Classification of Rajayoga Meditators Based on the Duration of Practice Using Graph Theoretical Measures of Functional Connectivity from Task-Based Functional Magnetic Resonance Imaging

Abstract

Context: Functional magnetic resonance imaging (fMRI) studies on mental training techniques such as meditation have reported benefits like increased attention and concentration, better emotional regulation, as well as reduced stress and anxiety. Although several studies have examined functional activation and connectivity in long-term as well as short-term meditators from different meditation traditions, it is unclear if long-term meditation practice brings about distinct changes in network properties of brain functional connectivity that persist during task performance. Indeed, task-based functional connectivity studies of meditators are rare. Aims: This study aimed to differentiate between long-term and short-term Rajayoga meditators based on functional connectivity between regions of interest in the brain. Task-based fMRI was captured as the meditators performed an engaging task. The graph theoretical-based functional connectivity measures of task-based fMRI were calculated using CONN toolbox and were used as features to classify the two groups using Machine Learning models. Subjects and Methods: In this study, we recruited two age and sex-matched groups of Rajayoga meditators from the Brahma Kumaris tradition that differed in the duration of their meditation experience: Long-term practitioners ($n=12$, mean $13,596$ h) and short-term practitioners ($n=10$, mean $1095$ h). fMRI data were acquired as they performed an engaging task and functional connectivity metrics were calculated from this data. These metrics were used as features in training machine learning algorithms. Specifically, we used adjacency matrices generated from graph measures, global efficiency, and local efficiency, as features. We computed functional connectivity with 132 ROIs as well as 32 network ROIs. Statistical Analysis Used: Five machine learning models, such as logistic regression, SVM, decision tree, random forest, and gradient boosted tree, were trained to classify the two groups. Accuracy, precision, sensitivity, selectivity, area under the curve receiver operating characteristics curve were used as performance measures. Results: The graph measures were effective features, and tree-based algorithms such as decision tree, random forest, and gradient boosted tree yielded the best performance (test accuracy $>84\%$ with 132 ROIs) in classifying the two groups of meditators. Conclusions: Our results support the hypothesis that long-term meditative practices alter brain functional connectivity networks even in nonmeditative contexts. Further, the use of adjacency matrices from graph theoretical measures of high-dimensional fMRI data yields a promising feature set for machine learning classifiers.

Keywords: Adjacency matrix, functional connectivity, functional magnetic resonance imaging, graph measures, machine learning, meditation

Introduction

Functional magnetic resonance imaging (fMRI) is used to study the functional capacity of the brain in good health as well as in diseases and enables studying the cognitive ability of the human brain in a noninvasive manner. Studies related to mind training such as meditation have yielded valuable insights regarding the changes in neural circuitry and the benefits that follow from meditation practice. Resting-state fMRI[1] is quite popular in studies related to meditation to determine patterns of brain activity changes and identify neural mechanisms. Considerable changes in the functional organization of the brain can take place in a short time. For example, brief mental training of 2 weeks revealed a change in the neural circuitry of resting-state networks related to attention, affective and cognitive processing, sensory

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integration, and awareness.[2] Long-term meditation practice brings in lasting changes such that it is possible to predict different forms of meditation expertise using functional connectivity patterns within and between brain networks.[3]

Multivariate pattern analysis (MVPA) techniques use machine learning algorithms to classify fMRI data. Several machine learning algorithms have been successfully applied to fMRI data[4] for the diagnosis of diseases such as attention deficit hyperactive disorder,[5] schizophrenia,[6,7] autism,[8,9] and major depressive disorder (MDD).[10] often achieving high accuracies. For example, the classification of MDD patients and controls[10] yielded accuracies of 91.67% using effective connectivity and 89.36% using functional connectivity as features. A few studies have applied machine learning techniques to classify meditators from controls. For example, Tang et al. differentiated functional connectivity before and after integrative body–mind training with an accuracy of 72% in an undergraduate group.[2] Another study used support vector machine (SVM) to classify Zen meditators and controls with an accuracy of 79%.[11]

