Technical Assessment: EEG and Foundation Models

Task 1:
EEG Data Processing, Visualization, and Classical Neural Networks

Objective:
Establish a high-fidelity EEG data processing pipeline and demonstrate a deep understanding of EEG signal characteristics through classical deep learning models.

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EEG Data Processing

SPD domain-specific batch normalization to crack interpretable unsupervised domain adaptation in EEG

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Their Datasets:

from table 5

- BNCI2014001
- BNCI2015001
- Lee2019
- Stieger2021
- Lehner2021
- Hehen.2021
- Hinss2021

Select 3 datasets:

1. BNCI2014001
2. BNCI2015001
3. Lee2019

According to paper, their dataset pre-processing steps are:

MOABB + MNE

MOABB

- Resample EEG → 250/256 Hz
- Bandpass / temporal filter → 4–36 Hz
- Short segments extract → ≤ 3 seconds window

Reproduce Steps

My data pre-processing steps are:

MOABB + MNE

MOABB

- FMIN, FMAX = 4, 36
- RESAMPLE = 250
- paradigm = MotorImagery(... fmin=FMIN, fmax=FMAX, resample=RESAMPLE)
- return_epochs=True epochs.get_data()
- labels LabelEncoder() encode + meta columns type clean
- resample + 4–36Hz bandpass
- ≤3s segmentation
- GroupKFold(n_splits=5)

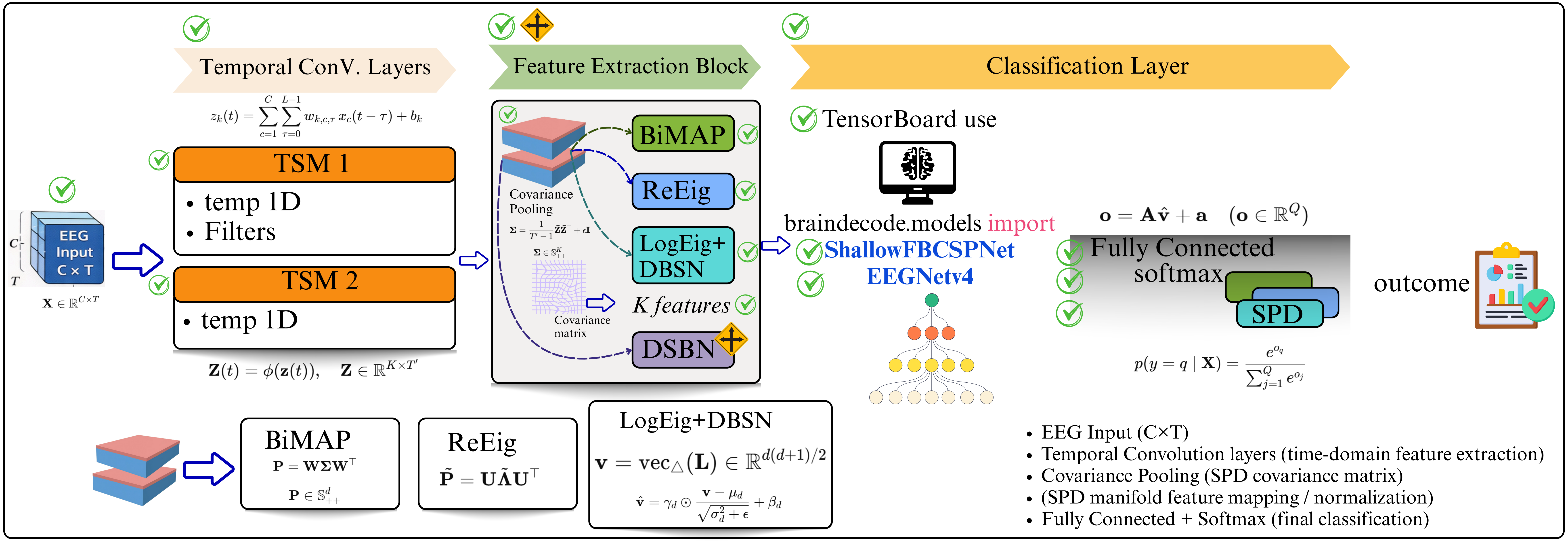
Reason

Enforcing an exact ≤3-second segment can truncate subject/dataset-specific informative activity and introduce short-window filtering edge effects or padding bias, making cross-dataset/cross-subject evaluation less stable and potentially unfair.

