Classifying EEG signals of Mind-wandering across different styles of Meditation

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Abstract. In the modern world, it is easy to get lost in thought, partly because of the vast knowledge available at our fingertips via smartphones that divide our cognitive resources and partly because of our intrinsic thoughts. In this work, we aim to find the differences in the neural signatures of mind-wandering and meditation that are common across different meditative styles. We use EEG recordings done during meditation sessions by experts of different meditative styles, namely shamatha, zazen, dzogchen, and visualization. We evaluate the models using the leave-one-out validation technique to train on three meditative styles and test the fourth left-out style. With this method, we achieve an average classification accuracy of above 70%, suggesting that EEG signals of meditation techniques have a unique neural signature across meditative styles and can be differentiated from mind-wandering states. In addition, we generate lower-dimensional embeddings from higher-dimensional ones using t-SNE, PCA, and LLE algorithms and observe visual differences in embeddings between meditation and mind-wandering. We also discuss the general flow of the proposed design and contributions to the field of neuro-feedback-enabled mind-wandering detection and correction devices.

Keywords: Meditation · Mind-wandering · Classification · Machine Learning · Deep Learning · Cognition · Neuro-feedback · EEG

1 Introduction

Mind-wandering, also known as task-unrelated thought, daydreaming, fantasizing, zoning-out, unconscious thought, and undirected thought, is a common phenomenon, that most of us experience for approximately 50% of our daily waking time [11]. There are two types of mind-wandering, intentional or stimulus-independent or self-generated and unintentional or stimulus-driven [11]. Sometimes, these thoughts could be productive, i.e., used for *creative* thinking, *future planning*, and *problem-solving*, and sometimes could be detrimental to our mental health, leading to *depression* [2], *anxiety*, *schizophrenia* and *negative mood* [23].

In contemporary times, our mind wanders in anticipation of a text message, email, or social media notification, or thinking about how we can level up in the game in which we are stuck. Mind-wandering takes our attention away from the present, which we regret later, leading to an unending spiral of despair. However, all hope is not lost. Meditation is one of the many ways to control our thoughts. *Meditation* is a set of exercises that helps in the regulation of emotion, and attention [24]. It is also known as an exercise in which the person orients their attention to dwell upon a single sound, concept, or experience [22]. Meditation has positive effects on our mood and mental health by reducing unnecessary mind-wandering and enhancing our cognitive performance [15] as shown in figure 1.

Although meditation has many benefits, it is hard to accomplish and sustain a state of mind where we must not get overwhelmed by our thoughts [8]. In some cases, meditators encountered troubling thoughts and, in other cases, it aggravated mental health issues such as anxiety and depression [8].

