Towards the development of personalized and generalized interfaces for brain signals across different styles of meditation*

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ABSTRACT

Human-computer interaction investigates how people learn from technology, and how they use technology in everyday life. Researchers have used brain-computer interfaces to understand how technology can be designed to support human cognition and behavior. The most famous and consumer-friendly approach to measuring brain signals is electroencephalography (EEG) due to its non-invasive, portable, relatively inexpensive, and high temporal resolution. In this study, we develop machine learning models to distinguish between the neural oscillations of meditators and non-meditators. Previous studies have used power spectrum density, entropy, and functional connectivity to distinguish various meditation traditions. We use EEG data set comprising neural activity of expert meditators of Himalayan Yoga (HYT), Vipassana (VIP), Isha Shoonya (SYN), and non-expert control subjects (CTR). We analyze the data using 13 different machine learning models for within-subject and cross-subject. We present the results for six classification conditions for both meditation and mind-wandering. Features extracted from the mean of 64 EEG time series are fed into machine learning classifiers during training. We obtain 100% accuracy for within-subject classification in both meditation and mind-wandering. In cross-subject analysis, we obtained 18.3% above chance level in meditation between control and Isha Shoonya, and similarly above 18% chance level in mind-wandering between control and Vipassana. We discuss the implications of this result for the emerging consumer EEG headset facilitating meditation practice. Our results indicate that personalized models (within-subject) and generalized models (cross-subject) could guide naive (beginner) practitioners to meditate and aim to modulate brain signals by practicing to reach the expert level.

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KEYWORDS

EEG Signals, Machine Learning, Brain-Computer Interface, Meditation

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1 INTRODUCTION

Electroencephalography (EEG) signals capture the brain's electrical activity and are widely used to study several cognitive processes [29–31]. Human-computer interaction (HCI) research has used EEG signals in a variety of ways, such as to measure cognitive load, assess user experience, or study how people interact with technology. Decades of neuroscientific research have demonstrated that meditation has numerous cognitive benefits [7]. However, a novice meditator may find it difficult to meditate in the beginning, as everyone does, and due to a lack of positive impact or feedback, may discontinue the practice [22]. Modern Brain-computer interfaces use advanced learning techniques such as machine learning and deep learning algorithms to find neural representations to decode texts and intentions. Since the brain areas responsible for different functions are spatially very close, it is difficult to determine which combination of brain regions are activated at what time points for decoding intentions. EEG brain recordings suffer seriously from the curse of dimensionality. They have a high dimensional features due to high temporal resolution as well as significant challenge with low signal-to-noise ratio. Recently, deep learning methods have shown substantial promise for brain signal decoding. Further, the examples for training in EEG datasets are considerably smaller than is typical of most deep learning architectures.

Neurotechnology leverages the availability of relatively inexpensive, portable, and readily available wireless EEG headsets to train novice meditators to meditate. Recent EEG mobile applications [1, 2] enable the meditator to monitor their meditation in real time. The illustration shown in figure 1 presents the exemplar explaining our findings that could be used in the application to guide the practitioner to achieve expert-level stages by continuing the practice. Neurotechnology allows researchers to work together and establish the neural correlates of varying meditation stages through the collaboration of cognitive scientists, computer scientists, and signal-processing researchers, enabling the analysis of neural activity for meditation.

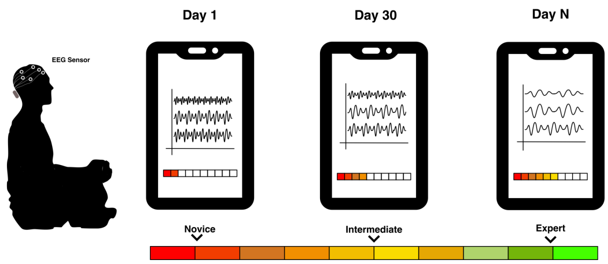

Figure 1: Exemplar machine learning enabled EEG application facilitating practitioners to observe the changes after daily practice and changes in brain activity concerning expert meditators.

Researchers have modeled the generated EEG signals into two cases: within-subject and cross-subject. Within-subject means using the signals of the same individual for training and testing the model. This case significantly improves accuracy and enables us to identify individualized neural responses. Cross-Subject modeling, also known as a subject-invariant representation of EEG signals, refers to identifying a common neural signature for a cognitive process across several participants. Transfer learning of EEG data is a popular challenge pertaining to invariant representation [21]. This is a challenging issue primarily because the brain representation of different higher-order cognitive processes differs among individuals due to synaptic plasticity and interactions with the environment. Despite these complexities, the brain-computer interface's computational society is interested in capturing the shared dynamics across subjects for an activity. EEG is a widely used technique to capture the electrical activity of the brain due to its ease of use, low operational costs, non-invasive properties, and high temporal precision. EEG systems also allow us to record brain activity in the laboratory setting and out in the environment to demonstrate the ecological validity of EEG studies. A significant disadvantage of EEG is that it has a low signal-to-noise ratio (SNR). This allows researchers to design new and sophisticated algorithms to denoise, decode and derive insights from EEG signals. This study attempts to identify a personalized and shared neural representation of meditation among different meditation traditions.

