Machine Learning-based Classification of Meditators using Functional Connectivity over Resting-State Networks

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Abstract: *Meditation has several health benefits and is also used as a complementary treatment for various ailments. Neuroimaging studies have shed light on the effects of meditation, especially on the brain. Functional Magnetic Resonance Imaging, a powerful non-invasive imaging technique is used in this study to determine the functional connectivity in meditator's brain. In this study, long-term effects of Rajayoga Meditation practice were considered where the difference in functional connectivity between two groups of subjects one with long duration and the other with short duration of Rajayoga meditation practice was found. Two groups of subjects with long-term and short-term practice of Rajayoga meditation were recruited. Task-based fMRI was acquired as the subjects performed a Neurocognitive task. Functional connectivity among the regions of Resting-State Networks was performed and four functional connectivity metrics were derived. Machine learning algorithms were used to classify these two groups based on functional connectivity metrics used as features. The ensemble learning algorithms Random Forest and Gradient Boosted Tree could differentiate Long-term and Short-term Rajayoga Practitioners with an accuracy of 62% when all four Functional Connectivity metrics were used as features.*

Keywords*:* fMRI, Functional Connectivity, Meditators, Machine Learning

1. INTRODUCTION

Meditation has been studied with various perspectives related to health and well-being. It is used as a complementary therapy for various diseases and ailments [1]. Functional Magnetic Resonance Imaging (fMRI) is one of the popular tools that has been used to study the effect of meditation. The activation in the voxels of the brain is measured using Blood Oxygenation Level Dependent (BOLD) contrast in the fMRI signal. Many functional activation studies are conducted for different meditation techniques. These studies have reported the regions activated due to meditation practice and highlighted its benefits [2,3,4]. Functional connectivity studies are also very popular concerning meditation techniques. Functional connectivity studies help find the networks of temporal correlations between different regions of the brain [5,6,7]. Nowadays, applying Machine Learning (ML) and Deep Learning (DL) algorithms to fMRI data analysis is gaining interest [8]. Previously, the General Linear Model analysis was used to provide group-level inferences in fMRI data. The p-values were used to conclude with the statistically significant regions of the brain. The ML techniques help in single-subject predictions to predict which group the subject belongs to. Features derived from fMRI data like Functional Connectivity Metrics, Graph

Measures, Amplitude of Low Frequency Fluctuations (ALFF) are used to perform such predictions by training the ML models.

In this study, Rajayoga (RY) meditation as taught by the Brahma Kumaris' (BK) World Spiritual organization was considered [9]. The effect of long-term practice of Rajayoga meditation was of particular interest. The impact of duration (number of years) of meditation practice has been studied in other forms of meditation techniques and with different perspectives related to health & well-being. The impact of Long-term and Short-term training of Mindfulness meditation on the response in the amygdala looking at emotional pictures was studied. Long-term meditators had less amygdala reaction to negative images. An increase in functional connectivity between the amygdala and ventromedial prefrontal cortex (vmPFC) was found in Short-term meditators for affective images which shows good emotion regulation ability [10]. The short-term effect of Mindfulness was observed with an increased regional homogeneity and altered functional connectivity in post central gyrus related networks. This proved the optimization of emotional processing [11]. A study that relates the short-term effects of Mindfulness practice to depression and anxiety showed a reduction in depression scores [12]. A Support Vector Regression was used to predict the years of Mindfulness meditation practice in two meditation styles Samatha (Focused Attention) and Vipassana (Open Monitoring) using functional connectivity matrices. The connections with the largest weights played an important role in this prediction [13]. In another study on Buddhist monks, functional connectivity patterns were used to predict the age and expertise of their long-term practice in Focused Attention and Open Monitoring meditations. They found expertise-related brain networks were meditation specific like regions of attention and affective monitoring. The brain networks associated with age were independent of the meditation type [14]. Likewise, there are studies on Rajayoga meditation carried out on physiological and psychological parameters [9,15,16,17].

