Meditation and Machine Learning: EEG-Based Classification of Meditative States

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ABSTRACT

With rising concerns around mental health and the growing demand for effective wellness strategies, scientific studies investigating meditation have become essential. One promising approach involves bridging the gap between subjective experiences and objective quantification by using tools such as EEG recordings to monitor brain activity. This study aims to determine whether an individual is an expert in meditation based on their brain signals using machine learning models. We implemented several models, including Logistic Regression, Random Forest, XGBoost, Artificial Neural Network, and Naive Bayes. Experimental results indicate that Random Forest outperforms the other models, achieving 98% accuracy. This study provides empirical validation for the benefits of meditation, thereby increasing its credibility and encouraging adoption in both clinical and everyday settings.

MIND WANDERING

Mind wandering refers to the shift of attention away from a task or the external environment toward internal thoughts, feelings, or daydreams. It often occurs unintentionally and can disrupt focus and performance, especially during activities that require sustained concentration. While commonly viewed as a distraction, mind wandering can also have benefits, such as fostering creativity, problem-solving, and self-reflection. Researchers study it using tools like EEG and self-reports to better understand its patterns and impact on cognitive performance and mental well-being.

Figure 1: Event-related spectral perturbation (ERSP) plots and differential plots of significance in theta (4–7 Hz) and alpha (9–11 Hz).

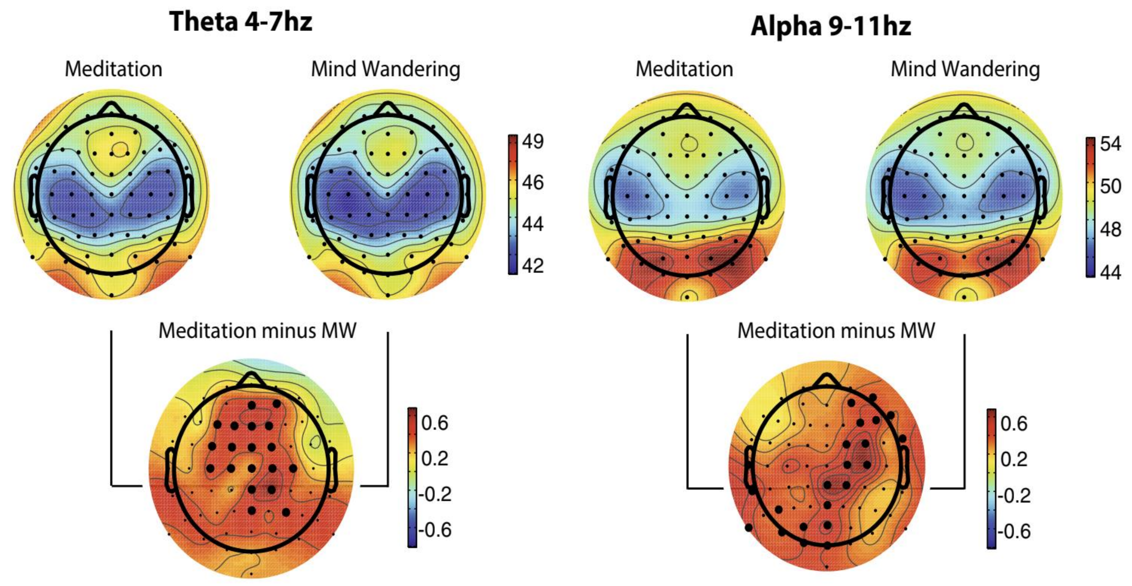


Figure 2: Timeline of experimental design.

Q1: Please rate the depth of your meditation. (0: low, 3: high)
Q2: Please rate the depth of your mind wandering.(0: low, 3: high)
Q3: Please rate how tired you are.(0: low, 3: high)

EXPLORING EEG DATA

Table 1: EEG and other Bio signals.

