Meditation-journey: Dataset and Benchmarks for Longitudinal Study of Different Meditation Techniques

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Overview

- **Context:** Meditation is a cognitive training designed to induce measurable, positive brain changes, from immediate effects after a session, to long-term neuroplasticity from consistent practice [1].
- **The Gap:** Effective practice is difficult due to mind-wandering. Progress is hard to track because identifying robust EEG biomarkers for the subtle, evolving neural activities associated with the practice of meditation remains a major scientific challenge.
- **Our Contribution:**
  - A novel longitudinal EEG dataset tracking 6-week changes in focused-attention meditation (Breath Focus and Mantra).
  - Comprehensive 3-Task Validation demonstrating the dataset's power to classify.
  - A robust classification benchmark using a stationary wavelet transform (SWT) module to identify key neural biomarkers for meditation.

Dataset & Study Design

- **EEG Device:** 64 channel EEG wireless cap made by mBrainTrain is used to collect data with sampling rate of 250 Hz.
- **Participants:** EEG data was obtained from 30 pre-screened participants (currently), all of whom signed IRB-approved consent forms. Participants were divided into three groups (see Table 1).
- **Techniques:** Three meditation techniques were used to form the groups: Hare Krishna (HK), Sa Ta Na Ma (SA), and Breath Focus (BF). The first two are mantra-based.
- **Study Design:** The meditation program lasts for six weeks. Each group followed the pipeline outlined in Figure 2.

Group	Hare Krishna		Sa Ta Na Ma		Breath Focus		Total
	M = 3	F = 9	M = 3	F = 6	M = 3	F = 6	30
Age (years)	22.0 ± 4.1		22.4 ± 3.0		22.4 ± 3.0		22.2± 3.2

Table 1: Information for three groups (mean ± std). Male (M) and female (F) counts in each group are also shown.

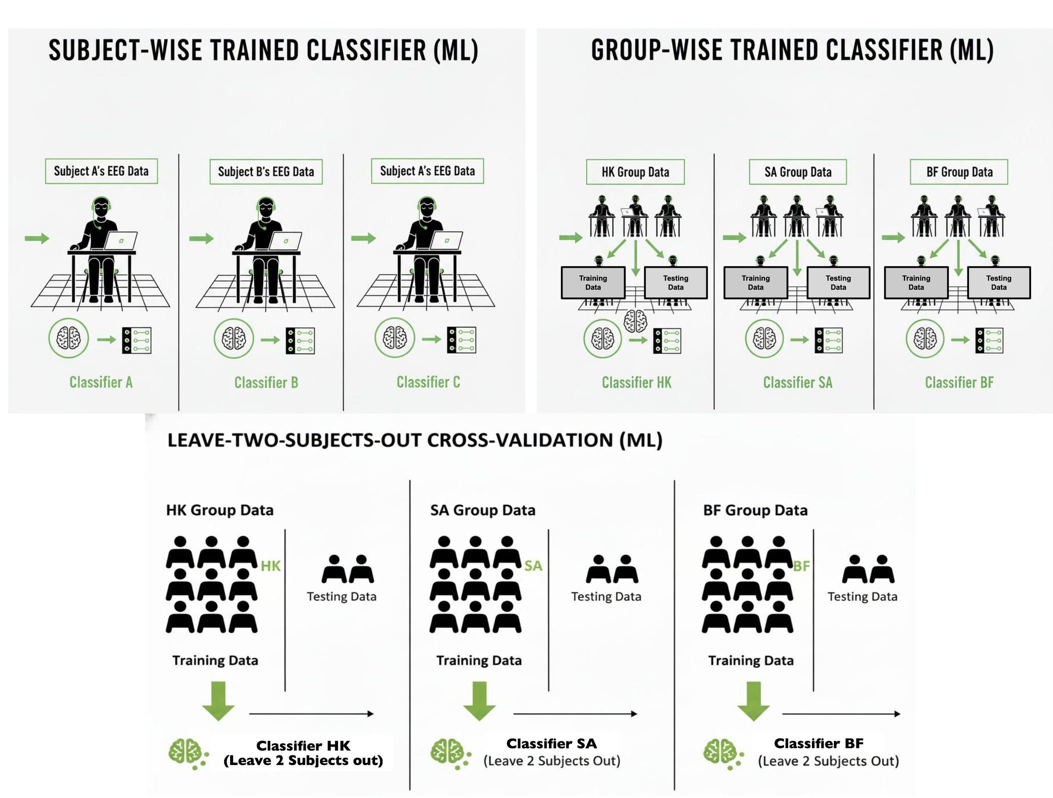

Figure 1: Three classifier training methods

Methods

- **Benchmark Tasks:** We benchmarked models to classify meditation: meditation versus rest, immediate effects and effects over time.
- **Models:** Models included traditional ML (Support Vector Machine (SVM), Random Forester (RF)) with selected features [2], the deep learning model EEGNet [3], and our proposed custom network.