In this study, we attempted to differentiate Long-Term (LTP) and Short-Term Rajayoga meditation practitioners (STP) while they performed a task, based on the reasoning that there must be a difference in functional connectivity between these two groups. Machine Learning models were trained using the Functional Connectivity (FC) metrics derived by performing correlation analysis between the average BOLD time series derived from the Regions of Interest (ROIs). The ROIs considered in this study belong to the Resting-State Networks (RSNs) namely Default Mode Network (DMN), Dorsal Attention Network (DAN), Ventral Attention Network (VAN), Sensori Motor Network (SMN), Visual Network (VIS), Fronto- Parietal Control Network (FPC), and Language Network (LAN). The Resting-State Networks especially the Default Mode Network is studied very keenly in meditation-related studies. The DMN shows a decrease in activity during cognitive tasks and is found to be active when at rest. In some studies, it has been related to mind wandering where the DMN along with frontoparietal control network areas, and other non-DMN regions are responsible for spontaneous thought [18]. A short time practice (40 days) of Mindfulness showed both structural and functional changes in posterior regions of DMN and precuneus [12]. A resting-state and task-based fMRI study were conducted on long-term Mindfulness meditation practitioners to test the effect in DMN and VIS. In the resting state as well as in the visual recognition memory task, an increase in activations in the visual cortex and reduction of activations in DMN were found in meditators compared to controls [19]. A functional connectivity study was conducted to see the effect of gratitude on the DMN, reward motivation, and emotion networks. They found resting-state connectivity in these regions to improve emotional regulation and self-motivation [20]. The Resting-State Networks are important biomarkers as they show activity during rest and task. Hence, 32 ROIs corresponding to the RSNs was used in this study as the brain atlas over which functional connectivity was performed.

2. DATASET

The Rajayoga Meditator's dataset used in this study was obtained from the National Institute of Mental Health and Neurosciences. This was acquired as a part of an EEG study [21]. For this study, a total of 22 subjects were recruited and in two groups: Long-Term Practitioners (LTP) and Short-Term Practitioners (STP). The details and demographics of the two groups are given in Table 1. Participants belonged to different age groups. They were right-handed, healthy subjects. They were multilingual and had diverse levels of education. Task-based fMRI was captured as the subjects performed the second level of the neurocognitive task called Assessing Neurocognition via Gamified Experimental Logic (ANGEL) paradigm [22]. Both structural and functional scans are acquired during the fMRI acquisition. The protocol followed for the data acquisition was rest, task, meditation and meditation, task, rest for alternate participants. During meditation, the subjects were instructed to be in the 'soul-conscious state' where they had to visualize the self as a star at the center of the forehead. This state is the first stage in any Rajayoga meditation practice. The rest/ meditation was for 7 mins 20 s and the task was carried out for 14 mins 48 s. The task facilitated the study of cognition for various conditions like face perception vs shape perception, rare versus frequent events, active response vs passive observation to task, etc.

Table 1. Details of the subjects recruited for the study.

Parameters	LTP	STP
Number	12	10
Males	6	6
Females	6	4
Number of years of meditation practice	10 years	Six months – Two years
Median meditation experience	13596 hours (range 7300 to 35040)	1095 hours (range 274 to 2190)
Age (min, max, median, mean, SD, ci)	33, 57, 45.5, 44.4, 8.78, 5.58	29, 61, 44.5, 43.1, 10.0, 7.16
Average Daily Meditation (hrs) (min, max, median, mean, SD, ci)	1, 3.5, 2, 2.17, 0.778, 0.495	0.5, 3, 1.5, 1.75, 0.791, 0.566
Overall Meditation practice (hrs) (min, max, median, mean, SD, ci)	7300, 35040, 13596, 14646, 6958, 4421	274, 2190, 1095, 1038, 647, 463
Years of Regular RY practice (min, max, median, mean, SD, ci)	11, 32, 18.5, 19.2, 6.44, 4.09	0.5, 3, 2, 1.68, 0.811, 0.580

3. METHODOLOGY

The methodology involved in this study includes preprocessing, functional connectivity analysis, feature representation in a data fame, training Machine Learning models, testing and measuring the performance of classifiers.

3.1. Preprocessing

Pre-processing is an essential step to prepare the raw data for further analysis. Pre-processing was performed on the raw fMRI data using the CONN Functional Connectivity Toolbox which is a MATLAB-based toolbox [23,24]. CONN uses SPM12 to perform pre-processing. The following are the steps of pre-processing. The pre-processing steps are performed on both structural and functional MRI scans.

1) Using B-spline interpolation the functional scans were realigned to register all the scans to a reference image (usually to the first scan).
2) Slice timing correction was performed on the functional scans to rectify the temporal misalignment.
3) ART-based scrubbing was used to identify outlier scans from the BOLD signal.
4) Structural and Functional data are normalized to Montreal Neurological Institute (MNI) space which is a standard used in fMRI data.
5) Segmentation was performed to separate white matter, gray matter, and cerebrospinal fluid (CSF).
6) Gaussian kernel (8mm FWHM) was used to smooth the functional data to increase the signal to noise ratio.