Functional connectivity analyses, also called functional connectome analyses, have used measures such as Pearson’s correlation coefficient, coherence, mutual information, warping path length, and dynamic time warping distance.[12] Graph measures based on forming a graph with the nodes as the regions of the brain and connections between them forming the edges are also beneficial to characterize complex brain-behavior.[13] Metrics of graph measures include local efficiency, global efficiency, clustering coefficient, between-nest centrality, degree, and cost. With several such metrics available to measure the functional connectivity between the ROIs of the brain, it is also important to judge the advantages and pitfalls of these metrics[14] and to find their usefulness for a particular application. When training a machine learning model to fit data and to be able to classify any unseen data, it is important to choose the best features and well discriminative features to help achieve a higher level of accuracy of classification.

A previous study among Brahma Kumaris Rajayoga meditators showed that both short-term and long-term meditators have enhanced well-being as compared to nonmeditators and that proficiency in meditation is a stronger predictor of progress in well-being than the duration of meditation practice.[15] Intriguingly, another study with the same group of meditators found that long-term meditators demonstrated mental mastery by being able to rapidly switch between rest and meditation states (as evidenced by electroencephalogram [EEG] changes) on demand, and under a variety of test conditions whereas short-term meditators were able to shift states when given about 15 min and only with their eyes closed.[16] In another study, to test the hypothesis that the duration of meditation practice might bring about changes in brain functional networks, it was checked if meditators could be reliably classified into distinct groups based on differences in brain functional connectivity. To avoid any confounds due to task difficulty or differences in attention span, functional connectivity metrics were obtained when the meditators were performing an easy and engaging task where everyone could perform the task with high accuracy. This study suggested that long-term meditation practice brings about neuroplastic changes that might underlie their higher well-being whereas the well-being gains in short-term meditators were likely due to cognitive reappraisal.[17]

In the present study, we enlisted two groups of Brahma Kumaris Rajayoga meditators-long-term practitioners (LTPs) with a minimum of 10 years of meditation practice, and short-term practitioners (STPs) with a maximum of 2 years of practice. We aimed to find if there was a difference in functional connectivity between these two groups when they perform an engaging task and be able to train a machine learning model to classify the two groups using suitable functional connectivity metrics as features for training the model. fMRI data were acquired while the subjects performed the gamified task.[17] Functional connectivity on 132 regions of interest (ROI) brain atlas was performed and additionally, another brain atlas of 32 network ROIs that include resting-state networks, was considered. Resting-state networks especially the default mode network have been of interest in meditation-related studies. Two graph theory-based features one representing a measure of integration (global efficiency) and the other representing a measure of segregation (local efficiency) were selected. The effectiveness of the graph measures, when used as features to classify meditators based on experience, had to be explored. To find the machine learning model suitable for this task, five different classifiers were trained using graph measures. To determine the best machine learning model the performance measures of the classifiers such as test accuracy, precision, sensitivity, specificity, and area under the curve receiver operating characteristics (AUC-ROC curve) of the classifiers were compared.

**Subjects and Methods**

**Participant data**

The neuroimaging data used in this study were part of a larger study involving EEG measures.[16] The study was initiated after receiving ethical clearance from the NIMHANS Institute Human Ethics Committee. A total of 22 participants were recruited for the study in two groups, LTP (n = 12) and STPs (n = 10). The LTP group had a minimum of 10 years of regular meditation practice and a median meditation experience of 13,596 h (range from 7,300 to 35,040). The STP group had 6 months–2 years
of meditation practice and a median meditation experience of 1,095 h (range: 274 to 2,190). Both groups were proficient in meditation, the primary difference being the duration of practice. People from all age groups and diverse socioeconomic conditions practice meditation. Therefore, the participants were selected on this criterion with the age group in the range of 27-65 years and were healthy, right-handed subjects from diverse socioeconomic conditions, diverse education levels, and multilingual. All participants provided written informed consent as approved by the ethics committee.