Variables	Positions	Remarks
Fp1, Fp2	Frontal pole (near forehead)	Thinking, Focus, Decision Making
AF7, AF3, AF4, AF8	Anterior frontal	–
F1, F2, F3, F4, F5, F6, F7, F8	Frontal cortex	Decision-making, attention
Fz	Frontal midline	Focus, cognitive tasks
FC1, FC2, FC3, FC4, FC5, FC6	Fronto-central	Motor control
C1, C2, C3, C4, C5, C6	Central cortex	Movement control
Cz	Central midline	Processing motor commands
T7, T8	Temporal lobe	Speech, sound processing
FT7, FT8	Fronto-temporal	Early auditory processing
TP7, TP8	Temporal-parietal	Memory, sensory integration
P1, P2, P3, P4, P5, P6, P7, P8	Parietal cortex	Sensory integration, attention
Pz	Parietal midline	Spatial reasoning
O1, O2	Occipital cortex	Visual processing
Oz	Occipital midline	Visual attention
PO3, PO4, PO7, PO8	Parieto-occipital	Processing movement, vision
CP1, CP2, CP3, CP4, CP5, CP6, CPz	Centro-parietal	Touch, sensory processing
POz	Parieto-occipital midline	Visual awareness
Iz	Inferior occipital	Vision processing
EXG1–EXG4	External channels	Record eye movements (EOG)
EXG5, EXG6	Left and right mastoids	Record additional physiological signals
EXG7, EXG8	Often unused or left empty	–
GSR1, GSR2	Galvanic Skin Response	Measures emotional arousal
Erg1, Erg2	–	Capture stomach muscle activity
Resp	–	Monitor respiratory activity
Plet	–	Measure blood volume changes
Temp	–	Body temperature

Figure 2: Gender and Age Distribution among Meditators.

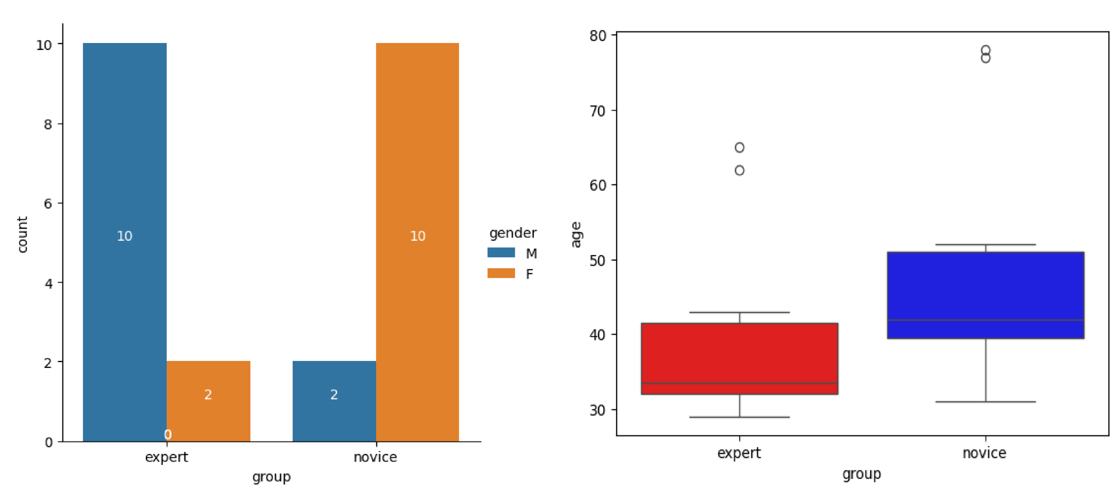


Figure 3: Meditation, Mind Wandering and Sleep Distribution.