Decades of neuroscientific research on meditation have already established the several benefits of meditation such as increased gray matter density in the brain stem [33], reduction of anxiety [20], regulation of emotion and attention [3, 18], control over post-traumatic stress disorder (PTSD), and depression symptoms [12, 13], enhanced attention span [15], pain control [4, 11], effectiveness for addiction prevention and treatment and multiple physical and emotional health benefits. There are different styles of meditation, such as Himalayan yoga (Focused Attention), Vipassana (Open Monitoring) and Isha Shoonya (Open Awareness Meditation), and Loving Kindness Meditation.

We have used a public dataset, originally collected by Braboszcz et al. [6]. In their work, they have discussed an increase in gamma activity in expert meditators of around 60 - 110Hz (Himalayan Yoga, Isha Shoonya, and Vipassana) when compared to control group meditators. Vivot et al. [34] noted an increased gamma band entropy in Vipassana meditators and an overall increase in global coherence among expert meditators from all traditions. Van Doorn et al. [32] found that breath-awareness meditation and instructed mind-wandering possessed different functional connectivity. We have extended these works by finding the differences and similarities between expert and non-expert meditators and across meditation traditions.

In this work, we train personalized and generalized models to differentiate EEG activity elicited while practicing meditation and instructed mind-wandering. To the best of our knowledge, this is the first time that an article presents a detailed analysis delving into three meditation traditions using various machine learning classifiers. The novelty of this work lies into incorporating different meditation and their detailed experimentation specially on cross-subject/cross-tradition generalization.

2 MOTIVATION

Non-invasive neuro sensors record brain activity to pass through signal processing techniques and advanced pattern recognition to decode human intentions. Some techniques, such as P300 speller that uses time domain event-related potentials, and Steady State Visual Evoked Potential (SSVEP), which are frequency domain-based devices, have proven beneficial to people with disabilities like tetraplegia, muscle atrophy, stroke, etc [17]. It helps them communicate with the outside world when they physically cannot. These devices measure the participant's brain activity and eventually help them type characters. However, these devices are often inaccurate, have low information transfer rates (ITR), and have a long training time per participant.

2.1 Cognitive Relevance

We can find numerous meditation techniques to improve attention and emotional response [19]. There are both short-term and long-term cognitive benefits to meditation practice [6]. In the short-term, studies have shown that meditation can help with attention and focus, working memory, and reaction times. In the long-term, meditation has been shown to improve cognitive function in older adults, and those with Alzheimer's and dementia [9, 14]. Meditation may also help to protect the brain from age-related decline. Different meditation styles have different benefits. Focused attention meditation is when you focus your attention on a certain object, such as your breath, a mantra, or a certain sound. This type of meditation can help one to focus and concentrate more easily, as well as calm your mind and body. Open monitoring meditation is when you become aware of your thoughts and emotions without judgment or attachment. This type of meditation can help you become more aware of your thoughts and emotions, as well as become more accepting of them. Loving-Kindness meditation is when you focus on sending positive thoughts and emotions, such as love, compassion, and forgiveness, to yourself and others. This type of meditation can help you become more compassionate and loving towards yourself and others.

2.2 Learning Representation

Feature engineering is a critical step in machine learning and can significantly impact a learning algorithm's performance. A computation model of meditation based on feature extraction of real-time signals can help the practitioner to get feedback and check their performance. Recently, there has been a surge in the development of machine learning models for meditation due to the availability of wearable EEG headsets for consumer use. Identifying differences between expert and non-expert have been in the rise of exploration using machine learning with signal processing techniques [10, 23–27]. Pre- and post-changes after a few weeks of practice are the quickest way to observe the effects with interpretability. SHAP explainable machine learning model is employed to identify the regions of change after mindfulness sessions [28]. An extensive spectrum of meditation-related mental states is discussed and further classified in a recent review paper [16]. The discovery of patterns that can be used in systems to guide naive practitioners brings enormous opportunities for cognitive, signal processing, and machine learning scientists. Along with this, mind-wandering detection is an interesting research area for feature engineering [8].

3 DATASET DESCRIPTION

We used the dataset curated by Braboszcz et al. [6] which contains electroencephalographic (EEG) activity of meditation practitioners (across three different meditation traditions – Vipassana (VIP), Himalayan Yoga (HYT), and Isha Shoonya (SNY) and a control (no prior meditation experience) group (CTR) during a meditative and instructed mind-wandering block. The data was collected at the Meditation Research Institute (MRI) in Rishikesh, India. The EEG data contains 64 channels, and 16 subjects were selected for each meditation technique group, making it overall 64 subjects. The EEG data is sampled at 256Hz. The time duration for each subject varies, so we crop the dataset for each subject to a specific minimum duration. We observe one significant outlier subject in the mind-wandering dataset and three significant outliers in the meditation dataset, which we remove from the corresponding datasets. Eventually, the dataset for each subject is cropped to 110976 timesteps in the mind-wandering and 111872 timesteps in the meditation dataset.