The data were acquired from a 3T Siemens SKYRA MRI scanner using a 20-channel head coil. Structural images (T1 weighted) with voxel resolution of 1 mm × 1 mm × 1 mm were acquired using a magnetization prepared rapid acquisition gradient echo sequence (TR: 1900ms, TE: 2.44 ms, flip angle: 9, 192 slices). A gradient Echo-Planar Imaging (EPI) sequence was used at a voxel resolution of 3 mm × 3 mm × 4 mm (TR: 2000 ms, TE: 30 ms, flip angle: 78, 37 slices).

**Experimental paradigm**

The fMRI protocol consisted of rest, task, and rest. One of the two rest blocks was meditation where the subjects were in a “soul-conscious state” and the order was counterbalanced across participants such that some had rest first and others had meditation first so that there were no order effects. The task run length was 14 min 58 s and rest/meditation was for 7 min 20 s. The task was a modified version of a gamified paradigm and was developed for performing a parametric evaluation of multiple neurocognitive functions simultaneously. It was a gamified adaptation of the visual oddball paradigm. For the fMRI version of the task, the trial length was increased to suit a TR of 2000 ms, and a few blocks contained passive trials (with no responses) to provide an additional baseline to compare with the rest of the trials. It was a mixed design experiment with sets of events coming in blocks with different regularity. There were 16 blocks, each block comprising 25 stimulus trials and 3 baseline trials and hence a total of 448 trials. The paradigm uses a gamification approach to make the task more engaging and enable decision-making capability in the presence of multiple audio and visual stimuli as distractors. This resembles a real-life scenario where there is a need for decision-making in the presence of multiple distractions. The participants lay in the MRI scanner and viewed stimuli that were projected onto an MRI-compatible 40-inch LCD monitor (NordicNeuroLab, Norway) via a mirror mounted on the head coil. The auditory stimuli were presented via MR-compatible headphones. Head movements were minimized by using soft memory foam cushions within the head coil. Participants responded using MR-compatible button presses. The task was administered using E-Prime 2.0 software (Psychology Software Tools, Sharpsburg, USA) and was synchronized with the fMRI acquisition. The task provides opportunities to study cognition across different event sets (active response vs. passive observation of task, face perception vs shape perception, rare versus frequent events). In this study, we focus on functional connectivity differences between the two groups of meditators while processing rare stimuli (condition “Rare”) as they have been demonstrated to elicit large responses and are an index of cognition (the P300) in event-related potential studies.

**Methodology of the study**

The workflow of the procedure followed in this study is given in Figure 1. fMRI blood oxygenation level-dependent (BOLD) time series were first preprocessed to increase the signal-to-noise ratio. The ROI-to-ROI functional connectivity analysis was done by finding correlation coefficients between the different ROIs of the brain. Two brain atlases were considered in this study: one consisting of 132 ROIs and the other with 32 ROIs. Details of these ROIs are elaborated in the further section. The adjacency matrices based on graph measures were then extracted to form the feature matrix and used to train the machine learning algorithms. The algorithm with the highest accuracy is the best model that can be used to classify LTP and STP groups based on their cognitive processing.

**Preprocessing**

The fMRI data contain artifacts due to the movement of subjects during long sessions of scans, physiological noise, etc. Hence, these data need to be preprocessed to increase the BOLD contrast to noise ratio. The preprocessing was performed using the CONN toolbox in MATLAB. The preprocessing includes the following steps: (1) Functional realignment was performed on the functional scans that overcome the artifacts caused by subject movements in the scanner. (2) Coregistration was performed between the structural and functional scans where they are manually compared and reoriented by applying displacements and rotations so that they align with each other and to the canonical Montreal Neurological Institute template. (3) Slice-timing correction was applied that interpolates between the same slice and voxel in neighboring acquisition TRs to help identify the signal in such a way that the slices appear to be acquired at the same time. (4) An anatomical component-based noise correction method, aCompCor, to eliminate spurious sources of variance in BOLD and perfusion-based fMRI was performed that increases the validity and the specificity and sensitivity of the analysis. (5) Bias correction was performed which improves the homogeneity of the structural image. (6) Segmentation was done to separate white matter, gray matter, and cerebrospinal fluid. (7) Normalization was performed on functional and structural images separately to fit them to a standard brain. (8) Smoothing was performed with a Gaussian FWHM (full width at half maximum) kernel of 8mm for each voxel to...
increase the signal-to-noise ratio. (9) An additional Denoising step was performed to define, explore, and remove possible confounds. Before computing connectivity measurements, undesired motion, physiological, and other artifact effects were eliminated from the BOLD data using linear regression and high-pass filtering (for task-based fMRI).