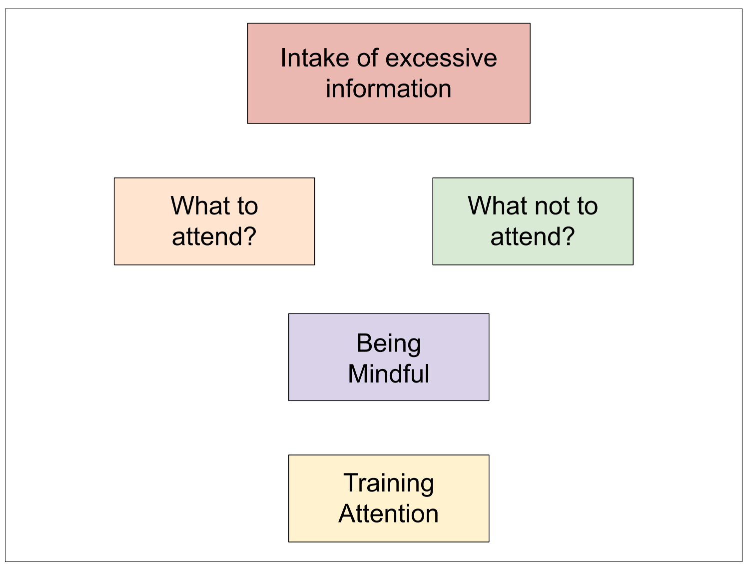

Fig. 1. Sustaining mind-full moments

The human brain generates movement by taking input from relevant sensory receptors, computing the desired inputs to stimulate motor neurons, which move the limbs. Brain-Computer Interface aims to capture the signals produced during these computations and process them to decode human intention to control external devices, say a joystick [4]. The decoding of human intentions is a difficult problem. The challenge here is to take a pattern of EEG signals and ascertain which brain regions contribute how much to the signal. In simpler terms, it is difficult to find out the representation of each brain region in the signal component, and an even more challenging task to model those contributions. Many recent papers aim to model this representation. In a recent paper, wavelet transformation-based feature extraction techniques were applied to capture the difference between expert and non-expert meditators. They used Bior3.5, Coif5 and db8 wavelets for this feature extraction [13]. Another approach to finding the representation of human intentions in EEG signals was to take topological maps generated from the EEG signals and feed them through a convolutional neural network [14]. Advancement in deep learning in the past two decades has ushered in an era of creating ever-larger networks to represent complex relationships. However, the problem arises when one questions on what basis the model is making these predictions. This is a problem highlighted by Riberio et al., wherein they discuss a model that performs well but has learned the wrong representation [17]. Recent work [12] uses the functional connectivity between brain regions as features to understand the significance and contribution of each region to the generated EEG signal. Previously, feature engineering-based methods were used to feed input to machine learning classifiers with varying degrees of success. [21] used the gamma-band entropy-based features and fed them through a Random Forest classifier to differentiate between meditators vs. non-meditators. [19] and [7] used numerous machine learning classifiers to discriminate between mental states. They concluded that machine learning classifiers that used hand-crafted features did not capture the most optimum representation to decode EEG signals. Deep learning-based algorithms have an advantage over traditional machine learning-based classifiers because they do not need hand-crafted features. These algorithms are designed to extract features from the raw data presented.

Previous works have distinguished between mind-wandering and attentive states and achieved a per subject mean accuracy of 65% using SVM and logistic regression and a mean AUC score of 0.715 using SVM and 0.635 using logistic regression. On the leave-one-out participant comparison, they achieved a mean accuracy of 59% using SVM and 58% using logistic regression [3].

This work attempts to detect whether the meditator is in a meditative or a mind-wandering state and generalize across meditative styles. We also lay the foundation for future work, where we aim to develop a real-time brain-computer interfacing technology to determine whether the user is in a meditative state or not. The system under consideration alerts the user when their mind beings to wander through a neuro-feedback mechanism and help them orient back to a calm meditative state.

2 Motivation

2.1 Impact on Cognition

The rapid pace of software and hardware innovations [10] enables us to perform multiple tasks simultaneously. This ability granted to us by contemporary technological advancements has positive effects, such as communicating with distant people, getting news about what is going on halfway around the world, and much more. However, at the same time, it has detrimental effects, which include sensory overloading or simply taking in more information than we can process, leading to accidents due to the usage of mobile phones while walking and driving. Hence, we need to evolve with technology, the ability to focus our attention on the things that we can control and on the things that matter. Hence, we need to learn to focus our attention and not let our minds wander.

Mind-wandering, sometimes also referred to as daydreaming, fantasizing, zoning-out, unconscious thought, or undirected thought, is defined as task-unrelated thought that occupies nearly 50% of our awake time daily. The benefits of focused attention or meditation have been highlighted by researchers throughout history [15]. Research on meditation has revealed that it is highly effective in regulating pain, and insomnia, increasing calmness, bringing psychological balance, and improvement of general well-being and physical and mental health [1].

2.2 Technological Considerations

The work resulting from this paper can help create a device that helps the user improve their focused attention through a neuro-feedback mechanism. For a certain period, the user wears an EEG headband capable of producing high-quality data once a day. A mobile app reading and processing the data captured by the headband determines whether the user is in a meditative state or a mind-wandering state. While meditating, the user will get an audio-visual neuro-feedback from their mobile phone if their mind begins to wander as shown in figure 2. Few neural markers for neuro-feedback have been discussed by Gupta et al. [16].

