HRT	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std
Block 1	Bagging	72%^{ab}	45%	13.18	9.14	10.24^{a}	5.61	9.89^{a}	5.44
	SVR	83%^{a}	38%	12.78	8.75	9.96^{a}	4.54	9.70^{a}	5.67
	MLP	62%^{b}	49%	17.50	11.48	23.05^{b}	12.32	17.82^{b}	7.96
Block 6	Bagging	93%^{a}	26%	9.20^{a}	6.81	9.68^{a}	6.27	11.43	6.32
	SVR	86%^{ab}	35%	11.92^{a}	8.33	10.30^{b}	5.25	10.51	6.30
	MLP	55%^{b}	51%	19.01^{b}	10.43	21.82^{c}	11.50	19.44	12.25
Block 1~6	Bagging	76%^{ab}	31%	11.99^{a}	5.44	9.86^{a}	5.16	10.34^{a}	5.68
	SVR	72%^{a}	30%	14.82^{a}	5.54	11.51^{a}	4.59	9.75^{a}	5.44
	MLP	52%^{b}	32%	15.44^{b}	6.32	16.51^{b}	5.56	12.69^{ab}	5.87

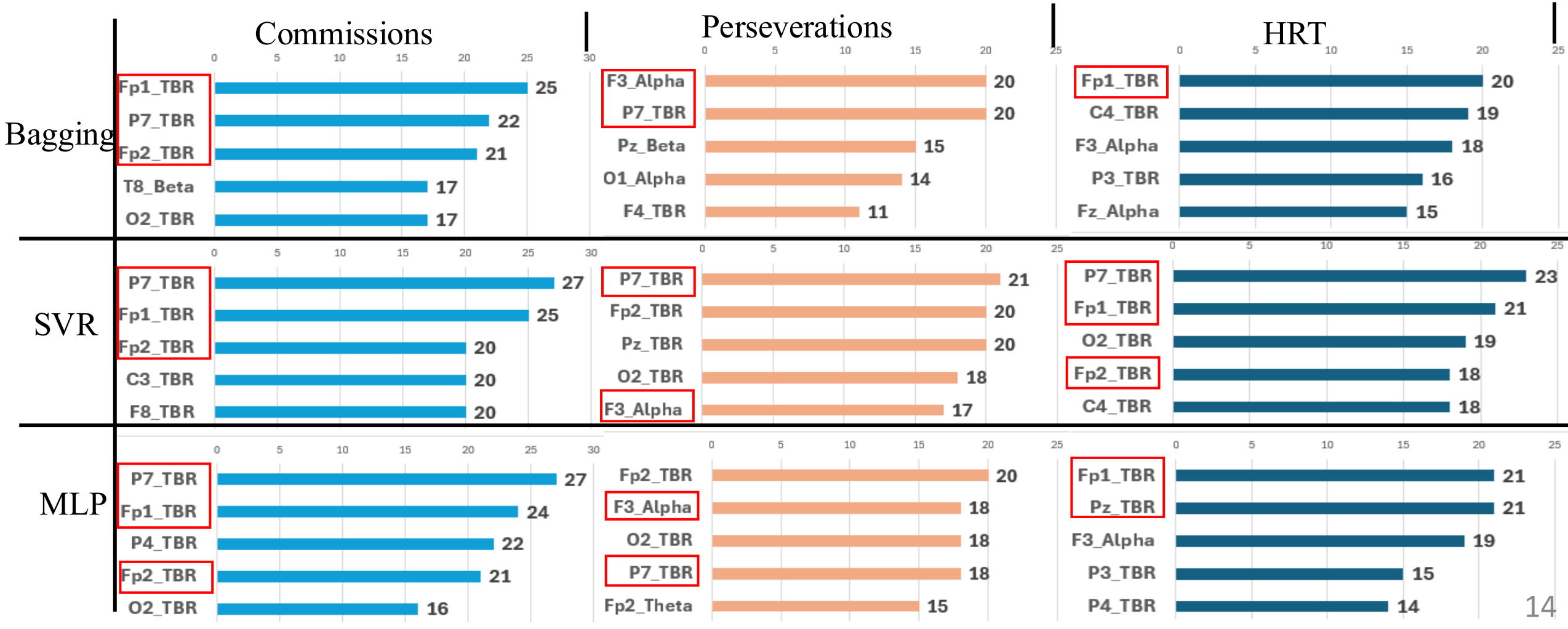
Task---ADHD---Key EEG Features for Impulsivity-Related CPT Scores

