Nonstationary Spatio-Temporal Data

Nonstationary: **New pattern appears every time.**

Examples: stock prices, climate, medical data (**EEG**, ECG)

We focus on **Alzheimer’s disease Eyes Open -EEG data**

Under my mentor's guidance, I established the reasoning process. At each stage, I conducted various experiments and selected the most appropriate choices to report the results.

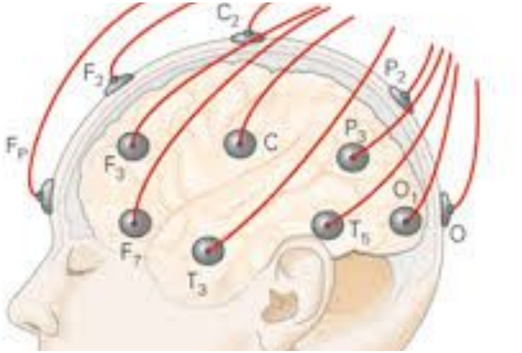
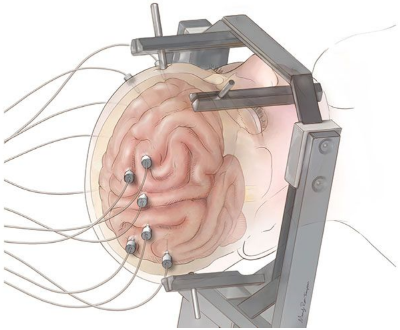
1. Target population: Alzheimer's patients (eyes-open condition)
2. Analytical tools: Dynamic Mode Decomposition (DMD) and CNN
3. Classification outcomes

CNN-based Framework for Alzheimer’s Disease Detection from EEG using Dynamic Mode Decomposition

Jacob Kang

Mentored by Jong-Hyeon Seo from Hanbat National University

Pros of EEG (measure of electrical activity in the brain)

EEG	fMRI	Intracranial EEG
		
Low Cost Non-invasive Wide Accessibility **Strong Temporal resolution** Weaker Spatial resolution Noisy	High Cost Non-invasive Limited Accessibility **Weak Temporal resolution**	Moderate Cost Invasive Limited Accessibility

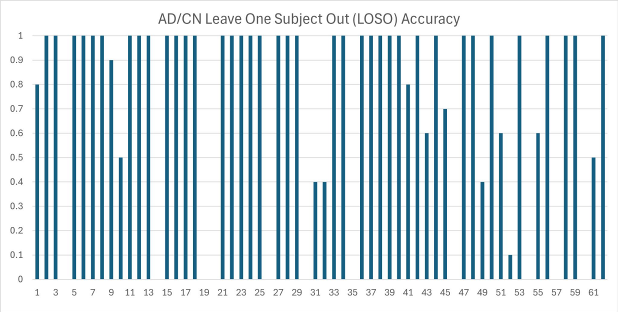
Cons of EEG

If we use Cross Validation

→ Samples from single subject (Patient) are assigned to both Train and Test set

→ Training focuses on learning pattern in measurement by subjects → Performance Exaggeration

→ **Leave One Subject Out (LOSO)** (Split by Subject)



Subject-level Generalization Challenge

Observation: **Polarization in LOSO accuracies**

→ Mostly 0% OR 100% for individual subjects, indicates **poor generalization** to new subjects

Why does this happen?

- Varying levels of subject compliance during measurement
- EO-EEG is more **variable** due to task engagement and visual artifacts → We need preprocessing, artifact removal

Eyes **Open** and **Closed** EEG Recordings

Eyes Open (EO) - Reveals task-evoked responses in active state

- Alpha power suppression by 70-90% (alpha desynchronization)
- Enhanced sensitivity to photic stimulation
- **More variability** in measurement than EC EEG

Eyes Closed (EC) - Reveals trait-like characteristics in resting state (RS)

- Alpha band (8-13 Hz) strongly emphasized
- Reflects subject specific baseline brain activity

→ EC-EEG had been actively investigated

→ EO-EEG is more challenging

Our study focuses on improving EO-EEG classification

Previous Studies: Baseline Approach

Data Type	AD vs CN	FTD vs CN
Eyes Closed	ACC: 0.770 F1: 0.809	ACC: 0.731 F1: 0.786
Eyes Open	ACC: 0.625 F1: 0.668	ACC: 0.710 F1: 0.673