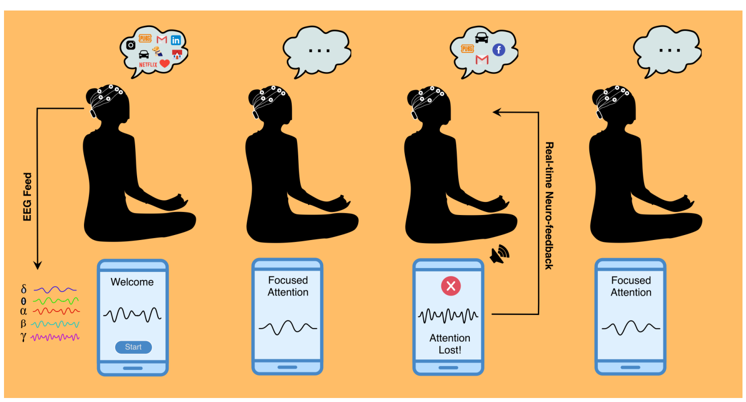

Fig. 2. A user is wearing a portable EEG headset while meditating. The real-time EEG signals are captured, processed, and meditative states are sent to the user's mobile phone. When the user's mind begins to wander, an audio neuro-feedback is given to them, enabling them to reorient their focus away from task-irrelevant thoughts.

3 Dataset Description

We have used the publicly available EEG dataset [24]. Electroencephalographic (EEG) recordings were conducted on participants from meditative communities in India, Nepal, and the United States. Their respective instructors selected highly experienced and skilled meditators from each community. Each community provided space for recording the meditation sessions. Participants studied at least one of the different meditation practices - Zazen, Dzogchen, Shamatha, and Visualization. Some participants recorded sessions for a single meditative style and, in some cases, multiple meditative styles. EEG activity was recorded when the participants were sitting in their usual posture for meditation, and mind-wandering [24]. We used a pre-processed version of the dataset acquired from the author. The pre-processed data is sampled at 128Hz.

4 Methods

4.1 Feature Extraction

Sliding Window We used the Yasa Sliding Window [20] library in python to create windows of 5 seconds for meditation recordings of 600 seconds each and a window of 5 seconds with a step size of 0.5 for the mind-wandering recordings of 60 seconds each. We obtained 1431 epochs of meditation and 1665 epochs of mind-wandering.

Multitaper Bandpower The Multitaper method is an approach to determine the power of a signal at different frequencies [24]. We extracted the five frequency bands from each channel of the EEG signals, namely: delta (0.5 - 4 Hz), theta (4 - 7 Hz), alpha (8 - 13 Hz), beta (14 - 30 Hz) and gamma (31 - 50 Hz). We calculated the power of each frequency band by integrating the power spectral density (PSD) of that particular frequency band [25]. We used the *mne.time_frequency.psd_multitaper()* in the MNE-Python package to calculate multi taper power spectral density (PSD) [5].

After pre-processing, the EEG recording of each participant had a different number of channels. Hence, to give the model a uniform input, we averaged the channel data across different frequency bands (delta, theta, alpha, beta, gamma), giving us five features as model inputs.

4.2 Validation

Leave one out meditation style Out of the four meditation styles (Zazen, Dzogchen, Shamatha, and Visualization), we picked one style as a test set and trained on the remaining three styles.

4.3 Classifiers

K Nearest Neighbors (KNN) K nearest neighbors is a non-parametric classifier. They work by determining the K (specified by the user) number of training samples closest in the distance to the new point and predict the labels from these k training samples.

Support Vector Machine (SVC): A maximal margin classifier that attempts to maximize the distance between the closest training patterns known as support vectors. Maximal margin regularization parameter C, which denotes the trade-off between margin width and the number of misclassifications for linear SVM can be optimized from $[10^{-3}, 10^{3}]$ using grid search-based hyperparameter tuning on the validation set extracted from the training set.

Decision Tree Classifier: A Decision Tree Classifier is a predictive model used in statistics and machine learning. It creates a decision tree to iteratively go from the observations about an item to classify it into either of the given target labels.

Random Forest Classifier: It is an ensemble method that consists of a set of mutually independent and random trees. Each tree is populated using a random subset of features. Selection is based upon the majority voting over all the tree outputs.

Multi Layered Perceptron (MLP): The objective function (Cross-Entropy loss function) for this non-linear function approximator was optimized on our dataset, using first-order gradient-based optimization called Adam [6]. The binary prediction was performed using sigmoid as the output function.

Ada Boost Classifier: Ada Boost classifier is a meta estimator that initially fits a classifier to the dataset. In subsequent training, it makes copies of the model and puts more weight on instances that are hard to classify.

Gaussian Naive Bayes: It is a generative model that learns the actual data distribution by assuming that likelihood probabilities come from a multidimensional Gaussian distribution, and that all features are class-wise independent.

Quadratic Discriminant Analysis (QDA): QDA is a generative model, which assumes that each class follows a Gaussian distribution. These are used in cases where a non-linear decision boundary works best.