4 METHODOLOGY

4.1 Experimental Setup

We split the EEG data for each subject into ten-second chunks (2560 timesteps in each chunk) with overlaps of five seconds to create a sequence of time splits. We average the timestamp inputs for each 64 channels to create the features. These features are then fed into various classifiers (details in subsection 4.2). Our experiments on meditation and mind-wandering classification are conducted in two settings:

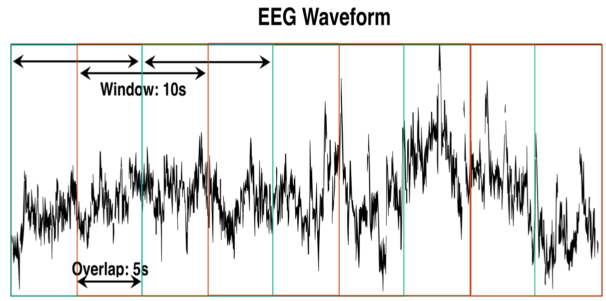

Figure 2: This figure shows how we created the within-subject data split with a 10-second window and a 5-second overlap. We randomly split windows into the train, validation, and test sets.

(1) **Within-subject:** The time splits for each user are randomly selected into the train, validation, or test split in the ratio 60-20-20 as shown in Figure 2.
(2) **Cross-subject:** This strategy selects 10-3-3 participants in the train-val-test set, and all the time chunks for that user are used in the corresponding data fold as shown in Figure 3.

We create five samples of train-val-test, wherein in each run, the validation fold is used for hyperparameter tuning, and the results (mean macro accuracy and standard deviation) are reported on the test folds. In the cross-subject case, we ensured that different users were in the test split in each of the five samples of the train-val-test.

4.2 Classifiers and Hyperparameter Tuning

The input space is constructed by averaging the EEG time series of 64 channels. To understand the distribution of input vectors in the reprsentation space, we employ linear as well as non-linear classifiers. Linear models for classification learn decision boundaries that are linear functions of the input, while nonlinear classifiers are effective when the classes cannot be separated via linear hyperplanes. We estimate the performance of models using the resampling strategy. We use 5-fold cross validation to select the best parameters. We experiment with around thirteen traditional machine learning classifiers and report average accuracies of 5 runs. We use Grid Search for hyperparameter tuning. The grid search method does an exhaustive search of hyperparameters over a specified range of hyperparameter values. We report the configurations and the search range for each model hyperparameter in Table 1.

5 RESULTS

The current dataset consists of meditation and mind-wandering performed by practitioners from 3 different meditation traditions - Vipassana (VIP), Himalayan Yoga (HYT), and Isha Shoonya (SNY). We also have a control group (CTR), with 64-channel EEG data. As described in the above sections, we performed within-subject and cross-subject analyses for meditation and mind-wandering in the following conditions:

(1) **Control vs. Expert (CTR / EXP):** We classify whether the test data point belongs to the control or expert participant.

Classifier	Hyperparameter	Grid Search Range
Decision Tree (DT)	Maximum depth	[2, 12, 22, ... 62]
Random Forest (RF)	Num of estimators	[5, 25, 45, ... 85]
	Maximum depth	[2, 12, 22, ... 62]
Logistic Regression (LR)	Maximum Iterations	500
	Solver	newton-cg, lbfgs, sag, saga
Logistic Regression + L1 Regularization (LR-L1)	Maximum Iterations	500
	Solver	liblinear, saga
Logistic Regression + L2 Regularization (LR-L2)	Maximum Iterations	1000
	Solver	newton-cg, lbfgs, liblinear, sag, saga
SVC Linear (SVC-L)	Kernel	Linear
	C	[0.5, 1.5, 2.5]
SVC Polynomial (SVC-P)	Kernel	Polynomial
	C	[0.5, 1.5, 2.5]
	Degree	[3, 4, 5]
	Gamma	scale, auto
SVC Others (SVC-O)	Kernel	RBF, Sigmoid
	C	[0.5, 1.0, 1.5, 2.0, 2.5]
	Gamma	scale, auto
kNN	Num neighbours	[3, 4, 5, ... 30]
Ridge Classifier (RC)	Maximum Iterations	1000
Gaussian Naive Bayes (GNB)	-	-
Bagging SVC (B-SVC)	Num of estimators	[5, 25, 45, ... 85]
	SVC Kernel	Linear, Polynomial
	SVC Degree (Poly)	[3, 4, 5]
	SVC Gamma	scale, auto
Bagging DT (B-DT)	Num of estimators	[5, 25, 45, ... 85]
	DT Max depth	[2, 5, 10]
Ada Boost (AB)	Num of estimators	[10, 30, 50, ... 90]
	DT Max depth	[2, 5, 12]
Extra Trees (ET)	Num of estimators	[5, 35, 65, ... 105]
	Max Depth	[2, 5, 10, 15]
Multi Layer Perceptron (MLP)	Hidden layer size	[50, 250, 450, ... 650]
	Num of layers	1, 2
	Activation	logistic, tanh, relu
	Solver	adam, sgd
	Early Stopping	True

Table 1: Configurations and grid search range for hyperparameter tuning for each model.