Acknowledgments

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References

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Methods (Continued)

- **Training Methods:** We evaluated models using subject-wise, group-wise, and Leave-Two-Subjects-Out cross-validation (L2SO-CV). See Figure 1.

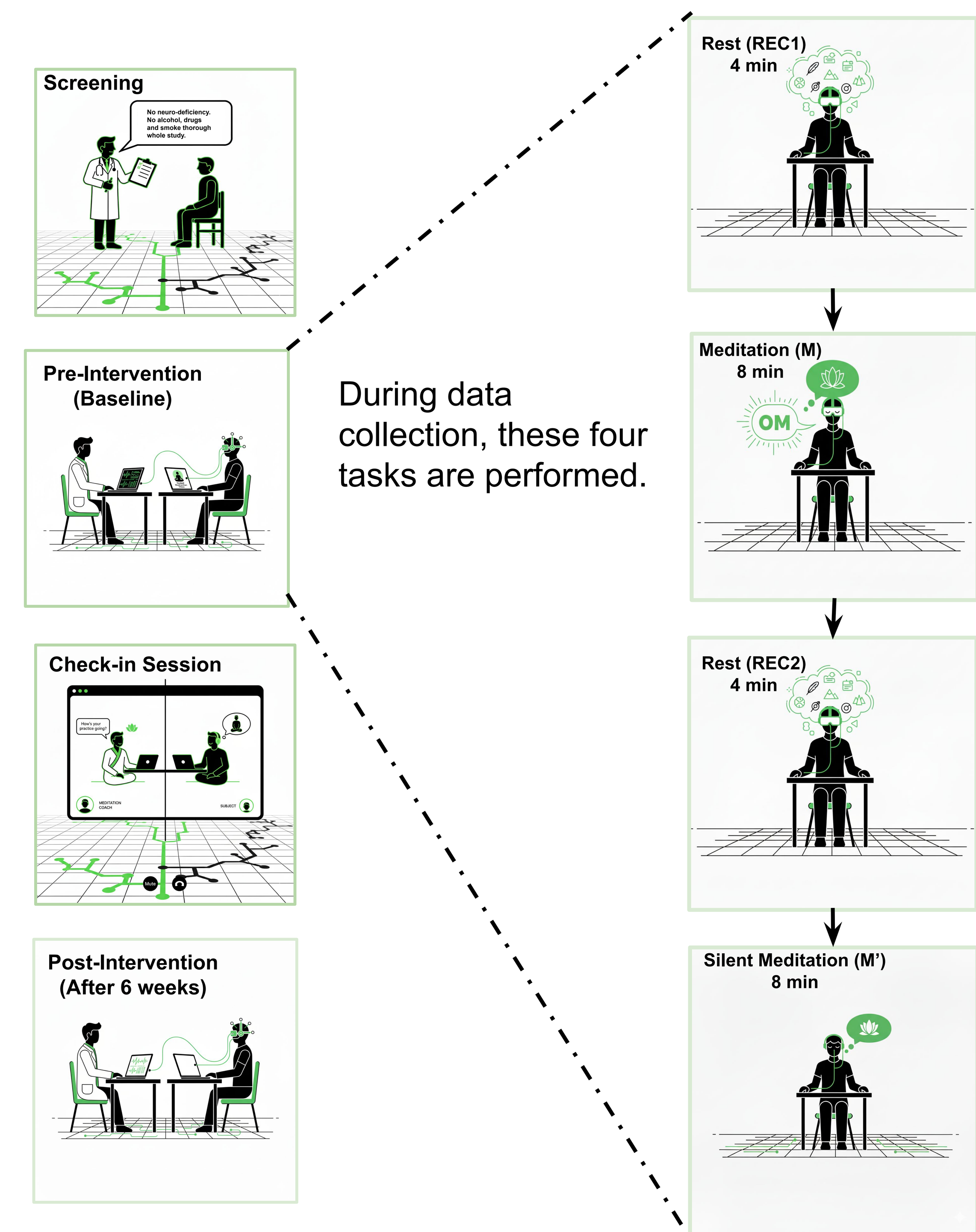

Figure 2: Pipeline for whole study setup

- **Proposed Model:** The architecture is based on EEGNet [3] with the following modifications:
  - A **Stationary Wavelet Transform (SWT)** module is introduced using two-level decomposition, where each level is processed by a 1D convolution with learnable weights.
  - Depth-wise and Separable convolution blocks are followed by batch normalization and ELU activation.