**Functional connectivity calculation**

An ROI-to-ROI functional connectivity analysis was performed on two brain atlases. One brain atlas has 132 ROIs which include 91 cortical areas, 15 subcortical areas from the FSL Harvard Oxford Atlas, and 26 Cerebellar areas from the AAL (Automated Anatomical Labelling) atlas. The other brain atlas consists of 32 ROIs, which include the regions of default mode network, sensorimotor, salience network, dorsal attention network, frontoparietal, and cerebellar area. Functional connectivity analysis was performed using the CONN toolbox in MATLAB. The 132 ROIs were taken (by Conn) from the Harvard-Oxford structural atlas and the 32 network ROIs were derived from ICA analyses of the HCP dataset and therefore functionally defined. The average BOLD time series of all voxels in a region was obtained. Pearson’s correlation coefficient between every pair of corresponding ROIs was calculated. Fisher’s transformation was applied to the correlation coefficients to obtain Z-scores. This analysis generates a $132 \times 132$ matrix for Atlas ROIs and a $32 \times 32$ matrix for Network ROIs for all subjects per condition.

**Graph network measures**

The graph measures were obtained from the nondirected graphs formed by considering the ROIs as nodes and edges by thresholded connections. The group contrast LTP > STP is chosen with ‘Rare’ stimuli. An adjacency matrix (binary matrix) was formed by thresholding the edges in an ROI-to-ROI correlation (RRC) matrix with a cost factor which is a percentage relative threshold. For example, the 10% cost function implies the top 10% of the highest correlation values in the RRC matrix converted to 1 and the other connections to 0. The cost factors that were considered were the highest 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45%, 50%, 55%, and 60%, to form the adjacency matrices. Such matrices were obtained for all subjects in each group separately and under all conditions. For each cost factor, two graph measures were found: global efficiency and local efficiency from the obtained graphs. The analysis threshold p-FDR corrected value (False Discovery Rate corrected $P$-value) $< 0.05$ (two-sided) was chosen. Global Efficiency at a node as given by Equation 1 is defined as “the average of inverse-distances between this node and all other nodes in the same graph.”

$$GE = \frac{\sum_{i \neq j} 1/D_{ij}}{N-1}$$

where $D$ is the shortest-path distance matrix, $N$ is the number of nodes in a graph, and $GE$ is the Global Efficiency.
of a graph (and of each node/ROI). Global efficiency at a node represents a measure of this node’s centrality within the network, characterizing the degree of global connectedness of each ROI. Similarly, network global efficiency represents a measure of inter-connectedness or radius of the entire network.

Local Efficiency at each node as given by Equation 2 is defined as “the Global efficiency of the neighboring subgraph of this node”:

\[
LE_{i} = \frac{\sum_{j \neq i} 1/D_{ij}}{d_i \cdot (d_i - 1)}
\]

\[
LE = \frac{\sum_{i} LE_i}{N}
\]

where \(d\) is the degree of each node, \(D\) is the shortest-path distance matrix within the neighboring subgraph at each node, characterized by all nodes neighboring this node and all existing edges among them, and \(LE\) is the Local Efficiency of a graph (and of each node/ROI). Local efficiency represents a measure of local integration or coherence, characterizing the degree of inter-connectedness among all nodes within a node neighboring subgraph. Similarly, network local efficiency represents a measure of local integration in a network.