(2) **Control vs. Himalayan Yoga vs. Isha Shoonya vs. Vipassana (CTR / HYT / SYN / VIP):** 4-class classification of whether the participant belongs to control, Himalayan Yoga, Vipassana, or Isha Shoonya.
(3) **Control vs. Himalayan Yoga (CTR / HYT):** 2-class classification to determine whether the participant belongs to control or Himalayan Yoga.
(4) **Control vs. Isha Shoonya (CTR / SYN):** 2-class classification to determine whether the participant belongs to control or Isha Shoonya.
(5) **Control vs Vipassana (CTR / VIP):** 2-class classification to determine whether the participant belongs to control or Vipassana.
(6) **Transfer Learning:** Training the model on control plus one expert meditation type (say X) and testing the model on the other two expert meditation types (say Y and Z) (2-class classification between CTR and Y+Z). We denote this setting as (CTR / (X –> Y+Z)). For example, CTR / (HYT –> SYN+VIP) denotes that the model was trained on CTR vs HYT classification, and then tested on CTR vs (SYN+VIP) classification.

5.1 Within-subject

Here we show the classification accuracy of different classifiers on different classification tasks as mentioned in Section 5. We trained and tested on other chunks generated for all subjects as mentioned in Section 4.1.

5.1.1 Meditation. As shown in Figure 4, most machine learning classifiers generalized well for non-transfer-learning conditions with accuracies nearing 100%. However, when we see the transfer learning conditions (for example, CTR / (HYT –> SNT+VIP), we can see that the generalisability is less among different models. For testing on:

(1) **SNY+VIP condition**, KNN classifiers performed best with 74.3% classification accuracy.
(2) **HYT+VIP condition**, Logistic Regression with L1 regularizer performed best with 73% classification accuracy.

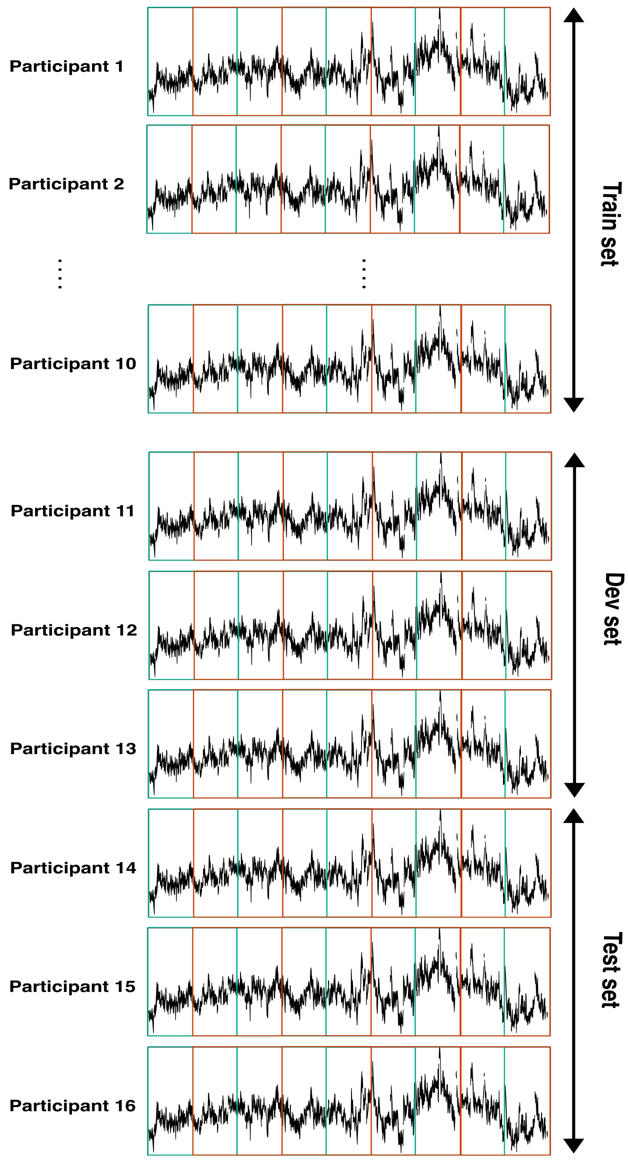

Figure 3: This figure shows how we created the cross-subject data split with initial splits of a 10-second window and a 5-second overlap for each participant. We then split the participants' chunks for the train-val-test set using the 10-3-3 rule.