- Predictions for **Perseverations** are primarily linked to **prefrontal features (Fp1, Fp2)**, while **Commissions** and **HRT** incorporate more features from the **mid-to-posterior regions (Cz, Pz, O2)**.
- **TBR** exhibits the highest selection frequency across all models and target objectives, validating its role as a stable neurophysiological marker for measuring levels of inattentiveness.



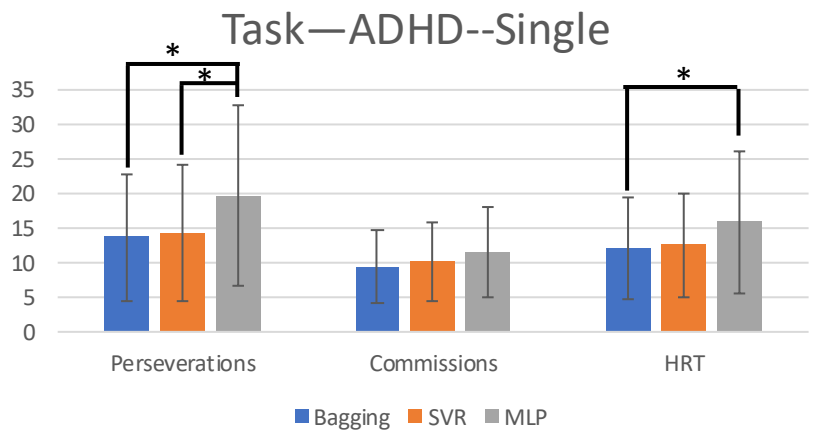
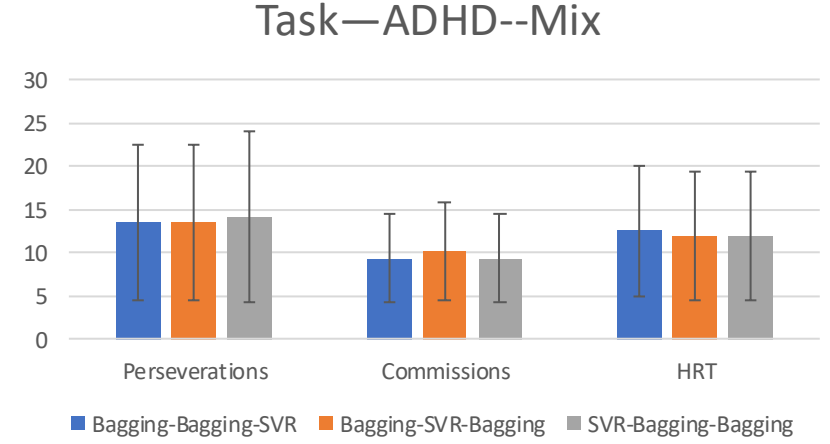
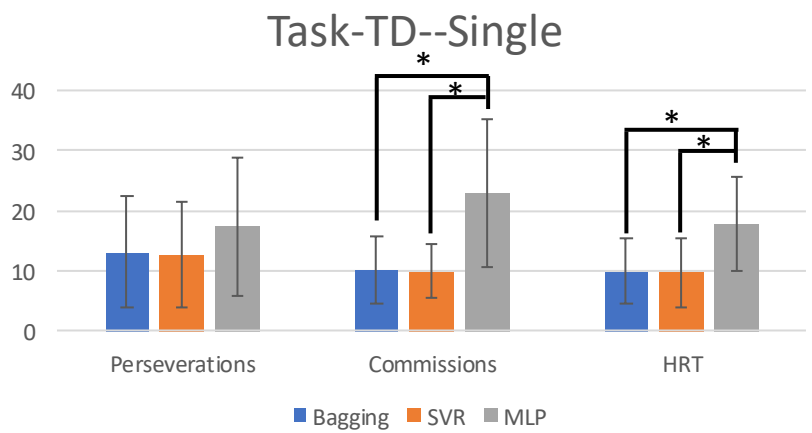
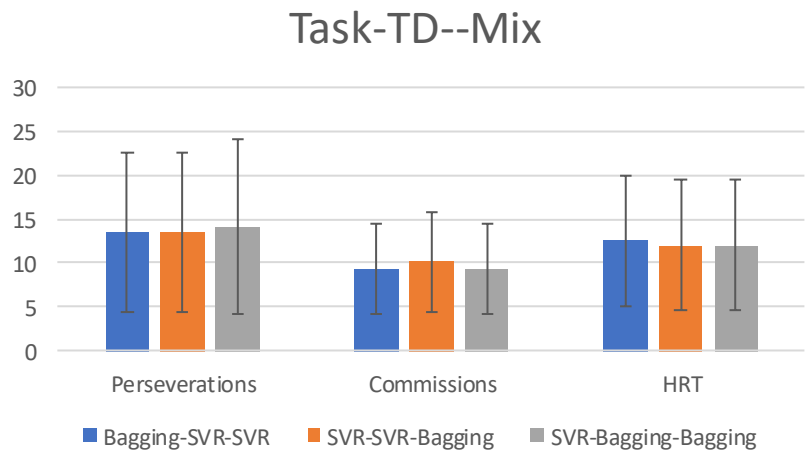
Task---TD--- Key EEG Features for Impulsivity-Related CPT Scores