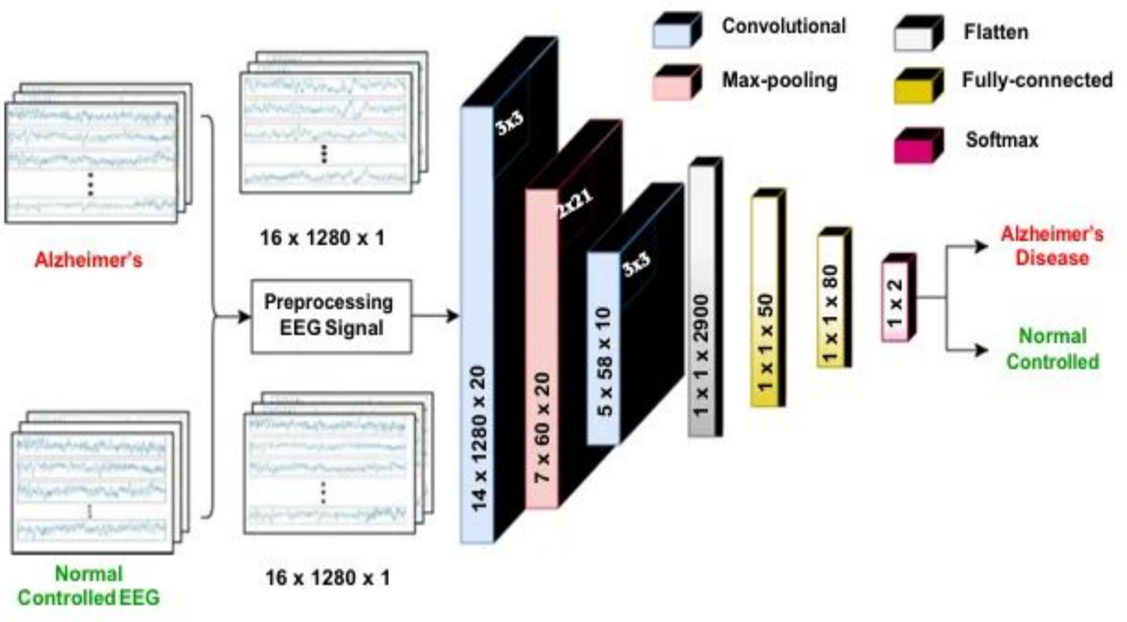
All experiment above had a common settings:

- Segmentation: 4 second epochs w/ 50% overlap
- Feature Extraction: Power Spectral Density (PSD) (FFT-based)

AD shows greater **performance drop in EO** (↓14.5%) compared to FTD (↓2.1%),

potentially due to AD-specific alpha desynchronization with photic stimulation

Previous Studies: Conventional CNN Approach



Problem:

Large data input size (16×1280)

Long Training time

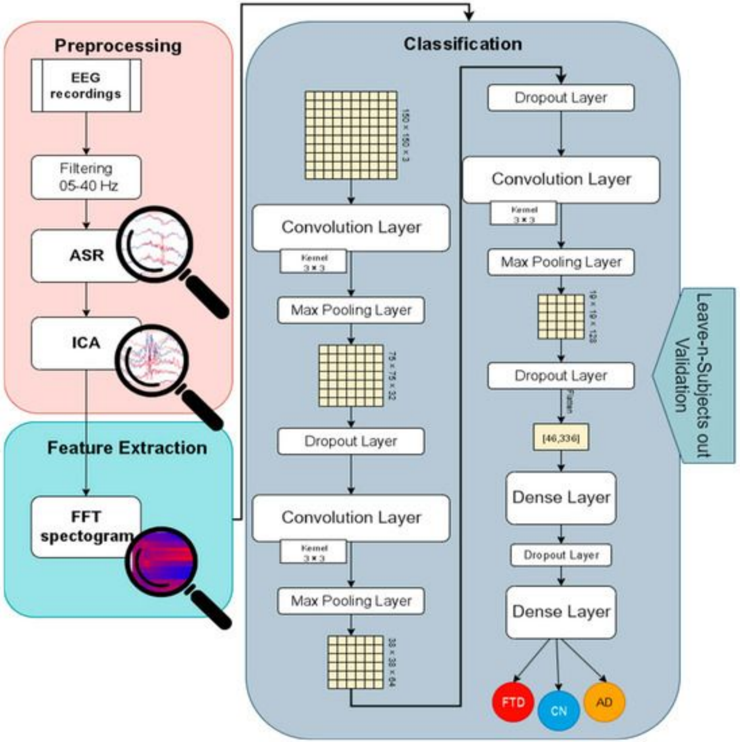
Observation:

No feature extraction step

Raw time-series as input, requiring massive parameters for deep network

Kachare, P., Puri, D., Sangle, S. B., Al-Shourbaji, I., Jabbari, A., Kirner, R., … Abualigah, L. (2024). LCADNet: a novel light CNN architecture for EEG-based Alzheimer disease detection. Physical and Engineering Sciences in Medicine, 47(3), 1037–1050. doi:10.1007/s13246–024–01425-w

Previous Studies: FFT & CNN Approach from EC-EEG



Temporal Segmentation:

- Long window (30-second epochs)
- 20 epochs extracted per subject
- Total: 1,760 samples (88 subjects × 20 epochs)

Feature Extraction:

- Fast Fourier Transform (FFT)

Spec	AD vs CN	FTD vs CN
Eyes Closed 4s window	ACC: 0.770 F1: 0.809	ACC: 0.731 F1: 0.786
Eyes Closed FFT & CNN 30s window	ACC: 0.795 F1: 0.776	ACC: 0.729 F1: 0.679

Stefanou, K., Tzimourta, K. D., Bellos, C., Stergios, G., Markoglou, K., Gionanidis, E., Tsipouras, M. G., Giannakeas, N., Tzallas, A. T., & Miltiadous, A. (2025). A Novel CNN-Based Framework for Alzheimer's Disease Detection Using EEG Spectrogram Representations. *Journal of Personalized Medicine*, *15*(1), 27. https://doi.org/10.3390/jpm15010027

About EO-EEG Data

EO-EEG shows greater nonstationarity than EC-EEG due to active visual processing.

Used preprocessed data to reduce noise and instrumental artifacts.

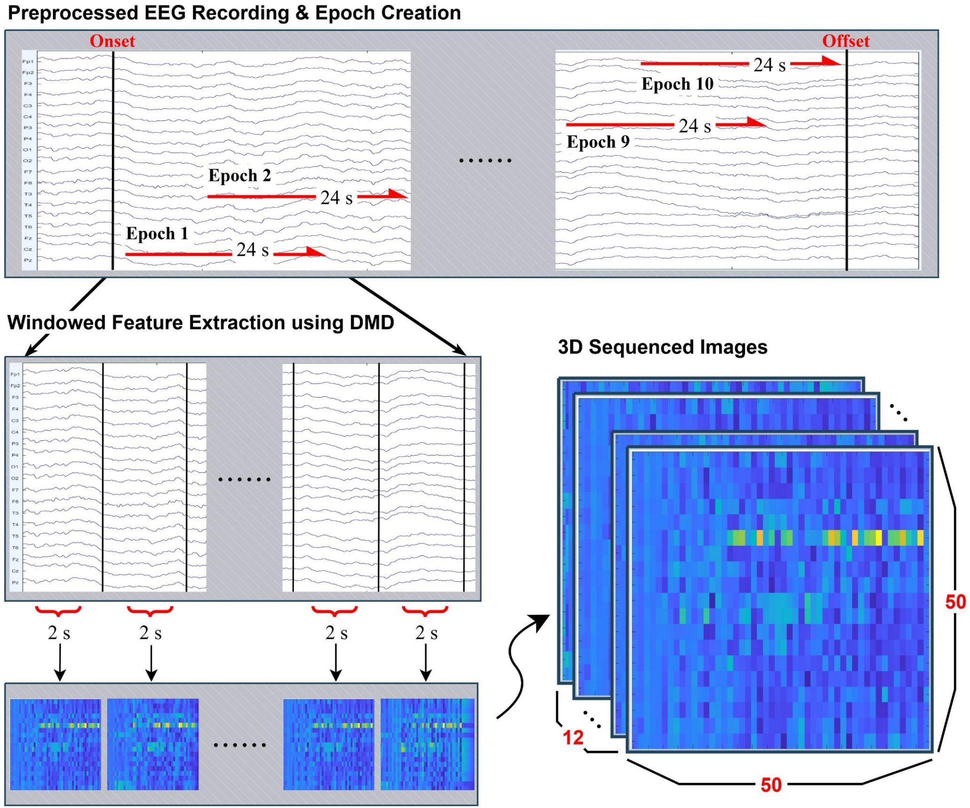
Previous FFT method:

- directly process long time windows under stationarity assumptions

Proposed DMD method:

- segments these windows into shorter epochs, enabling better characterization of temporal dynamics in nonstationary EO-EEG signals.