3.2. Functional Connectivity Analysis

The Brain Atlas that was used for the Functional Connectivity analysis consisted of 32 ROIs of the RSNs. Functional Connectivity analysis was performed using the CONN toolbox. Functional Connectivity analysis is the calculation of correlation coefficients between every pair of ROIs. ROI-to-ROI functional connectivity was performed by evaluating Pearson's correlation coefficients between every pair of ROI. Fischer's z-transform was then applied to normalize the values. This is called the RRC metric and is a 32x32 matrix. Similarly, three other metrics namely weighted RRC (wRRC), multivariate RRC (mRRC), and Generalized Psycho-Physiological Interaction (gPPI) were evaluated. wRRC gives the condition or task-based functional connectivity between every pair of ROI. mRRC is a semi-partial correlation coefficient evaluated between two ROIs after removing the effects caused by other ROIs. gPPI is a measure of task modulated effective connectivity between every pair of ROI. All four measures are calculated for all the 22 subjects and all the 12 conditions in the fMRI experiment. These are the features that were used for training the classifiers.

3.3. Feature Representation

The correlation matrices obtained from Functional Connectivity analysis must be represented in a suitable form that can be used to train a Machine Learning model. This is the feature representation step where the data frame is prepared for classification. The correlation matrices are symmetric and therefore only the upper triangular matrix without the diagonal elements are unique. These elements are converted to a column vector. So, for a 32x32 matrix, the dimension of the column vector will be 32 x 31 / 2 = 496. Each subject will have 496 correlation values. Since there are 22 subjects, the number of rows will be 496 x 22 = 10912. Each column corresponds to one metric per condition and represents a feature in the data frame for classification. RRC, wRRC, and mRRC were calculated for 12 conditions (rare vs frequent, shapepresent vs shapeabsent, CDon vs CDoff, etc.) and gPPI was calculated for 11 conditions (rest condition was not considered as gPPI is a task-based metric). Therefore, there are 47 features from these four Functional Connectivity metrics. All these metrics are normalized so that the values are in the range [-1,1]. The Source ROI and Destination ROI are also included in the columns. The target class is set as '0' for LTP and '1' for STP.

3.4. Classification & Performance evaluation

The Machine Learning algorithms that were selected for training were Tree-based algorithms like Decision Tree (DT), and its ensembles Random Forest (RF) and Gradient Boosted Tree (GBT). An algorithm that is commonly used in fMRI analysis, the Support Vector Machine (SVM), and a simple algorithm, Logistic Regression (LR) was also trained for comparison. The purpose was to train these five Machine Learning algorithms and compare their performance on this dataset. The algorithms were implemented in Python using Scikit Learn and XGBoost packages [25]. The data frame consisting of features and class in csv file format was imported. Since there were an unequal number of samples in the two classes: 5952 in LTP and 4960 in STP, data balancing was performed by removing the samples from the LTP class at random. The data was then split into training and testing data in the proportion of 70% and 30% respectively. Since the effectiveness of the features had to be assessed, different combinations of features were first used to train the simple LR model. For the other four ML models, individual metrics were used as features and trained. Then all four metrics were used as features to train the five Machine Learning models. The performance measures of the classifier namely Accuracy, Precision, Recall, f1-score was calculated in each case using the Confusion Matrix and Classification Report. The Receiver Operator Characteristic (ROC) curve was also plotted.

4. RESULTS & DISCUSSION

To find the best feature or a combination of features that can distinguish the two groups, the Machine Learning algorithms were trained with different combinations of features. In each case, the performance of the classifiers was noted and compared. The experimental results obtained are listed in the following sections.

4.1. Performance of Machine Learning Models

Logistic Regression: A Logistic Regression model was trained with regularized Ridge regression. For each case of the database, the C parameter was varied for values {0.001, 0.01, 0.1, 1, 10, 100}. The accuracy was noted in each case. The combinations of features that were used for classification along with the accuracy obtained are shown in Table 2. The highest accuracy obtained for a feature combination (column-wise in the table) is highlighted. Comparing these accuracies, it can be seen that the feature combination RRC+wRRC+gPPI has given the highest accuracy of 58.6% which is very close to the value of 58.4% obtained while taking all four metrics. Though the accuracy has crossed 50% for the LR model, still we cannot conclude that Logistic Regression is an effective model to classify the two groups.

Table 2. Accuracy of Logistic Regression model for different feature combinations.

C-parameter	Accuracy							
	RRC	wRRC	mRRC	gPPI	RRC+wRRC	RRC+wRRC+mRRC	RRC+wRRC+gPPI	RRC+wRRC+mRRC+gPPI
0.001	0.531	0.537	**0.519**	0.539	0.534	0.539	0.548	0.546
0.01	0.543	0.539	0.504	0.547	0.542	0.545	0.551	0.559
0.1	0.542	0.531	0.497	**0.548**	0.563	0.554	0.564	0.558
1	0.549	0.540	0.498	**0.548**	0.572	0.564	0.569	0.567
10	**0.561**	**0.544**	0.496	**0.548**	0.574	0.573	**0.586**	0.577
100	0.557	0.542	0.496	**0.548**	**0.584**	**0.575**	0.585	**0.584**

To evaluate the performance of ML models, it is also important to find the other performance measures like Precision, Recall, and f1-score. These parameters are listed in Table 3 for individual features and in Table 4 for a combination of features.