**Preparation of training data**

For each cost factor, considering global efficiency as the analysis measure, the adjacency matrices for LTP were exported from CONN toolbox (version 18a). These were a set of 12 matrices corresponding to 12 LTPs. A probability matrix was then calculated as the sum of all 12 matrices divided by 12. The upper triangular elements of this matrix were converted to a column vector and placed under the feature global efficiency in a data frame. A target value of 0 is assigned to the corresponding values under the target/class column in the data frame, as these belong to the LTP class. The same procedure was repeated for STP with 10 matrices and the target value of 1. Hence, for each cost factor, the number of rows that were generated were ((number of ROIs \(\times\) (number of ROIs-1)/2) \(\times\) 2) for LTP and STP together. This was repeated for all the 11 values of cost factor (0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, and 0.6). To generate the next feature column in the data frame, the same procedure was repeated taking local efficiency as the analysis measure. The source and the destination ROI numbers were placed as two more columns in the data frame. The features in the training data were cost factor, source ROI, destination ROI, global efficiency, and local efficiency. The target column contains the classification class of 0 corresponding to LTP and 1 for STP.

**Classification**

The aim is to determine the best classifier for this problem, so five different machine learning algorithms logistic regression, SVM, decision tree, random forest, and gradient boosted tree (XGBoost) were selected. Logistic regression, SVM, decision tree, and random forest models were imported from the scikit-learn (v0.23.2) library, and gradient boosted tree was imported from the XGBoost library and implemented in Python (v3.8.5). The models were trained with the Grid Search algorithm being used to find the best parameters for a model along with 5-fold cross-validation for the training data. The accuracy for best parameters on training data was tabulated. The performance metrics like accuracy, precision, specificity, sensitivity, and AUC-ROC curve were evaluated on the test set for all the machine learning models and compared. The workflow for training, cross-validation, and testing is shown in Figure 2.

**Machine learning models**

Five machine learning models were trained with suitable hyperparameters. The hyperparameters used with these models are listed here. A regularized Ridge Logistic Regression model was trained with Limited-memory Brodльen–Fletcher–Goldfarb–Shanno algorithm as the solver. The grid parameters specified were: C parameter in a logarithmic range from 3 to 7 and two values for penalty L1 lasso and L2 ridge with 5-fold cross-validation. A support vector classifier with radial basis function kernel was used. To find the optimum set of hyperparameters, a grid search was performed with C parameter values of 0.1, 1, 10, 100, 1000 and gamma values of 1, 0.1, 0.01, 0.001, 0.0001. Five-fold cross-validation was used. Decision tree was trained using the Gini criterion. The hyperparameter max_depth values in the range from 3 to 20 were used. Random Forest was trained using an ensemble of 200 decision trees and the Gini criterion was used. Bootstrap samples were used in the tree-building process. The other
Hyperparameters used were max_depth values of 80 to 110 in steps of 10, max_features values of 2 and 3, min_samples_leaf values of 3, 4, 5, min_samples_split values of 8, 10, 12 and n_estimators values of 100, 200, 300, 1000. An eXtreme Gradient Boosted (XGB) classifier was trained, using a version of the regression tree as the weak learner.[28] The ensemble had 200 trees, and a constant learning rate of 0.3 was used. The hyperparameters used were n_estimators values of 400, 700, 1000, colsample_bytree values of 0.7 and 0.8, max_depth values of 15, 20, 25, reg_alpha values of 1.1, 1.2, 1.3, reg_lambda values of 1.1, 1.2, 1.3, subsample values of 0.7, 0.8, 0.9.

**Training and testing procedure**

The csv file containing the features and target class was imported using the Pandas library. The imported file was stored as a Pandas Dataframe in memory. The Dataframe so obtained were split into two Dataframes, one containing all the features and the other containing the target classes. The training data and the test data (hold out data) were split into 70% and 30% respectively. Logistic Regression, SVM, Decision Tree, and Random Forest models were imported from the Scikit-Learn library.[23] Gradient Boosted Tree was imported from the XGBoost library. The hyperparameters were specified and GridSearch was performed with the corresponding model to obtain the best parameters. Five-fold cross-validation was used to fit the training data to the retrained model. The accuracy reported by cross-validation was noted. The holdout data were then used to test the retrained model and the metrics Test Accuracy, Precision, Sensitivity, Specificity, and ROC curve for the five models were calculated.