- Predictions for **Perseverations** show an increased prominence of **F3** **and** **P7** features, while **Commissions** and **HRT** rely heavily on a combination of **prefrontal (Fp1, Fp2)** and **parietal (P7, Pz)** regions.
- **TBR** remains the dominant indicator across all models, an increased frequency of **Alpha** and **Beta** bands is observed in specific targets, indicating more diverse feature contributions.



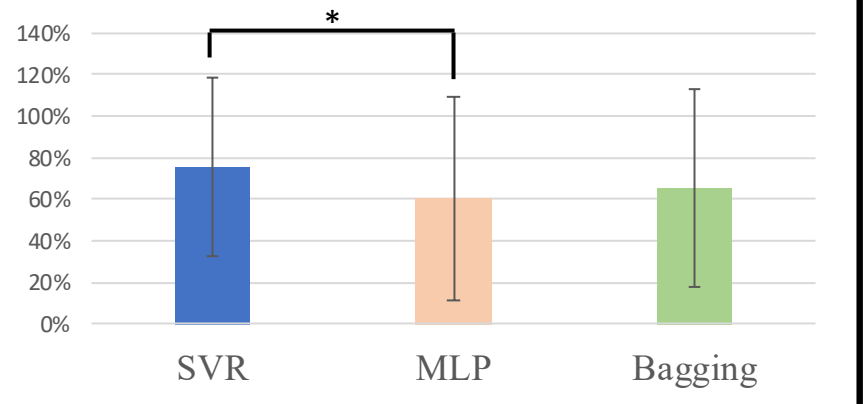
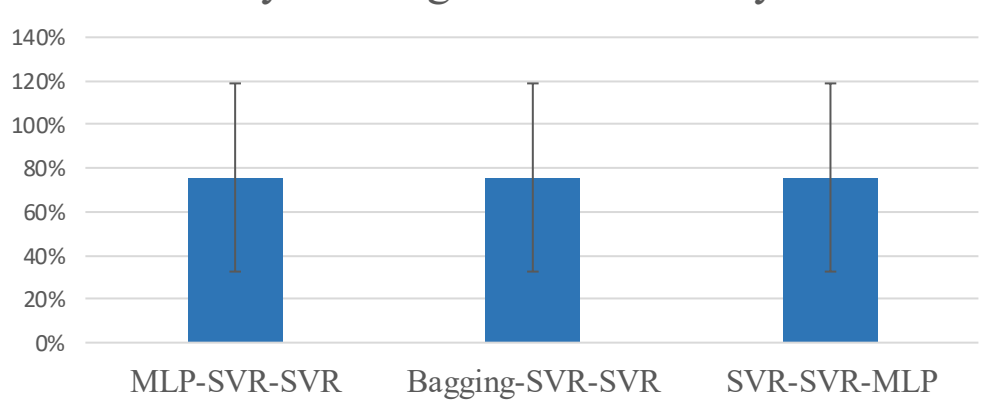
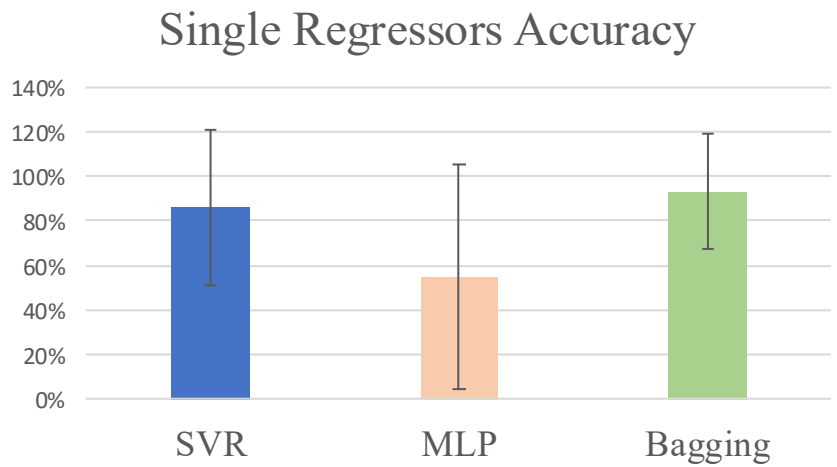
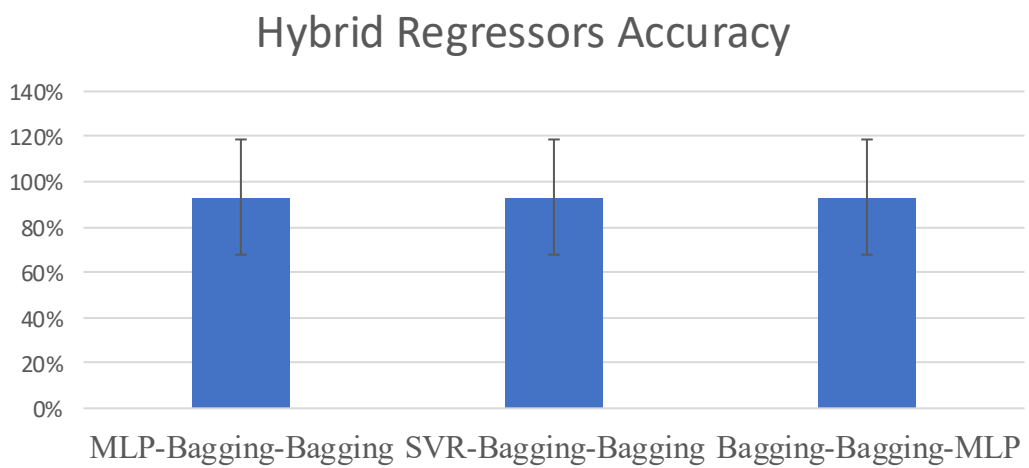
System performance ---Task---RMSE

- For both ADHD and TD groups, Bagging and SVR performed similarly, whereas MLP underperformed. Transitioning to the hybrid architecture reduced inter-model variance but failed to significantly improve prediction errors.