Done match with the suggested paper
Do not match with the suggested paper
New method;

Architecture

Ours Reproduce 92% of their architecture 8% uniqe



Their: Temporal conv → Covariance pooling (SPD) → BiMap → ReEig → LogEig → (DSBN) → FC+Softmax

block: SPDDSMBN (SPD manifold momentum BN)

We changed DSBN/BN proxy → same "domain-specific normalization idea

Done reproduce

Changes icons

Visualization

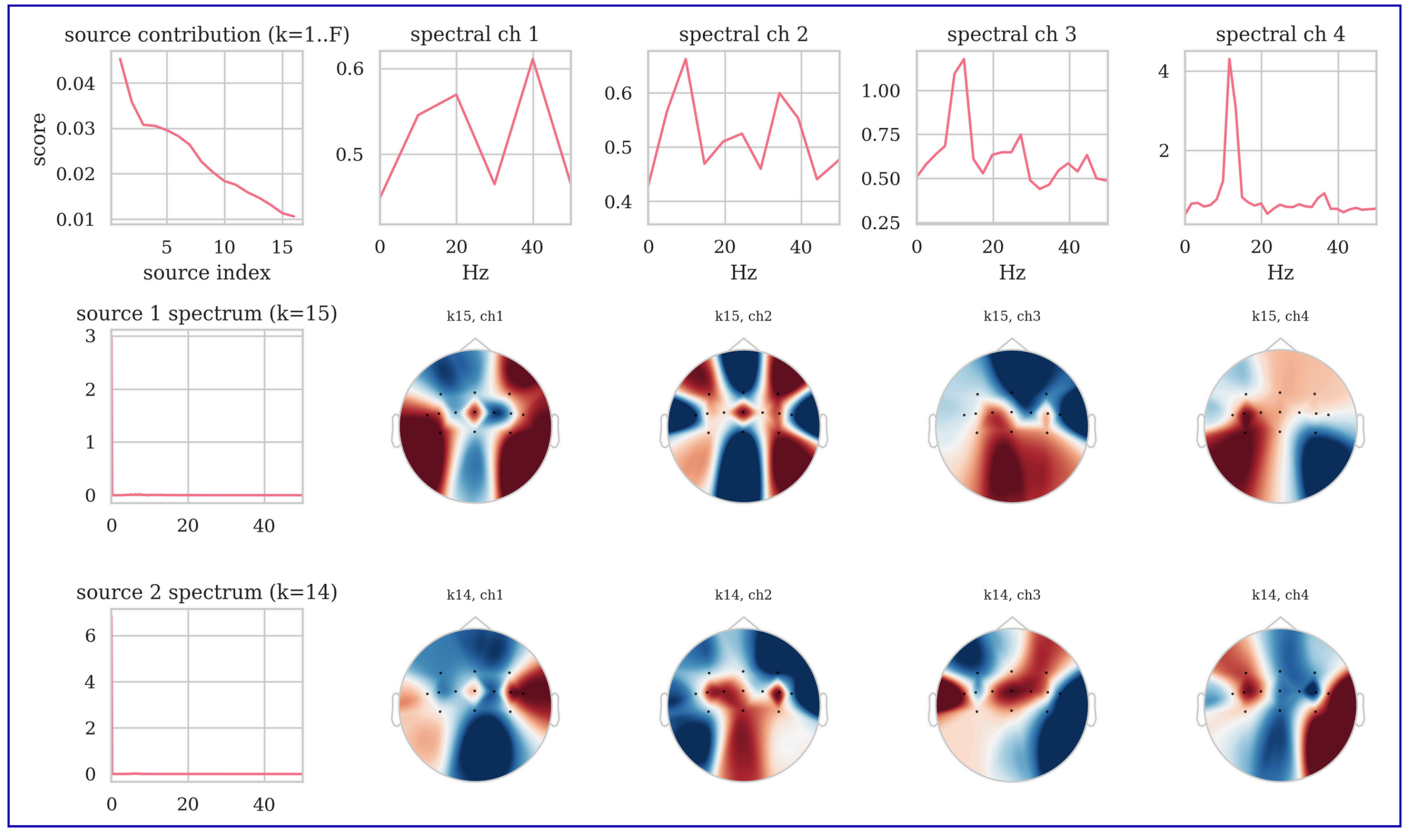
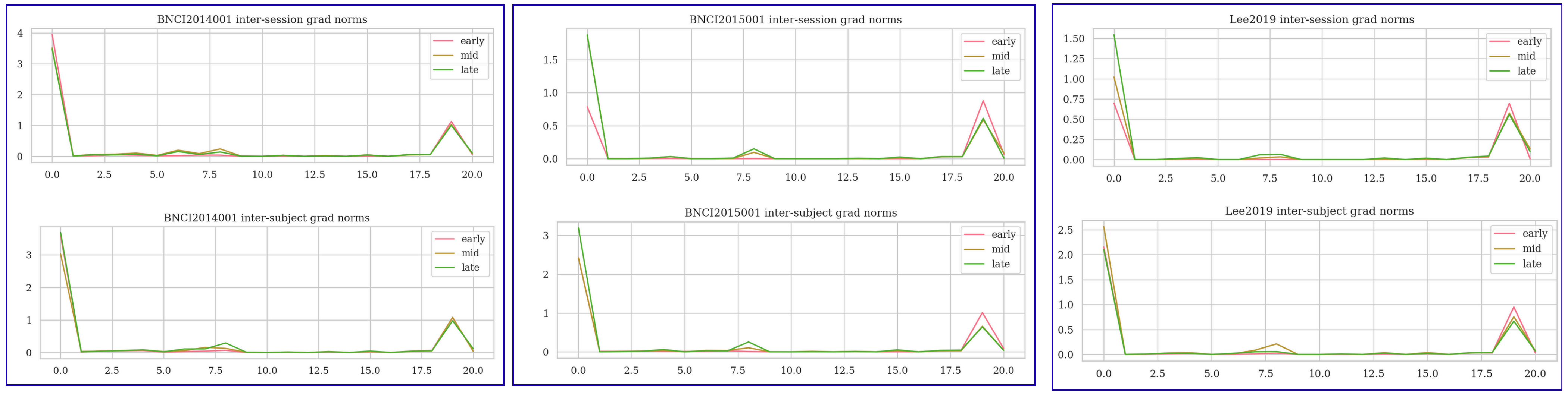