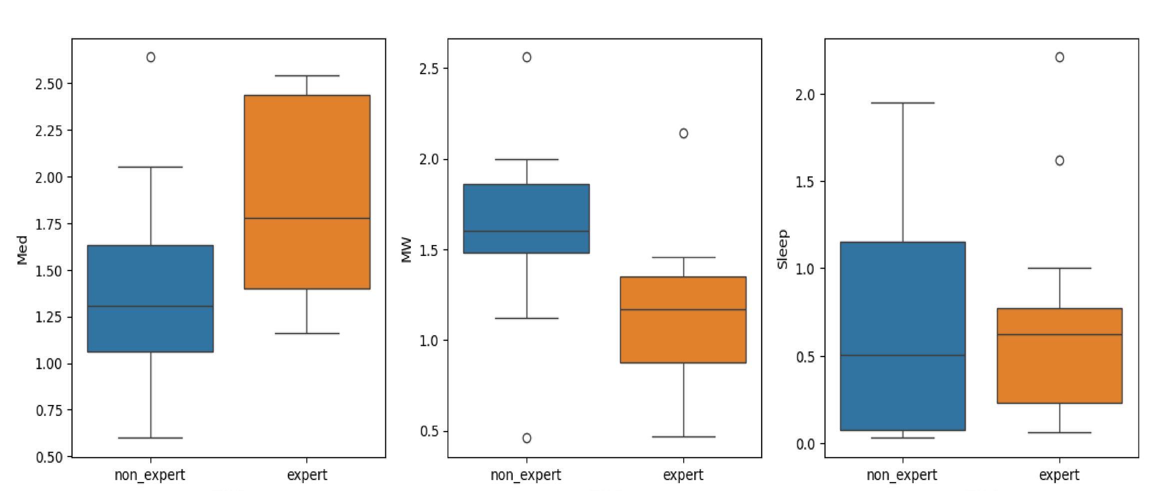
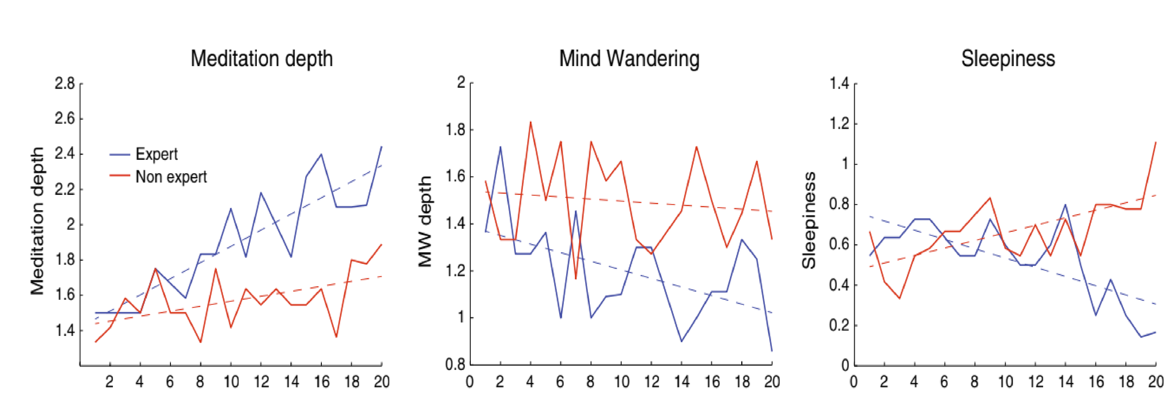


Figure 4: Meditation, Mind Wandering, and Sleep Trend.



MACHINE LEARNING MODELS PERFORMANCE

Figure 5: Kmeans Clustering Visualization.