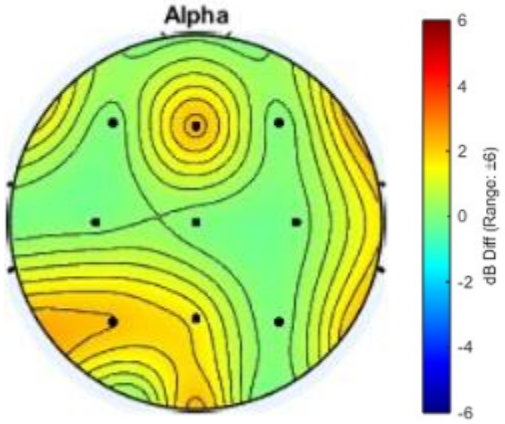
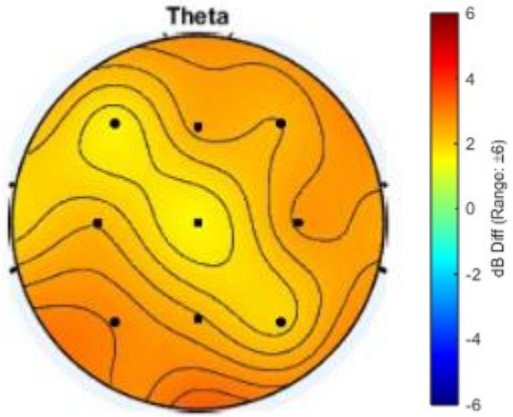
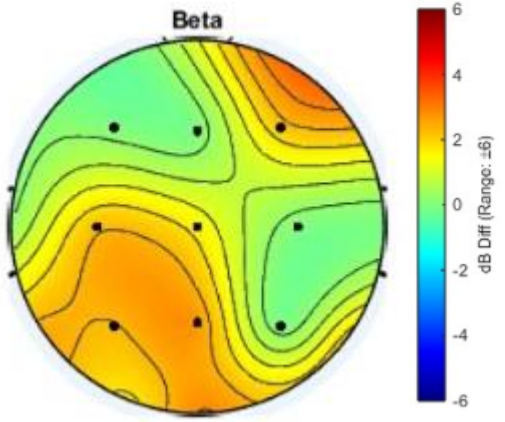
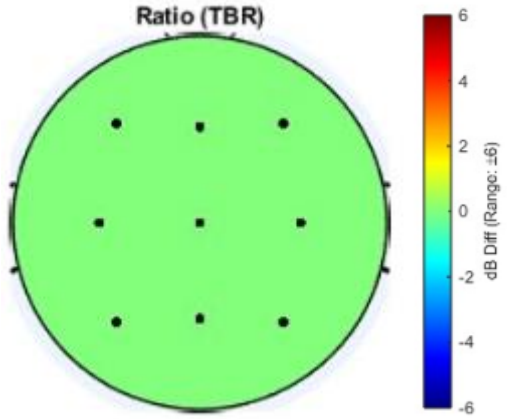
	Single	Hybrid
ADHD		
TD		