Our Featuring Process



Why do we split into shorter time window?

Why our CNN framework for EO-EEG

Previous study used samples with **longer window**, 30 seconds in EC-EEG

However, our EO-EEG contain sequential photic stimulation with inconsistency b/w subjects

(**different stimulus combinations & durations** (5, 10, 15, or 30 Hz) for each subjects)

→ Long windows would mix multiple stimulus conditions

"SSVEP (Steady-State Visually Evoked Potential) responses exhibit time-ordered, frequency-dependent changes in phase synchrony and propagation" Norcia et al. (2015); Tsoneva et al. (2021)

→ Lose NONSTATIONARY dynamics

We used shorter windows (2 seconds) and stacked 12 windows in sequence

DMD Algorithm

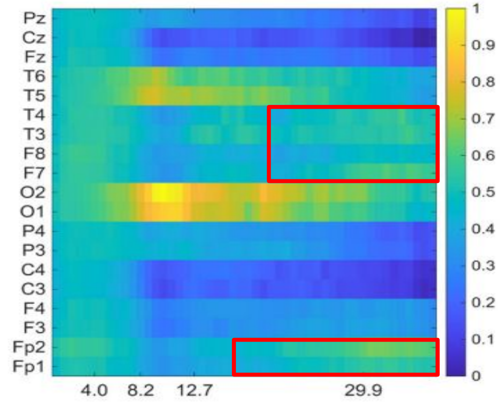
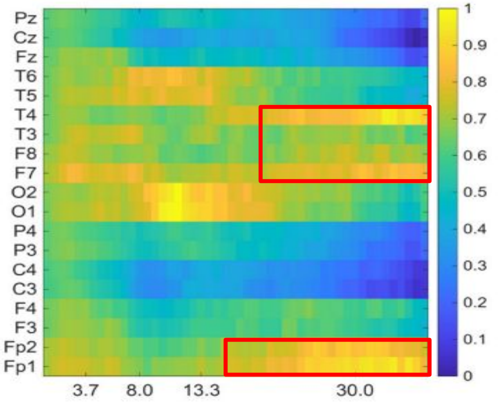
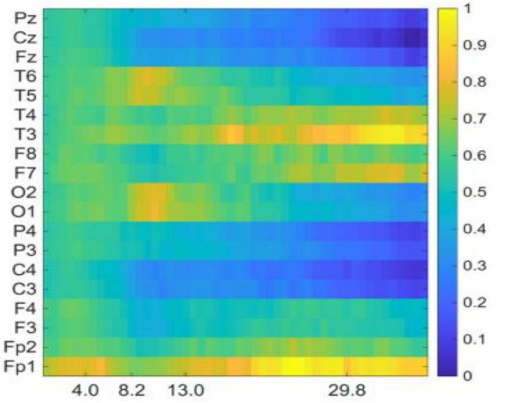
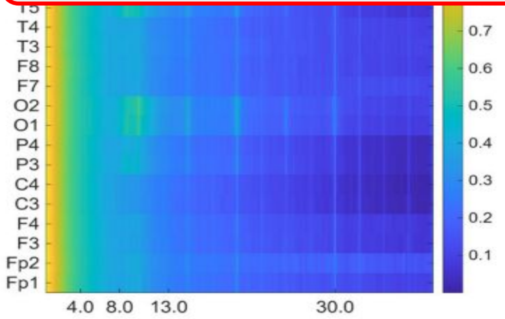
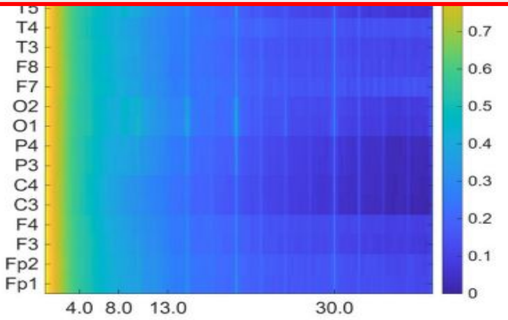
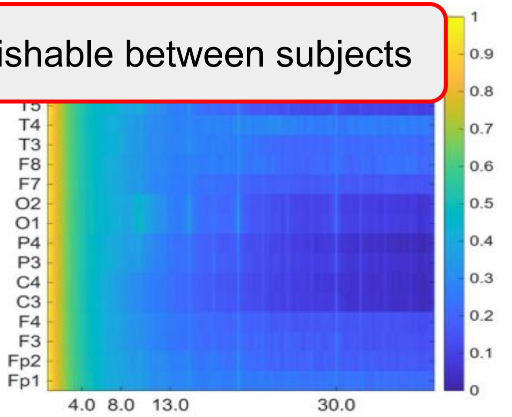
Suitable for nonstationary data: EO-EEG strongly exhibits nonstationarity, and DMD effectively captures these temporal variations