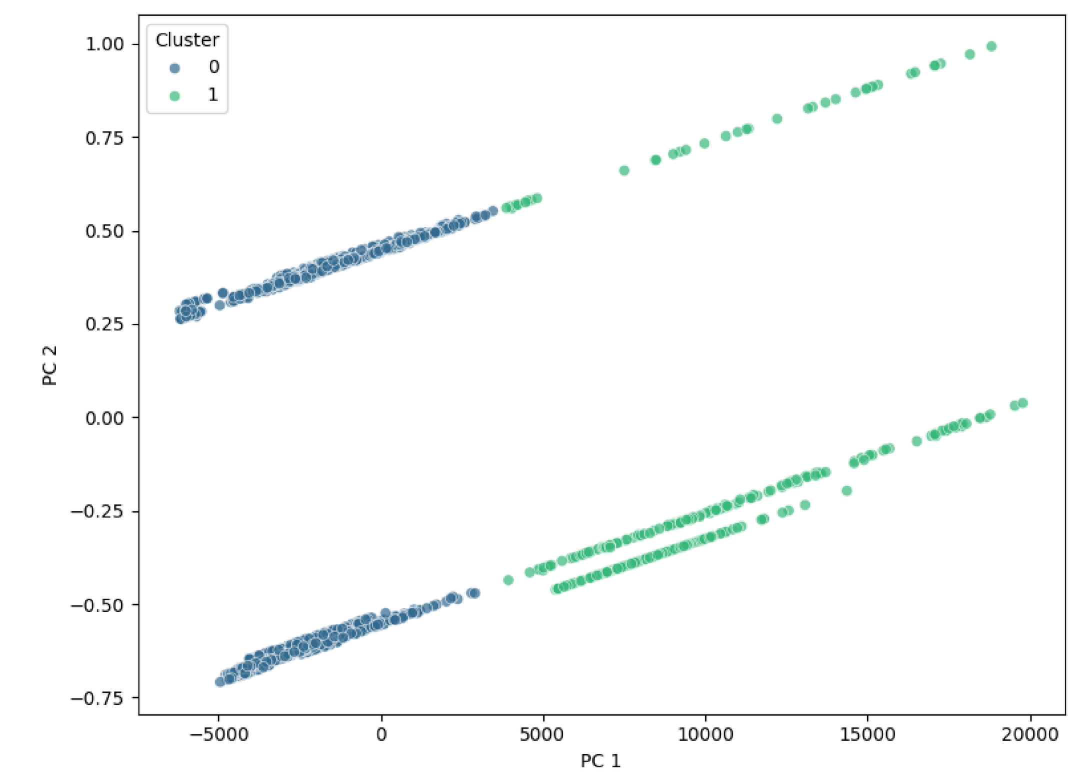
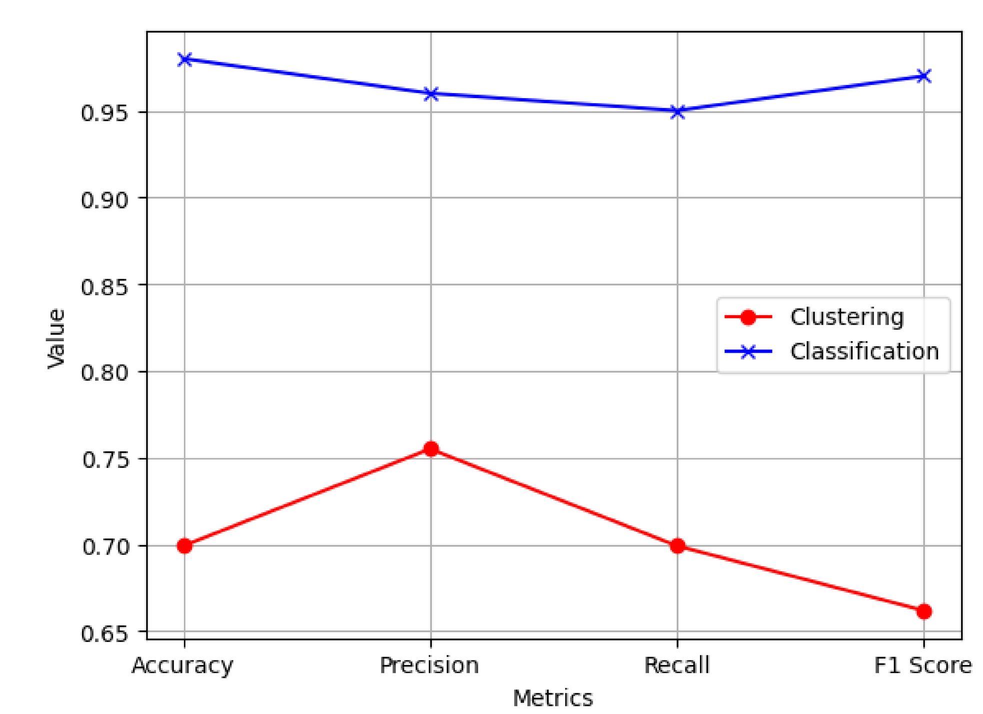


Figure 6: Classification Models Metrics.



Models performed: Logisitic Regression, Random Forest, XGBoost, and Artificial Neural Network

Figure 7: Top 10 Features Correlation.