**Results**

Complex network analysis has shown very promising results with functional connectivity data and can quantify the networks in the brain with measures that are easily computable and meaningful neurologically.[29,30] Classification of two brain atlases (132 ROIs and 32 ROIs) with graph measures as features were performed using five different classifiers. The accuracy reported by cross-validation on training data and the best hyperparameters obtained for the corresponding model is tabulated in Table 1. The models have not been overfitted as the training and test accuracy are approximately equal.

We have compared the performance of five classifiers in terms of the following metrics: Test Accuracy, Precision, Sensitivity, Specificity, and AUC-ROC curve for test data. The results of performance measures of all five classifiers are shown in Figure 3 for 132 ROI brain atlas and in Figure 4 for 32 ROI brain atlas. The Decision Tree and models of ensemble Decision Tree i. e. Random Forest, and Gradient Boosted Tree show better performance compared to Logistic Regression and SVM. The performance of the

![Figure 3: Comparison of classifier performance metrics for 132 ROIs brain atlas](image)

![Figure 4: Comparison of classifier performance metrics for 32 ROIs brain atlas](image)

**Table 1: Training accuracy and best parameters obtained for the machine learning models**

| Machine learning model | 132 ROIs brain atlas | 32 ROIs brain atlas |
|------------------------|----------------------|---------------------|
| **Best parameters**    | **Training accuracy**| **Best parameters**  | **Training accuracy** |
| Logistic Regression    | C=0.001 penalty=L2 ridge | 50.28               | C=10 penalty=L2 ridge  | 51.5 |
| Support Vector Machine| C=1000 gamma=1       | 62.3                | C=100 gamma=0.1        | 58.8 |
| Decision Tree          | max_depth=17         | 85.3                | max_depth=16           | 77.93 |
| Random Forest          | max_depth=110 max_features=3 min_samples_leaf=5 min_samples_split=12 n_estimators=200 | 84.42 | max_depth=80 max_features=3 min_samples_leaf=5 min_samples_split=12 n_estimators=100 | 80.31 |
| Gradient Boosted Tree  | N_estimators=400 colsample_bytree=0.7 max_depth=15 reg_alpha=1.3 reg_lambda=1.2 subsample=0.9 | 85.34 | N_estimators=400 colsample_bytree=0.7 max_depth=20 reg_alpha=1.3 reg_lambda=1.2 subsample=0.9 | 78.67 |

Note: ‘Best parameters’ refer to the final hyperparameter values that were used to train the corresponding machine learning model. See the online documentation referred to by Pedregosa et al., 2011 for specific details for each machine learning algorithm. Training accuracies are the best classification performance achieved by each classifier on the training set. ROI: region of interest.
tree-based machine learning algorithms i.e. Decision Tree, Random Forest, and Gradient Boosted Tree are mostly similar with less than or equal to 1% difference in each of their performance measures for 132 ROI brain atlas and 1-5% difference in their performance measures for 32 ROI brain atlas. Hence, the Decision-Tree based algorithms are the best performing algorithms for this task of classifying LTP from STP using Graph measures of functional connectivity. The AUC-ROC curve obtained for the five classifiers is shown in Figure 5.

It can also be seen that the classifier performance is better when 132 Region ROIs are considered in the functional connectivity analysis. There is almost an increase of 7% in the accuracy for the Gradient Boosted Tree model. There is an increase of 4-7% in the other models as well except in Logistic Regression. The least performing model for all the measures is Logistic Regression. Thus, an exhaustive search for the best performing machine learning algorithm for the application on hand is performed in this study on two brain atlases. This study is also unique because despite having a small data sample, we were able to get good results in training the machine learning models using a suitable way of representing features for training.

It is critical to display the confidence interval for a performance measure alongside the measure in machine learning. When generating predictions on data, confidence intervals provide a range of the performance measure and the likelihood that the performance measure falls between the range. The bootstrap method is used to compute the confidence interval. It is a statistical estimation technique that can be used to construct empirical CI regardless of the distribution of the performance measure. Table 2 gives the 95% confidence interval for the classification error calculated for the 132 ROIs brain atlas and 32 ROIs brain atlas.