System performance ---Task---Accuracy

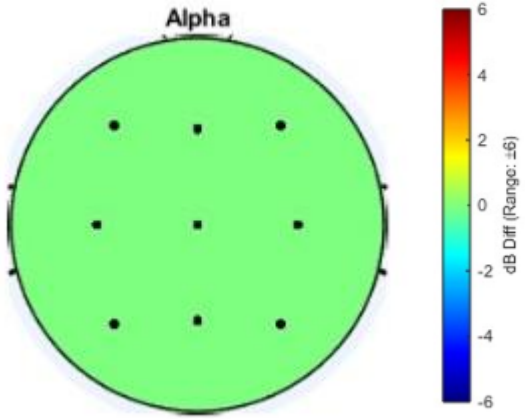
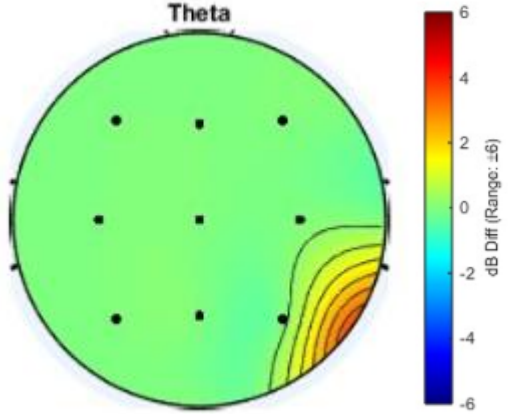
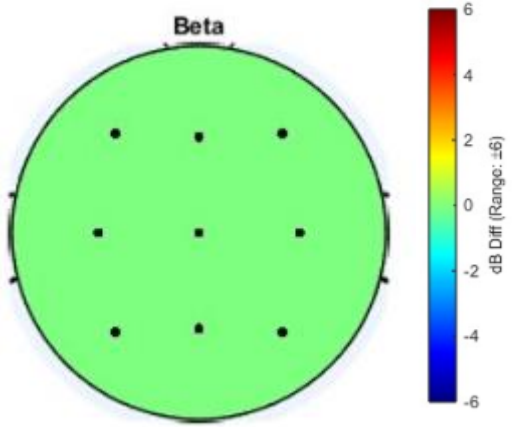
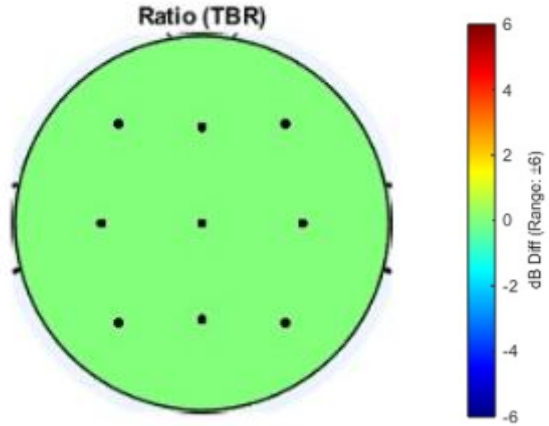
- In the ADHD group, the single SVR achieved a relatively high average accuracy of around 76%, while hybrid models fell within the 70–80% range. For the TD group, the single Bagging regressor showed higher accuracy at 93%, which remained stable in the 90% range when using hybrid models.

	Single	Hybrid
ADHD		
TD		

Impulsive vs Non-Impulsive----TASK---ADHD

Band	**Impulsive vs Non-Impulsive**	Band	**Impulsive vs Non-Impulsive**
Alpha	Higher power observed in the posterior region for the impulsive group. 	**Theta**	Higher power in the impulsive group, particularly in the frontal and posterior areas. 
Beta	Increase in power for the impulsive group across the central-parietal an 	**TBR**	Minimal spatial difference; largely uniform green. 

Impulsive vs Non-Impulsive----TASK---TD

Band	**Impulsive vs Non-Impulsive**	Band	**Impulsive vs Non-Impulsive**
Alpha	Minimal difference; largely uniform green. 	**Theta**	Higher power observed in the posterior region for the impulsive group. 
Beta	Minimal difference; largely uniform green. 	**TBR**	Minimal difference; largely uniform green. 

Conclusion

•An EEG-based Impulsivity-Related CPT Score Prediction System was developed in this study, capable of estimating impulsivity-related scores using machine learning regression models.

•Among the evaluated models, Bagging demonstrated the most stable and accurate performance in predicting behavioral indicators of impulsivity, such as commissions, perseverations, and reaction time.

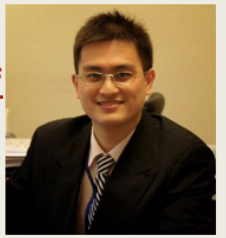
•In this study,tasking-related features are predominantly concentrated in the prefrontal and midline-posterior regions.

•This system provides a quantitative and individualized approach for assessing impulsivity traits, with potential applications in ADHD evaluation, neurofeedback training, and personalized behavioral interventions.

Thanks for Your Listening!!

I do need your support for the BoG votes.

Li-Wei (Leo) Ko, Ph.D.



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I do appreciate for supporting Taiwan!!!