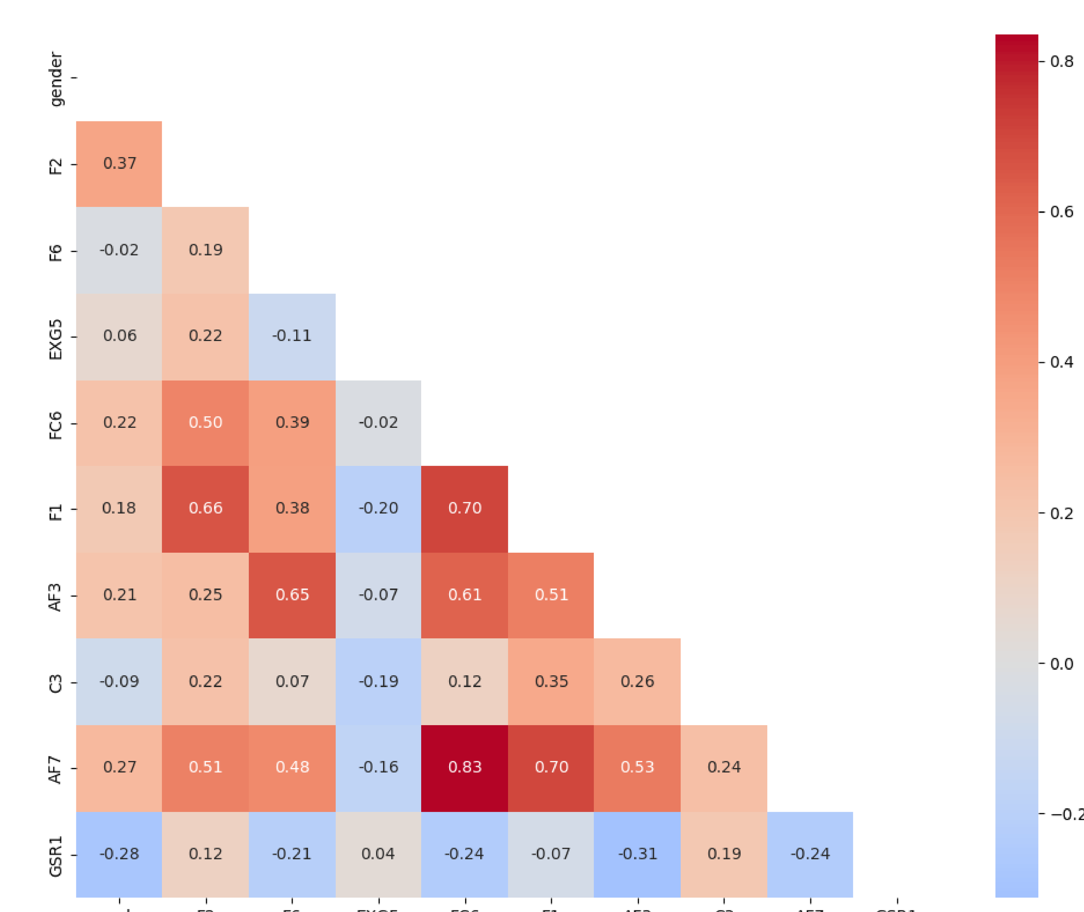


Table 2: Top 10 Features predicting Meditator expertise using Random Forest.

Feature	Importance
Gender	0.115
F2 (Frontal Cortex)	0.046
F6 (Frontal Cortex)	0.045
AF7 (Anterior Frontal)	0.038
C3 (Central Cortex)	0.037
AF3 (Anterior Frontal)	0.037
GSR1 (Galvanic Skin Response)	0.029
C2 (Central Cortex)	0.028
F1 (Frontal Cortex)	0.026
FC6 (Fronto-Central)	0.025

CONCLUSIONS

- The project accurately classified individuals as expert or novice meditators using EEG recordings. All supervised machine learning models—including Logistic Regression, Random Forest, XGBoost, and Artificial Neural Networks—achieving high **accuracy**, confirming the high predictive power of EEG-based features. Unsupervised **KMeans clustering** further supported these results by forming two clearly distinct groups, as visualized through PCA.

- **Feature importance analysis** highlighted top predictors such as **gender**, and EEG channels including **F2, F6, AF7, C3, AF3**, and **GSR1**, reinforcing the role of both neurophysiological and demographic factors in identifying meditation expertise.

- Self-reported behavioral metrics showed that **experts reported higher meditation quality**, **lower mind wandering**, and **fewer sleep-related experiences** during the session, as illustrated in the boxplots. These consistent patterns across objective and subjective data strongly validate our approach and emphasize EEG's potential in meditation and mindfulness research.

REFERENCES

Arnaud Delorme and Tracy Brandmeyer (2024). EEG meditation study. OpenNeuro. [Dataset] doi: doi:10.18112/openneuro.ds001787.v1.1.1

Brandmeyer T, Delorme A (2018). Reduced mind wandering in experienced meditators andassociated eeg correlates. Experimental brain research, 236: 2519–2528.