Fig.3 (reproduce). Source contribution + Spectral profiles + Spatial topographies (topomaps)

Fold 5 *Fold 5* *Fold 5*

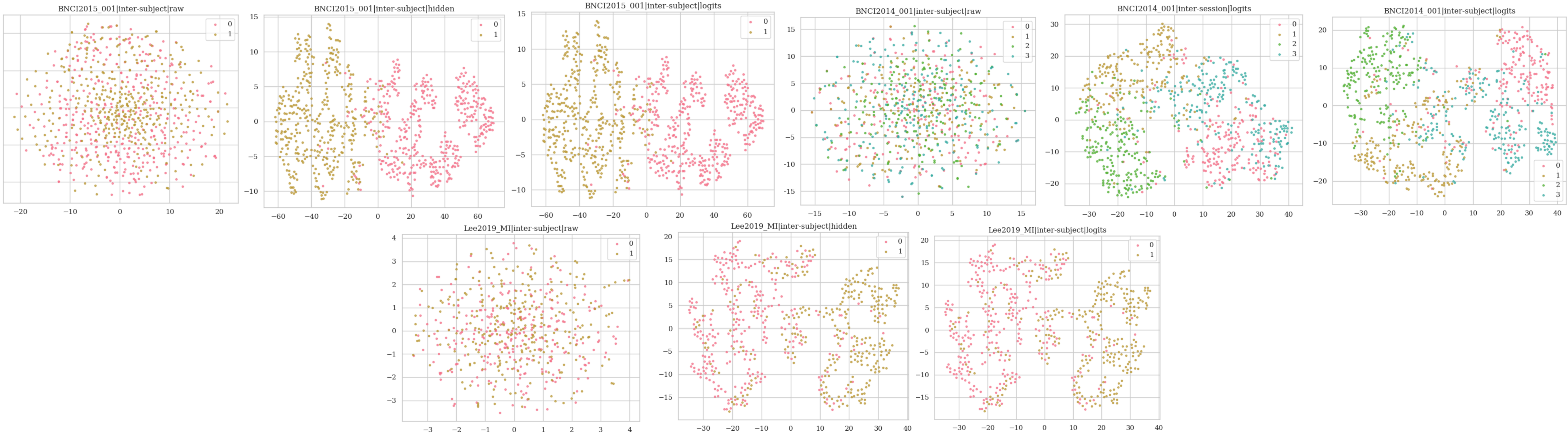


Last fold visualization gradient (inter session, and inter subject)

cross-X settings : 5-fold group CV (≈20% subjects per fold test)