(3) **HYT+SNY condition**, Support Vector Machine performed best with 80.4% classification accuracy.

Key Findings: The significantly higher accuracy of transfer learning models over chance level shows there are common neural signatures between novice and expert meditators of Himalayan Yoga, Isha Shoonya, and Vipassana.

5.1.2 mind-wandering. As shown in Figure 5, most machine learning classifiers generalized well for non-transfer-learning conditions with accuracies nearing 100%. However, when we know the transfer learning conditions (for example, CTR / (HYT –> SNY+VIP), we can see that the generalisability is less among different models. The Support Vector Machine worked best for testing on SNY+VIP (trained on HYT), HYT+VIP (trained on SNY), and HYT+SYN (trained on VIP) conditions with classification accuracies of 84%, 80.7%, and 83.1%, respectively.

Key Findings: Here also we can see that transfer learning produced significantly higher accuracy over chance level indicating common neural signatures among novice and expert meditators while their minds wander.

5.2 Cross-subject

Here we show the classification accuracy of different classifiers on different classification tasks as mentioned in Section 5. We trained on chunks of 10 participants and validated and tested on chunks of 3 participants each, as discussed in Section 4.1.

5.2.1 Meditation. Compared to within-subject classification, the models faced difficulty generalizing for cross-subject predictions. Condition-wise classification results are as follows:

(1) **Control vs. Expert (CTR / EXP):** Polynomial Support Vector Machines performed the best with an increase of 7% over the chance level.
(2) **Control vs Himalayan Yoga vs Isha Shoonya vs Vipassana (CTR / HYT / S / V):** Decision tree with bagging achieved the highest classification accuracy with a 6.3% increase over the chance level (25%).
(3) **Control vs Himalayan Yoga (CTR / HYT):** Neural Network achieved the highest classification accuracy with a 5.3% increase over the chance level (50%).
(4) **Control vs Isha Shoonya (CTR / SYN):** Decision tree achieved the highest classification accuracy with an 18.3% increase over the chance level (50%).
(5) **Control vs Vipassana (CTR / VIP):** Polynomial Support Vector Machines achieved the highest classification accuracy with an 8.2% increase over the chance level (50%).
(6) **SYN+VIP condition**, Gaussian Naive Bayes achieved the highest classification accuracy with a 9.4% increase over the chance level (50%).
(7) **HYT+VIP condition**, Polynomial Support Vector Machines achieved the highest classification accuracy with a 9.2% increase over the chance level (50%).
(8) **HYT+SYN condition**, Gaussian Naive Bayes achieved the highest classification accuracy with an 11.3% increase over the chance level (50%).

Key Findings: As shown in Figure 6, most other models could not generalize well with a decrease in performance below chance levels. However, we see clear classifiability between control and Isha Shoonya meditators indicating varied neural patterns.

5.2.2 mind-wandering. Compared to within-subject classification and similar to the meditation data-set, the models faced difficulty generalizing for cross-subject predictions. Condition-wise classification results are as follows:

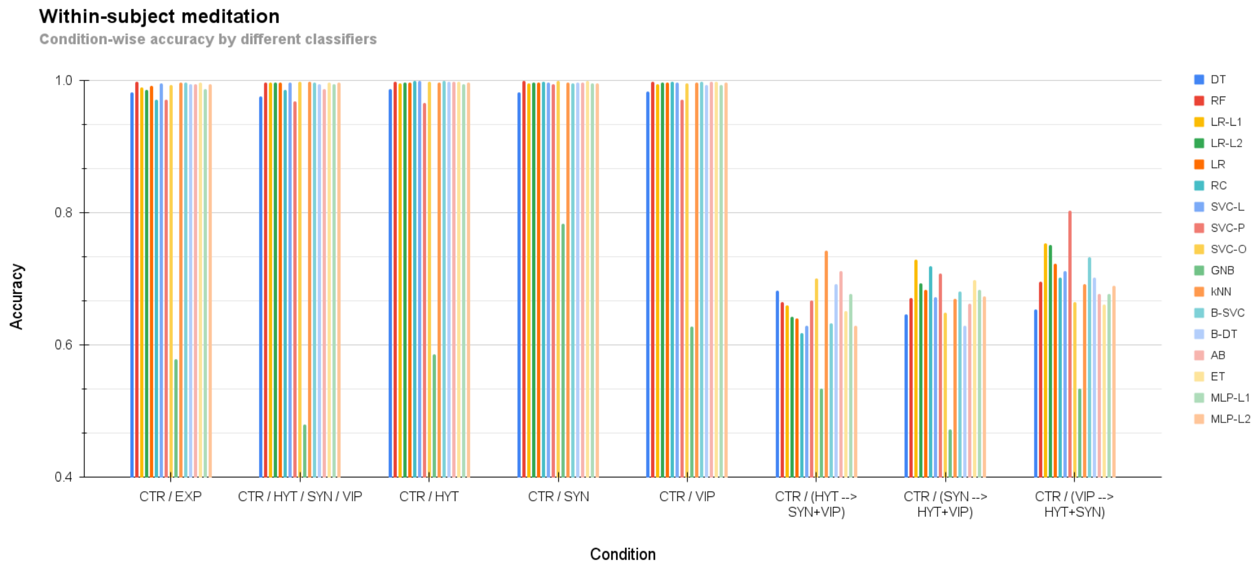

Figure 4: This figure shows the performance of different machine learning classifiers in the classification tasks mentioned in Section 5 on the meditation dataset. This has been done using a within-subject data split.

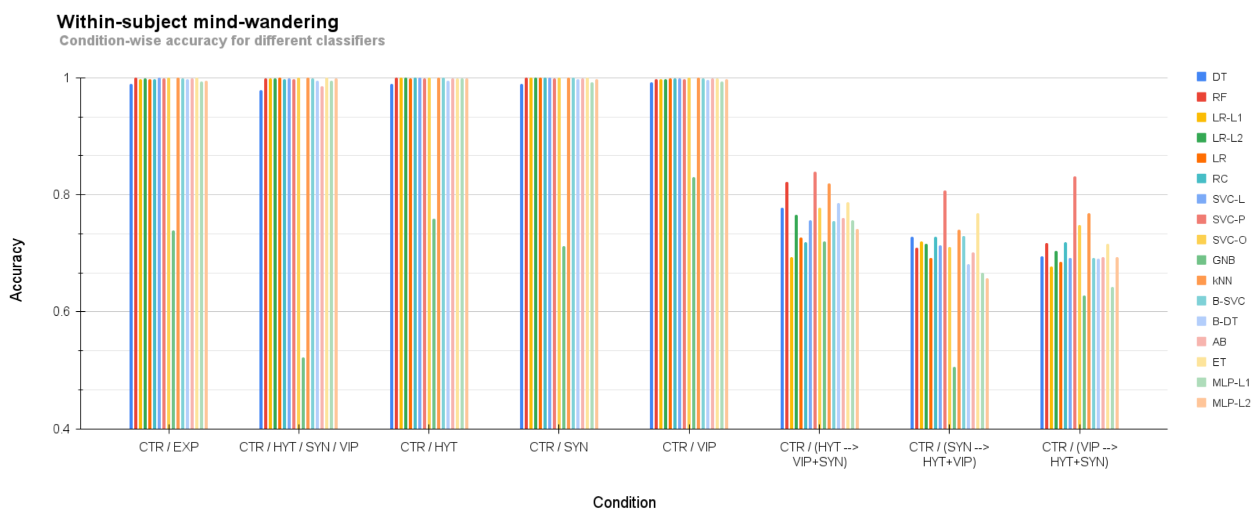

Figure 5: This figure shows the performance of different machine learning classifiers in the classification tasks mentioned in Section 5 on the mind-wandering dataset. This has been done using a within-subject data split.

(1) **Control vs. Expert (CTR / EXP):** KNN classifier performed the best with an increase of 6.1% over the chance level.
(2) **Control vs. Himalayan Yoga vs. Isha Shoonya vs. Vipassana (CTR / HYT / S / V):** Polynomial Support Vector Machines achieved the highest classification accuracy with a 9.9% increase over the chance level (25%).
(3) **Control vs. Himalayan Yoga (CTR / HYT):** Polynomial Support Vector Machines achieved the highest classification accuracy with a 9.3% increase over the chance level (50%).
(4) **Control vs. Isha Shoonya (CTR / SYN):** Ridge classifier achieved the highest classification accuracy with a 15.4% increase over the chance level (50%).