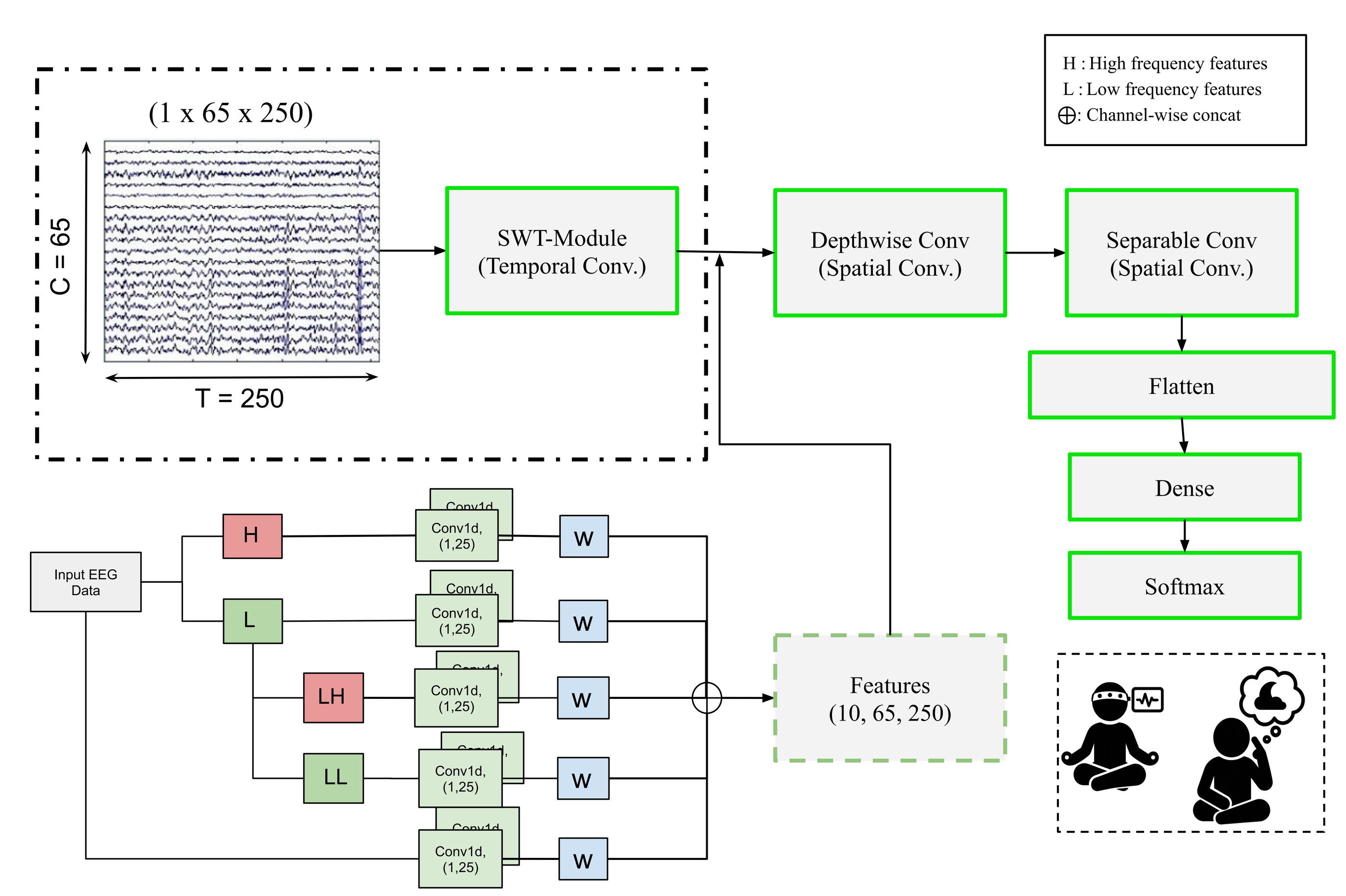

Figure 3: Stationary wavelet transform (SWT) convolution module and full model architecture

Benchmark Results

	Model	Subject-wise	Group-wise	L2SO-CV
HK Group	SVM	0.85 ± 0.07	0.75 ± 0.05	0.55 ± 0.04
	RF	0.83 ± 0.07	0.75 ± 0.03	0.58 ± 0.07
	EEGNet	0.99 ± 0.03	**0.95 ± 0.01**	0.63 ± 0.03
	SWT-EEGNet (Ours)	**0.99 ± 0.05**	0.93 ± 0.02	**0.67 ± 0.05**
SA Group	SVM	0.85 ± 0.07	0.73 ± 0.1	0.51 ± 0.04
	RF	0.83 ± 0.05	0.75 ± 0.02	0.49 ± 0.04
	EEGNet	0.98 ± 0.07	0.97 ± 0.01	0.56 ± 0.02
	SWT-EEGNet (Ours)	**0.98 ± 0.02**	**0.97 ± 0.02**	**0.57 ± 0.07**
BF Group	SVM	0.80 ± 0.07	0.71 ± 0.06	0.55 ± 0.03
	RF	0.79 ± 0.06	0.71 ± 0.12	**0.57 ± 0.05**
	EEGNet	0.97 ± 0.06	0.98 ± 0.03	0.50 ± 0.01
	SWT-EEGNet (Ours)	**0.98 ± 0.06**	**0.99 ± 0.01**	0.52 ± 0.02