Simultaneous dimensionality reduction and feature extraction: DMD efficiently processes high-dimensional EEG data by extracting a compact set of interpretable modes

Preserves spatial relationships across channels: DMD modes represent coordinated activity patterns across the electrode montage, preserving the spatial network structure that distinguishes different dementia subtypes

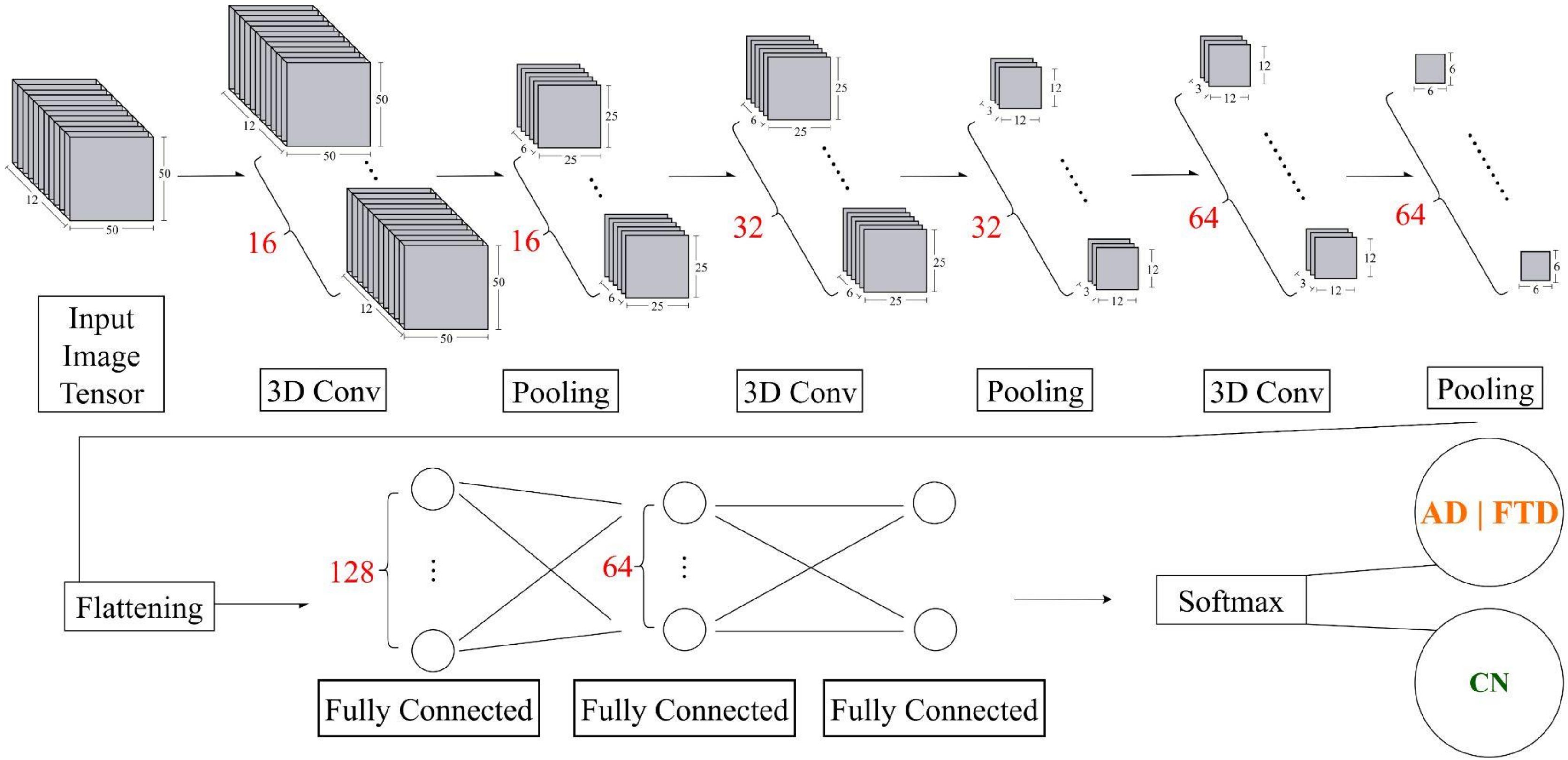
Why our DMD framework for EO-EEG

Averaged and normalized
DMD mode & FFT heatmaps

	Healthy Control	Alzheimer’s Disease	Frontotemporal Dementia
DMD			
FFT			

DMD clearly extracts Spatiotemporal Pattern that is distinguishable between subjects

