

Supplementary Materials for F2FNet

Robust Knowledge Transfer in EEG-based Depression Recognition

This document provides additional experimental results, dataset descriptions, and detailed performance analyses to support the findings presented in the main manuscript. These materials specifically address concerns regarding dataset diversity, channel configurations, and cross-device generalizability.

1. Extension of Dataset Diversity: The Arizona Dataset (Dataset III)

To enhance the robustness of the F2FNet framework, we incorporated a third independent public dataset (Dataset III). This ensures that the model's performance is not overfitted to specific hardware or demographic groups.

1.1 Dataset Description and Source

The Arizona dataset was collected by the John J.B. Allen lab at the University of Arizona and is hosted on OpenNeuro [1]. It consists of resting-state EEG recordings from 122 participants.

- Subject Selection:** To maintain class balance and diagnostic reliability, we selected 28 MDD patients and 28 Healthy Controls (HC) who exhibited stable Beck Depression Inventory (BDI-II) scores across multiple assessments.
- Clinical Thresholds:**
 - Depression Group: **BDI > 13**
 - Healthy Control Group: **BDI < 5**

1.2 Demographic and Clinical Characteristics

The table below summarizes the characteristics of the participants included in this study.

Table 1: Dataset III Information (Sub-cohort for Analysis)

Feature	Depression Group (MDD)	Health Control Group (HC)
Total Participants	45	76
Age (Mean +/- SD)	18.69 +/- 1.09	19.00 +/- 1.22
Sex (Male/Female)	33 / 12	41 / 35
BDI-II Score (Mean +/- SD)	22.22 +/- 4.90	2.00 +/- 2.83

1.3 Pre-processing Protocol

Following the standard practices established by Cavanagh et al. (2021), the data underwent the following pipeline:

1. **Re-referencing:** Re-referenced to mastoids (M1, M2).
2. **Filtering:** Bandpass filtering from 0.5 to 40 Hz.
3. **Artifact Removal:** Independent Component Analysis (ICA) was utilized to isolate and remove EOG and EMG artifacts.
4. **Feature Extraction:** Differential Entropy (DE) features were extracted across five frequency bands (delta, theta, alpha, beta, and gamma).

2. Cross-Device Transfer Paradigm: 62-channel to 3-channel

We extended our knowledge transfer paradigm to evaluate F2FNet’s ability to bridge the gap between medium-density (62-channel) and ultra-low-density (3-channel) devices.

2.1 Methodology

The Knowledge Extraction Module (KEM) was trained on the 62-channel Arizona dataset, providing a **310-dimensional feature space** (calculated as: 62 channels x 5 frequency bands). The Knowledge Transfer Module (KTM) then distilled this information into a 3-channel configuration (Fp1, Fpz, Fp2).

2.2 Performance Comparison

The experimental results demonstrate that F2FNet significantly outperforms conventional machine learning baselines in cross-device transfer tasks.

Table 2: Performance Comparison under 62-channel to 3-channel Transfer Paradigm

Models	62-ch (Source) Acc	62-ch F1-score	MODMA 3-ch Acc	MODMA 3-ch F1	Self-collected 3-ch Acc	Self-collected 3-ch F1
KNN	91.07%	90.08	58.33%	37.56	52.08%	48.82
SVM	91.07%	91.21	68.17%	27.09	53.45%	33.53
DT	78.57%	75.57	62.92%	40.43	55.08%	49.29
LR	87.50%	87.59	68.58%	33.81	49.73%	53.67
NB	82.14%	81.95	63.17%	21.60	48.97%	59.79
F2FNet	94.69%	94.71	78.76%	79.99	77.62%	74.55

3. Discussion on Robustness and Scalability

3.1 Analysis of Knowledge Distillation Efficiency

Experimental evidence confirms that F2FNet mitigates the information scarcity of few-channel setups. While direct classification on 3-channel data yields near-chance accuracy (50%-60%), F2FNet improves accuracy by **10% to 24%**.

We observe that the 62-to-3 channel transfer accuracy (**78.76%**) is slightly lower than the 128-to-3 channel transfer (which exceeded **84%** in previous tests). This can be justified by the **Information Bottleneck Theory**:

- **128-channel Source:** Provides denser spatial sampling and richer functional connectivity patterns, offering a higher "knowledge ceiling" for the teacher (KEM).
- **62-channel Source:** While effective, the reduction in spatial resolution limits the intricate topological features available for distillation, thus affecting the upper bound of the student model's adaptive capacity.

3.2 Conclusion on Generalizability

The consistent superiority of F2FNet across Dataset I (MODMA), Dataset II (Self-collected), and Dataset III (Arizona) validates its universal applicability. The model effectively handles the distribution shifts caused by heterogeneous devices, varying electrode counts, and distinct subject populations.

4. References

- [1] Cavanagh, J. F., et al. (2021). *Resting EEG data with 122 college-age participants*. OpenNeuro. doi:10.18112/openneuro.ds003478.v1.1.0
- [2] Cai, H., et al. (2020). *MODMA dataset: a multi-modal open dataset for mental-disorder analysis*.
- [3] Mumtaz, W., et al. (2017). *A machine learning framework for MDD diagnosis using EEG*.
- [4] Li, X., et al. (2019). *Cross-dataset MDD recognition using deep transfer learning*.