**Discussion**

Rajayoga meditation in the Brahma Kumaris tradition is practiced with eyes open [16], whereas most other meditation techniques are practiced with eyes closed. The concentration that can be achieved with eyes closed is much better than with eyes open. However, the practice of being in a meditative state while keeping eyes open makes it more useful in day-to-day life while doing mundane activities. These brain training techniques practiced every day induce a change in the structural and functional connectivity thus bringing about practice-induced plasticity. There have been several MRI studies on the long-term and short-term effects of different meditation techniques but there are just three MRI studies with Brahma Kumaris Rajayoga meditators. An EEG-MRI study of Brahma Kumaris meditators [31] to investigate the temporal and spatial changes in the Default Mode Network caused by meditation found evidence of both state and trait effects of meditation in terms of altered microstate dynamics. A diffusion-weighted imaging study in this tradition revealed that as compared
Our study is unique in the sense that task-based functional connectivity is differentiated between long-term and short-term Rajayoga meditators using machine learning models. The challenge with this dataset was its small sample size which is not very encouraging to train machine learning models. Feature extraction and representation play a very important role. Graph measures of functional connectivity have been increasingly used to characterize patterns of brain activity in clinical conditions, and mental traits and enable to understand the brain connectivity.[13] Several measures can be obtained from Graph theory.[30] Many such measures either individually or collectively have been used as features to train machine learning models. Measures such as global efficiency are considered superior among the measures of integration.[20] Hence, global efficiency and local efficiency are used as features in our algorithms. Graph measures of functional connectivity have proven to be good features that can be used in our task of classifying Rajayoga meditators based on their experience using machine learning models as can be seen from the results. Since not all machine learning models perform the same for the data, different algorithms had to be trained and tested to find the best performing one.

Conclusions

By measuring brain functional connectivity during creative cognitive processing and utilizing graph metrics as features to construct machine learning models, we were able to effectively distinguish between long-term and short-term proficient Brahma Kumaris Rajayoga meditation practitioners. Machine learning models designed for one application may not work for others and are very much application-dependent. Hence, it is important to choose the best machine learning model for the data at hand. We trained five machine learning models and evaluated their performance. We found that tree-based algorithms like decision tree, random forest, and gradient boosted tree, which are ensemble algorithms, work best in classifying the two groups of meditators. Even though the dataset is small, the effect of long-term practice in bringing about structural and functional changes, careful feature construction, as well as the sensitivity of the machine learning models, enabled effective classification between groups. This study, to the best of our knowledge, happens to be the first one.

| Machine learning model | Classification error | CI          | Classification error | CI          |
|-------------------------|----------------------|-------------|----------------------|-------------|
| Logistic Regression     | 0.4999               | 0.4999±0.0041 | 0.4926               | 0.4926±0.0171 |
| Support Vector Machine  | 0.3664               | 0.3664±0.0039 | 0.4059               | 0.4059±0.0168 |
| Decision Tree           | 0.1446               | 0.1446±0.0028 | 0.2223               | 0.2223±0.0142 |
| Random Forest           | 0.1525               | 0.1525±0.0029 | 0.20678              | 0.2067±0.0138 |
| Gradient Boosted Tree   | 0.1488               | 0.1488±0.0029 | 0.2159               | 0.2159±0.0140 |

ROIs: Regions of interests, CI: Confidence interval
where graph theory-based functional connectivity measures obtained from task-based fMRI of Rajayoga meditators are used to classify two groups based on the experience of meditation. It would be useful to explore other measures of graph theory as features for training and assess if this would lead to increased accuracy. It would be beneficial if such a study is carried out with other forms of meditation to be able to contribute to the study of well-being.

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Ethical statement

The study was approved by the Institutional Human Ethics Committee of the National Institute of Mental Health and Neurosciences (NIMHANS) as per approval no: NIMH/DO/SUB-COMMITTEE/2011/SL.No.1, Basic Sciences.

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Conflicts of interest

There are no conflicts of interest.

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