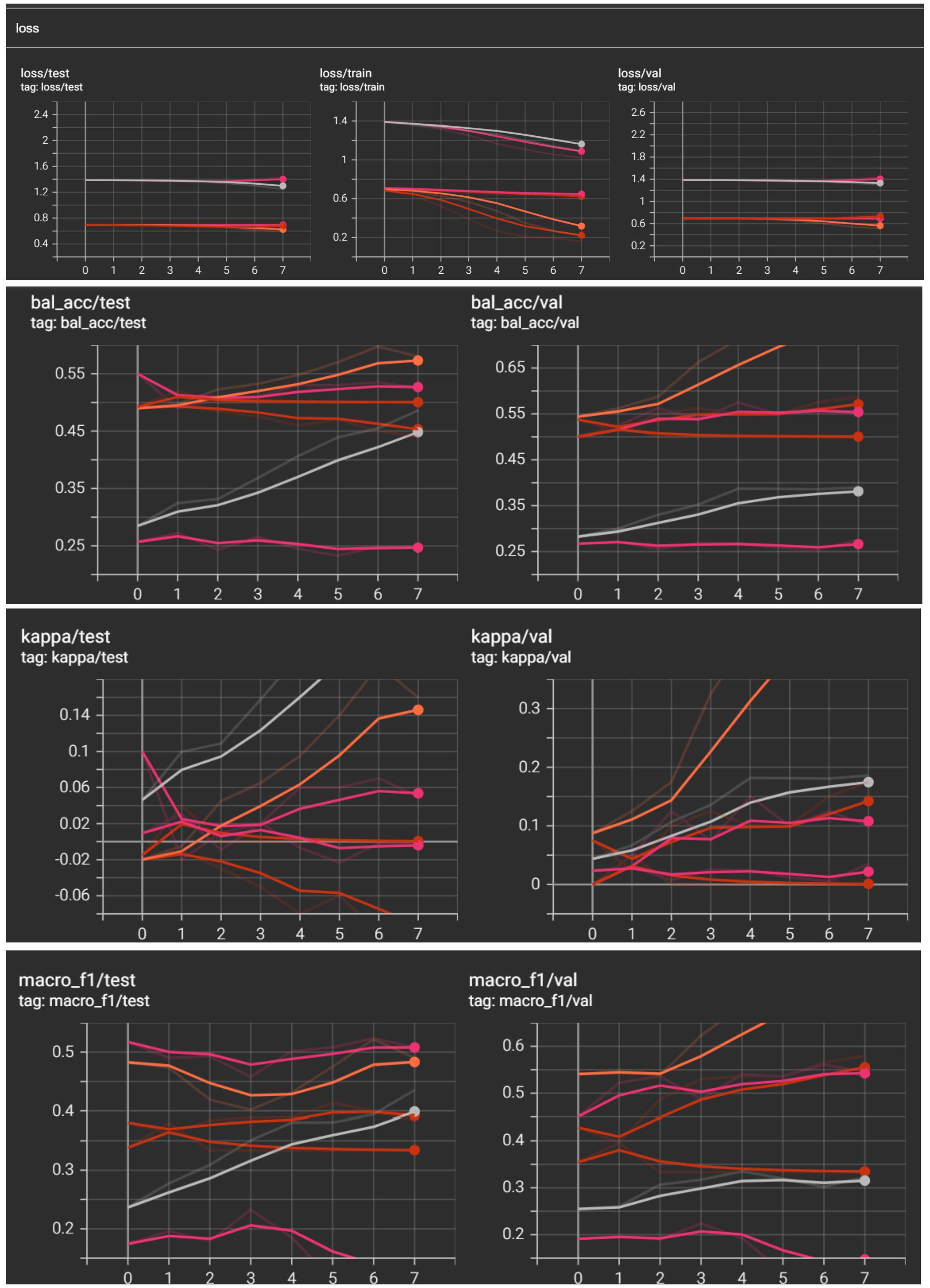
mode="inter-subject" groups = meta["subject"]GroupKFold(n_splits=5)

it_m, ... = eval_crossX(... mode="inter-subject", ...)
is_m, ... = eval_crossX(... mode="inter-session", ...)