CNN Network / Architecture



Result

Task	Method	Accuracy
AD/CN	Baseline (SVM)	62.50%
	FFT with delta-band	70.69%
	FFT without delta-band	70.56%
	DMD with delta-band	72.96%
	Proposed: DMD w/o delta-band	**74.23%**
FTD/CN	Baseline (LightGBM)	71.00%
	FFT with delta-band	74.39%
	FFT without delta-band	73.24%
	DMD with delta-band	76.67%
	Proposed: DMD w/o delta-band	**77.06%**
(AD+FTD)/CN	FFT with delta-band	67.43%
	FFT without delta-band	69.85%
	DMD with delta-band	73.25%
	Proposed: DMD w/o delta-band	**73.32%**

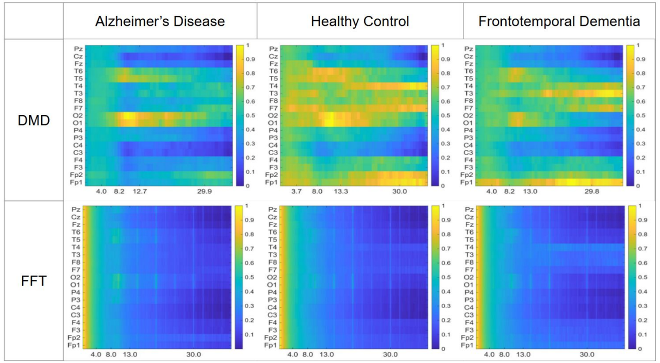
Key Improvements:

1. DMD outperforms FFT:
   - AD: 74.23% (DMD w/o delta) vs 70.56% (FFT)
   - Captures spatial-temporal coordination patterns

2. Delta (0.5-4 Hz) band effect:
   - Excluding delta significantly improves AD detection
   - +1.27% accuracy increase (72.96% → 74.23%)
   - Indicates delta preturbance in AD

3. Method comparison:
   - Baseline (SVM): 62.50%
   - Our approach: 74.23% (+11.73% improvement)

Conclusion



1. DMD outperforms FFT for EO-EEG classification
⟶ Captures spatial-temporal coordination
⟶ FFT averages out critical patterns

2. Sequential short windows preserve nonstationary dynamics
⟶ Critical for photo-stimulation, EO-EEG
⟶ Balances frequency resolution with temporal precision

3. Delta band (0.5-4 Hz) is preturbative in AD Detection
⟶ Excluding delta improves AD detection (+1.27%)
⟶ Confirms instability of low frequencies in EO conditions

Future Works

1. Multi-modal fusion:
   - Combine EC-EEG + EO-EEG features

2. Interpretability analysis:
   - Identify discriminative DMD modes for each condition
   - Visualize attention maps from CNN layers

3. Improve subject-level generalization:
   - Analyze per-subject loss patterns during training
   - Identify characteristics of "hard-to-classify" subjects
   - Goal: Reduce LOSO polarization in Slide 4

LNSO Validation

Our strategy:

- Split 61 subjects into **5 groups**
- Use **4 groups for training**, **1 group for testing**
- For each of the 5 splits:
  - Repeat training/testing **5 times**
  - Here, **5 splits × 5 repetitions = 25 experiments**

This whole procedure is repeated 5 times with different seeds for splitting

Note: Many more split combinations are possible, but we use 5 random splits for computational efficiency.

Conclusion

EO EEG를 FFT말고 DMD를 사용했을 때 정확도 증가

긴 시간을 짧은 시간으로 쪼개서 학습했을 때 정확도 증가

FFT(30초) CNN

AD같은 강한 자극이 주어질때 민감한 데이터일때는 쪼개서 학습하는게 중요

FFT 보다 DMD는 쪼갰을 때 그런 데이터의 변화를 잘 포착

델타 포함 비포함 (AD가 저주파에서 민감하다)