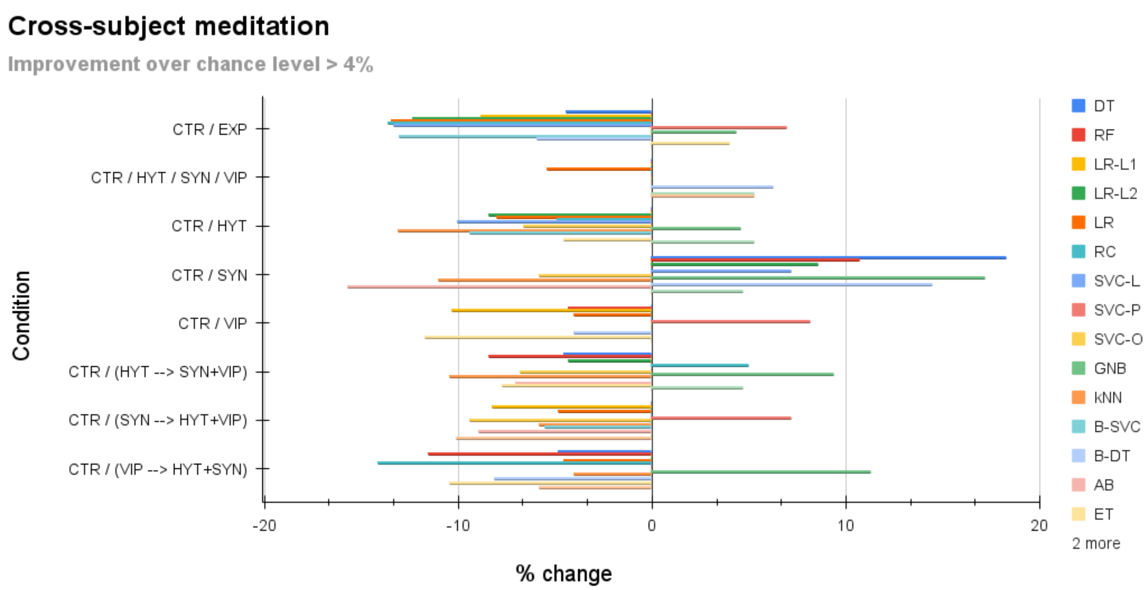

Figure 6: This figure shows the performance of different machine learning classifiers in the classification tasks mentioned in Section 5 on the meditation dataset. This has been done using a cross-subject data split.

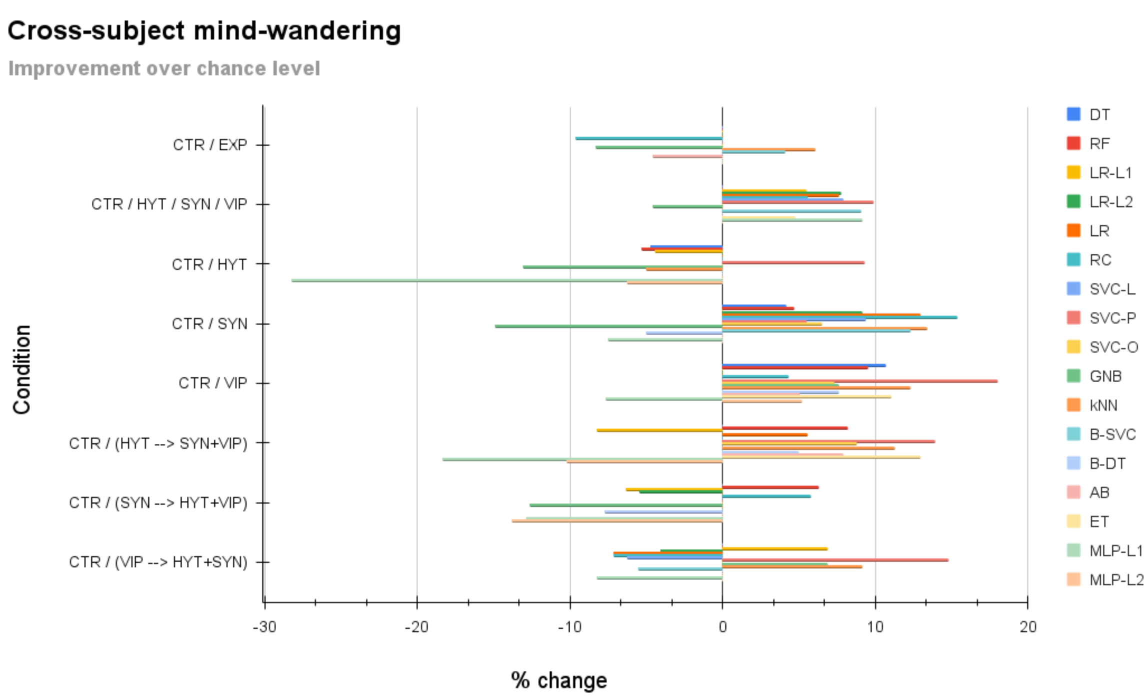

Figure 7: This figure shows the performance of different machine learning classifiers in the classification tasks mentioned in Section 5 on the mind-wandering dataset. This has been done using a cross-subject data split.