t-SNE visualization of representations (raw, logits, and hidden embeddings)

EEGNetv4
TensorBoard based



Results

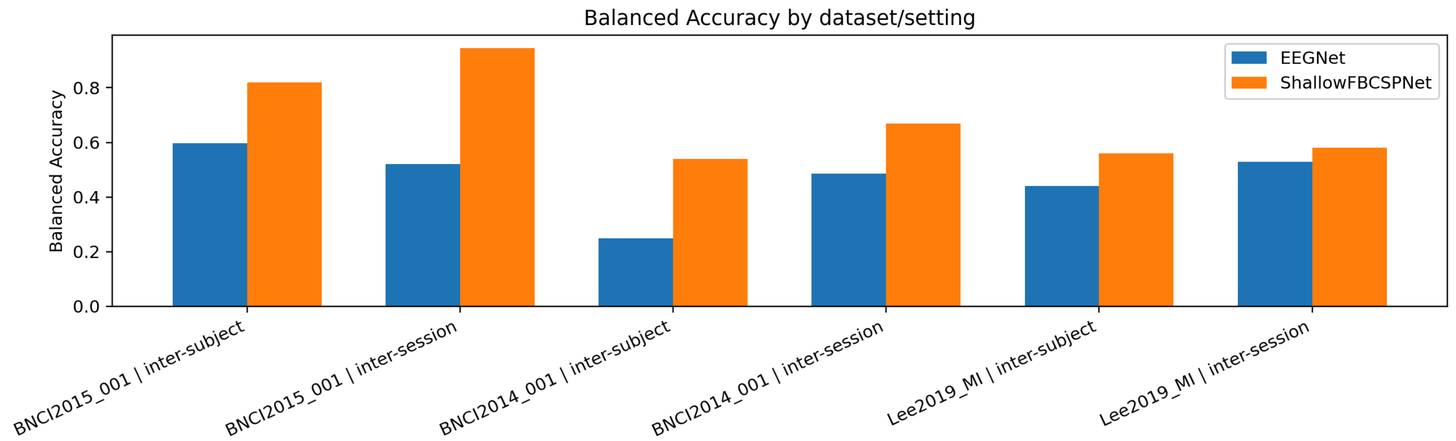


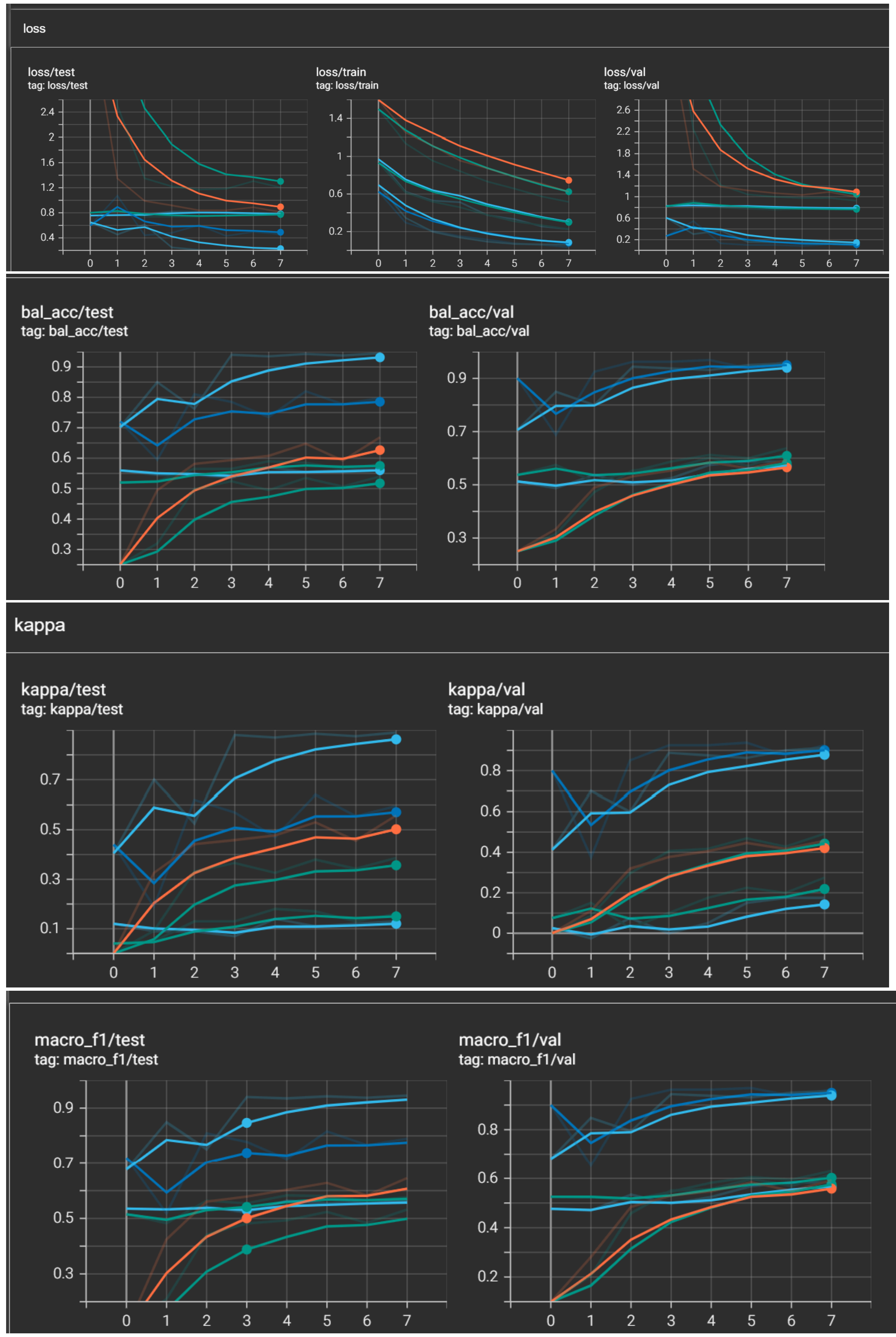
TABLE I
REPRODUCED TABLE-5 STYLE RESULTS ON BNCI2015_001, BNCI2014_001, AND LEE2019_MI DATASETS.

Dataset	Setting	Classes	Model	BalAcc	MacroF1	MCC	Kappa
BNCI2015_001	inter-subject	feet, right_hand	EEGNet	0.598	0.522	0.321	0.195
BNCI2015_001	inter-subject	feet, right_hand	ShallowFBCSPNet	0.820	0.816	0.671	0.640
BNCI2015_001	inter-session	feet, right_hand	EEGNet	0.520	0.380	0.128	0.040
BNCI2015_001	inter-session	feet, right_hand	ShallowFBCSPNet	0.945	0.945	0.890	0.890
BNCI2014_001	inter-subject	feet, left_hand, right_hand, tongue	EEGNet	0.248	0.109	-0.010	-0.002
BNCI2014_001	inter-subject	feet, left_hand, right_hand, tongue	ShallowFBCSPNet	0.540	0.532	0.392	0.387
BNCI2014_001	inter-session	feet, left_hand, right_hand, tongue	EEGNet	0.486	0.435	0.363	0.315
BNCI2014_001	inter-session	feet, left_hand, right_hand, tongue	ShallowFBCSPNet	0.668	0.646	0.567	0.558
Lee2019_MI	inter-subject	left_hand, right_hand	EEGNet	0.440	0.385	-0.150	-0.120
Lee2019_MI	inter-subject	left_hand, right_hand	ShallowFBCSPNet	0.560	0.560	0.120	0.120
Lee2019_MI	inter-session	left_hand, right_hand	EEGNet	0.530	0.501	0.068	0.060
Lee2019_MI	inter-session	left_hand, right_hand	ShallowFBCSPNet	0.580	0.577	0.163	0.160

We believe performance could be further improved by exploring additional/alternative preprocessing and augmentation strategies. However, due to current resource and time constraints, we limited preprocessing to a lightweight, reproducible pipeline in this study.

ShallowFBCSPNet
TensorBoard based

MINDxAI Lab



GitHub Code Link: https://github.com/Shazzad-Shaon3404/Task-1/tree/main