4.4 Visualization

t-distributed stochastic neighbor embedding (t-SNE): t-SNE is a statistical dimensionality reduction algorithm that reduces high dimensional data into dimensions, which aids in the visualization of the data [9]. We have employed the use of t-SNE to reduce five dimensional (five bands) data points into two-dimensional to visualize the difference between meditative and mind-wandering stages.

Principal Components Analysis (PCA): PCA is an unsupervised dimensionality-reduction machine learning algorithm. This algorithm generates new uncorrelated variables that successively maximize variance in the data. The algorithm helps reduce the dimensions of the data to visualize the data with the least information loss.

Locally Linear Embedding (LLE): LLE is an unsupervised method for dimensionality reduction. It does so by projecting the data to a lower dimension while preserving distance in the local neighborhoods [18].

5 Results

5.1 Classification Insights

We used the leave-one-out method to iteratively train on three meditative practices and test on the left-out practice. With this as our train and test sets, we applied various machine learning and neural network classifiers to separate meditation and mind-wandering states. The classification accuracies in Fig. 3 and Fig. 4 represent the testing accuracy on the left-out meditation style.

Machine Learning Classifiers: We achieved the best test accuracy on different machine learning models for meditation styles. For Shamatha meditation, we achieved the best accuracy of 77.7% using the K Nearest Neighbor classifier with k values as 2. For Visualization meditation, we achieved the best accuracy of 68.6% using the Random Forest classifier. For Zazen meditation, we achieved the best accuracy of 73.8% using the Quadratic Discriminant Analysis classifier. For Dzogchen meditation, we achieved the best accuracy of 74.7% using the K Nearest Neighbor classifier with k values as 2.

Neural Network Classifiers: We achieved different classification accuracies for different network architecture sizes. We achieved the highest average classification accuracy using the network with the following configuration [80, 140, 100]. For Shamatha meditation, we achieved the best accuracy of 73.83% on most network architectures. For Visualization meditation, we achieved the best accuracy of 68.33% using the more extensive networks. For Zazen meditation,

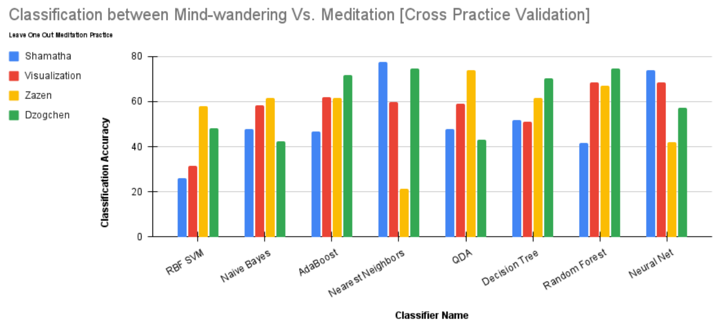

Fig. 3. Classification results for different machine learning classifiers.

we achieved best the accuracy of 58.11% using the [40, 80, 60] architecture. For Dzogchen meditation, we achieved the best accuracy of 63.8% using the [40, 80, 60] architecture.

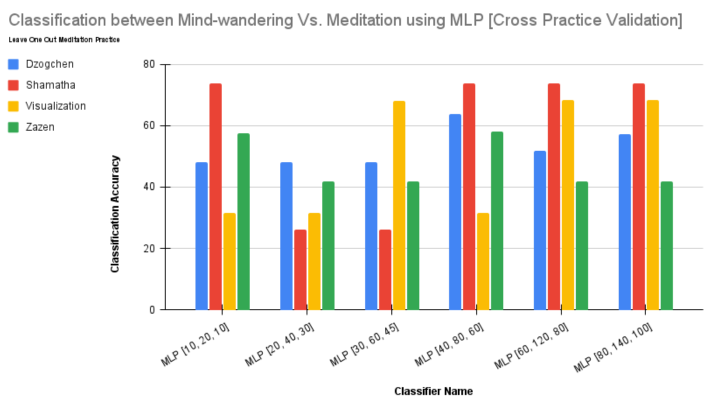

Fig. 4. Classification results for neural network classifiers with varying network architectures.