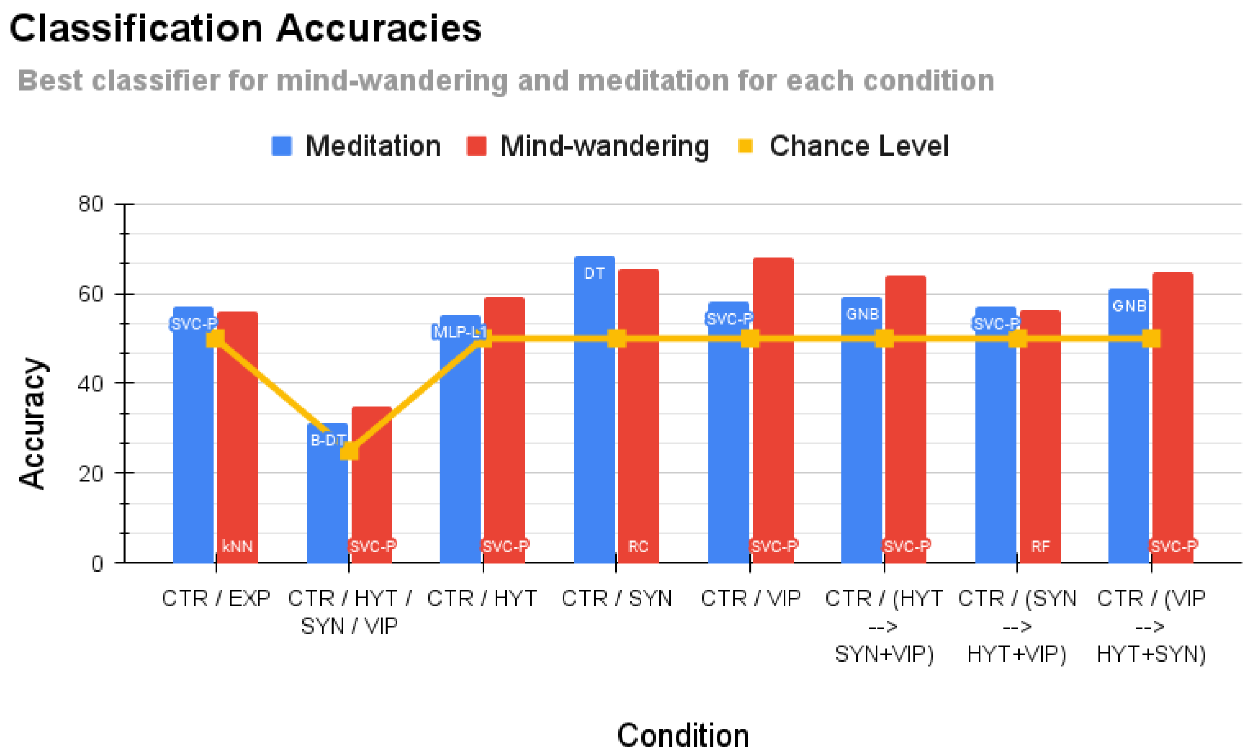

Figure 8: This figure shows the best classifiers for all conditions in meditation and mind-wandering dataset and their improvement over respective chance levels.

(5) **Control vs Vipassana (CTR / VIP):** Polynomial Support Vector Machines achieved the highest classification accuracy with an 18% increase over the chance level (50%).
(6) **SYN+VIP condition**, Polynomial Support Vector Machines achieved the highest classification accuracy with a 13.9% increase over the chance level (50%).
(7) **HYT+VIP condition**, Random forest achieved the highest classification accuracy with a 6.3% increase over the chance level (50%).
(8) **HYT+SYN condition**, Polynomial Support Vector Machines achieved the highest classification accuracy with a 14.8% increase over the chance level (50%).

Key Findings: As we can see in Figure 7, most of the other models in mind-wandering could generalize well, unlike the meditation data-set with a less frequent decrease in performance below chance levels. We see high classification accuracy for classification between control and individual expert meditators, indicating different neural patterns between control and the rest of the meditation traditions.

In Figure 8, we have shown the best models for meditation and mind-wandering for different conditions.

6 CONCLUSION

Our findings indicate that there are different neural signatures between novice and expert meditators during meditation and mind-wandering as shown by transfer learning results in figures 4, 5. We can also observe from figures 6, 7 that there are clear distinctions between individual expert and novice meditators that can be generalized over all participants. We propose a system for guiding a novice meditator to obtain and sustain mindful moments. In our future work, we would provide real-time neuro-feedback and show the progress of practitioner over time. We do this by incorporating personalized and generalized models of brain oscillatory activity [34] in comparison to experts (figure 1).

Focusing on the meditation object instead of mind-wandering leads to progress in reaching the meditative state. Our article differentiates the neural signature between expert and novice meditators comprising two conditions (i) meditating and (ii) mind-wandering. We develop personalized (within-subject) and generalized (cross-subject) models classifying six binary sets between two groups. Our findings reveal that personalized models learn features effectively and recent work emphasizes learning individualized evolution of stages[5]. We achieve maximum accuracy in classifying the within-subject and above 18% of chance level in cross-subject analysis. The accuracy could also drive us to spend more time learning the representation for cross-subject/cross-tradition. This study also include limitations and can be refined in further works.

Although more work is required to find the near-perfect general model, our work shows common neural patterns among different meditation traditions. This research provides a significant step toward bringing ancient wisdom to the forefront of Neurotechnology for monitoring brain health and maintaining wellness.

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