Table 2: **Task 1:** Real-time states (Silent Meditation (M') vs. Rest (REC1))

	Model	Subject-wise	Group-wise	L2SO-CV
HK Group	SVM	0.84 ± 0.09	0.74 ± 0.03	0.58 ± 0.05
	RF	0.81 ± 0.08	0.73 ± 0.04	0.59 ± 0.5
	EEGNet	**0.99 ± 0.03**	**0.98 ± 0.03**	**0.97 ± 0.03**
	SWT-EEGNet (Ours)	0.98 ± 0.03	0.97 ± 0.03	0.96 ± 0.02
SA Group	SVM	0.86 ± 0.04	0.76 ± 0.05	0.48 ± 0.07
	RF	0.85 ± 0.09	0.74 ± 0.05	0.50 ± 0.07
	EEGNet	0.89 ± 0.05	0.95 ± 0.04	0.89 ± 0.02
	SWT-EEGNet (Ours)	**0.91 ± 0.06**	**0.99 ± 0.02**	**0.93 ± 0.05**
BF Group	SVM	0.83 ± 0.08	0.70 ± 0.07	0.50 ± 0.04
	RF	0.81 ± 0.08	0.77 ± 0.03	0.49 ± 0.03
	EEGNet	0.96 ± 0.03	0.94 ± 0.06	**0.98 ± 0.04**
	SWT-EEGNet (Ours)	**0.97 ± 0.08**	**0.97 ± 0.02**	0.96 ± 0.02

Table 3: **Task2:** Immediate effects (Rest (REC1) before Meditation vs. Rest (REC2) after)

	Model	Subject-wise	Group-wise	L2SO-CV
HK Group	SVM	0.85 ± 0.07	0.70 ± 0.03	0.52 ± 0.06
	RF	0.83 ± 0.07	0.72 ± 0.04	0.48 ± 0.07
	EEGNet	1.00 ± 0.00	0.97 ± 0.05	0.52 ± 0.03
	SWT-EEGNet (Ours)	**1.00 ± 0.00**	**0.97 ± 0.02**	**0.57 ± 0.06**
SA Group	SVM	0.85 ± 0.07	0.73 ± 0.07	0.50 ± 0.05
	RF	0.82 ± 0.07	0.74 ± 0.08	0.50 ± 0.05
	EEGNet	0.94 ± 0.05	0.95 ± 0.03	0.56 ± 0.06
	SWT-EEGNet (Ours)	**0.94 ± 0.04**	**0.96 ± 0.02**	**0.60 ± 0.05**
BF Group	SVM	0.84 ± 0.08	0.72 ± 0.06	0.50 ± 0.05
	RF	0.83 ± 0.07	0.75 ± 0.04	0.49 ± 0.05
	EEGNet	1.00 ± 0.00	1.00 ± 0.00	0.54 ± 0.07
	SWT-EEGNet (Ours)	**1.00 ± 0.00**	**1.00 ± 0.00**	**0.55 ± 0.01**

Table 4: **Task3:** Long-term neuroplasticity (Post- vs. Pre-intervention Silent Meditation (M'))

Discussion

- Across all three tasks and almost all three meditation groups, the deep learning models (EEGNet and SWT-EEGNet) dramatically outperformed the classical models (SVM and RF).
- Task 2's exceptionally high L2SO-CV scores strongly suggest the immediate effect of meditation creates a powerful, consistent, and generalizable neural signature that is not subject-specific.
- Our SWT-EEGNet outperforms the baseline EEGNet in the challenging L2SO-CV setting (Tasks 1 & 3). This superior generalization suggests that the SWT module extracts features that are more robust to inter-subject variability, making it more effective for identifying cross-subject biomarkers.

Ongoing and Future Work

- A detailed analysis of the learnable scalar weights could be conducted to further explore how the module prioritizes specific sub-bands, enhancing model interpretability (eg. Grad-CAM).
- Additional ablation studies could be performed to more comprehensively analyze the impact of hyperparameters, such as a wider range of wavelet families or deeper decomposition levels.
- Testing the models on diverse public EEG datasets and integrating them into other deep learning architectures.