5.2 Lower Dimensional Visualization Insights

We used t-SNE, PCA, and LLE algorithms to reduce the dimensionality of our input feature space from five features to two features to plot them on a 2-D plane.

t-distributed stochastic neighbor embedding (t-SNE): As shown in the Fig. 5, we obtained a good separation of meditative and mind-wandering states using t-SNE, close to a linear separation. The perplexity measure for this reduction is 5.

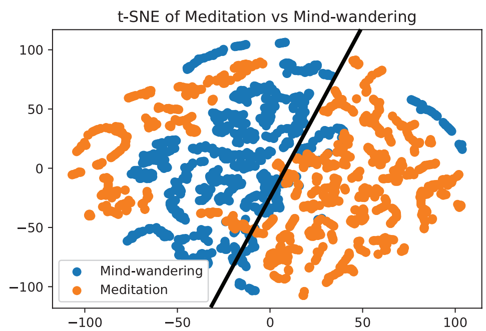

Fig. 5. Linear separation of classes using t-SNE with perplexity 5.

Principal Components Analysis (PCA): Using the PCA algorithm, we were able to see a separation between the meditative vs. mind-wandering classes, as shown in Fig. 6. However, some portions of their representation were mixed and could not be easily separated. We were able to separate the 2-D representation using an ellipse manually.

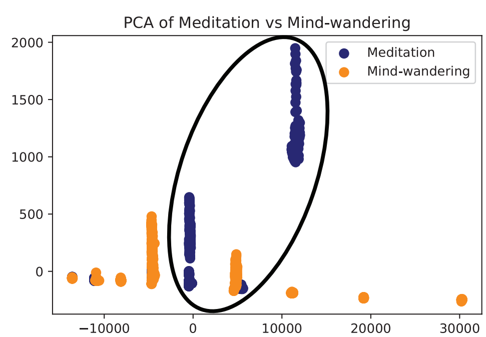

Fig. 6. Principal Components Analysis based dimensionality reduction.

Locally Linear Embedding (LLE): Using the LLE dimensionality reduction algorithm, we clustered the mind-wandering classes together. At the same time, the meditative state data points were spread out all over the 2-D plane, as shown in Fig. 7.

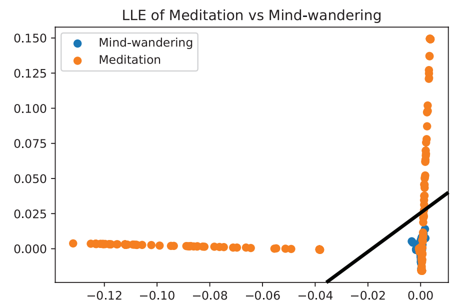

Fig. 7. Locally Linear Embedding based dimensionality reduction.

6 Discussion and Conclusion

Mind-wandering is often characterized as our attention being oriented away from the task at hand towards our internal, self-generated thoughts. This phenomenon is most often linked to a disruption in normal cognitive functions [3]. Too frequent mind-wandering can lead to depression, anxiety, insomnia, negative mood, and other detrimental effects. This study showed a difference in neural signals between mind-wandering and meditation across meditation styles practices worldwide. We showed this difference by windowing the recordings and extracting the EEG signals' band-wise multi-taper power spectral density (PSD).

Using the machine learning models specified in section 4.3, we got the highest classification accuracy using the KNN classifier for Shamatha and Dzogchen, QDA for Zazen, and Random Forest for Visualization styles when these were left-out as test sets. Using the Neural Network classifiers with architectures specified in 4, we achieved the highest average classification accuracy for all styles from the biggest network, i.e., [80, 140, 100]. We got good separation using t-SNE, PCA, and LLE with almost linear separation between mind-wandering and meditation sample points.

This research is essential since the computing power doubles every 18 months, and we have more and more devices with higher computational power. Each year, significant advancements are made towards technology, giving us everything at our fingertips. In these times, it is of utmost importance that we do not let our minds get lost in this sea of information, most of it not very important to us, leading to overuse and drain of sensory, perceptual, and cognitive resources. For this reason, practicing meditation may help us train our minds to gain control of our thoughts, focus our attention, and increase our metacognitive awareness and our propensity for compassion.

7 Limitation

This study is limited only to expert meditators and does not consider how the neural signatures differ between novice/non-meditators, which will be further investigated in future studies. We observed the classification outcome by varying only a few of the hyperparameters. Further experiments are needed to tune to the best hyperparameters. However, our results show a significant distinction between the two states, and future research can explore the involvement of region and frequency-specific discrimination.

8 Acknowledgement

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