Table 3. Performance measures of Logistic Regression model for Individual FC metrics

Class	RRC			wRRC			mRRC			gPPI		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.57	0.54	0.55	0.55	0.53	0.54	0.54	0.35	0.42	0.56	0.52	0.54
1(STP)	0.55	0.59	0.57	0.54	0.56	0.55	0.51	0.69	0.59	0.54	0.58	0.56

RRC: ROI-to-ROI Connectivity, wRRC: Weighted ROI-to-ROI Connectivity, mRRC: Multivariate ROI-to-ROI Connectivity, gPPI: Generalized Psycho-Physiological Interaction, Pre: Precision, Rec: Recall, Fs: f1-score

Table 4. Performance measures of Logistic Regression model for the Combination of FC metrics

Class	RRC+wRRC			RRC+wRRC+mRRC			RRC+wRRC+gPPI			RRC+wRRC+ mRRC+gPPI		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.59	0.56	0.58	0.58	0.55	0.57	0.60	0.56	0.58	0.60	0.55	0.57
1(STP)	0.57	0.61	0.59	0.57	0.60	0.58	0.58	0.61	0.59	0.57	0.61	0.59

The other four Machine Learning models were trained using individual metrics and a combination of all metrics together. The results obtained with them are as given below.

Support Vector Machine: Support Vector Machine can be used for classification as well as regression tasks. In this training, Radial Basis Function (RBF) kernel was used in the SVM model. Grid search for hyperparameter tuning was performed with gamma values={1, 0.1, 0.01, 0.001, 0.0001} and C parameter values = {0.1, 1, 10, 100, 1000}. This model was trained with individual features as well as all the features taken together. The classifier performance in terms of Accuracy, Precision, Recall, and f1-score were noted in all the cases and is as given in Table 5 for models trained with individual metrics.

Table 5. Performance measures of Support Vector Machine for Individual FC metrics

Class	RRC			wRRC			mRRC			gPPI		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.60	0.55	0.57	0.59	0.55	0.57	0.55	0.51	0.53	0.59	0.55	0.57
1(STP)	0.58	0.62	0.60	0.57	0.61	0.59	0.53	0.57	0.55	0.57	0.61	0.59

Decision Tree: A Decision Tree consists of several nodes and branches. The nodes are where a decision is made. The leaf nodes represent the final classification. Gini Criterion was used to train the Decision Tree. The performance measures for individual FC metrics are given in Table 6.

Table 6. Performance measures of Decision Tree for Individual FC metrics

Class	RRC			wRRC			mRRC			gPPI		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.55	0.55	0.55	0.56	0.53	0.54	0.54	0.54	0.54	0.54	0.53	0.54
1(STP)	0.54	0.53	0.53	0.54	0.56	0.55	0.53	0.53	0.53	0.53	0.53	0.53

Random Forest: Random Forest is created by a multitude of Decision Trees. The individual results of the Decision Trees are combined to give better accuracy. They are ensemble algorithms. In this study, 200 Decision Trees were used to build the Random

Forest. Bootstrap samples and Gini Criterion was used. Table 7 gives the performance measures for Random Forest trained using individual FC metrics.

Table 7. Performance measures of Random Forest for Individual FC metrics

Class	RRC			wRRC			mRRC			gPPI		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.59	0.55	0.57	0.60	0.57	0.58	0.59	0.55	0.57	0.57	0.55	0.56
1(STP)	0.57	0.60	0.58	0.58	0.60	0.59	0.57	0.61	0.59	0.56	0.58	0.57

Gradient Boosted Tree: Another ensemble algorithm of the Decision Tree is the GBT. In GBT, the combining of trees happens at the start and the trees are built one after another unlike in Random Forest where the trees are combined later. GBT was built using 200 trees with a learning rate of 0.3. Table 8 gives the performance measures of GBT with individual FC metrics.

Table 8. Performance measures of Gradient Boosted Tree for Individual FC metrics

Class	RRC			wRRC			mRRC			gPPI		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.59	0.55	0.57	0.60	0.57	0.58	0.59	0.55	0.57	0.57	0.55	0.56
1(STP)	0.57	0.60	0.58	0.58	0.60	0.59	0.57	0.61	0.59	0.56	0.58	0.57

4.2. Comparison of Accuracy for Individual Functional Connectivity metrics

The classification accuracy for all the five Machine Learning models was evaluated. The classification accuracy for a Machine Learning model gives the percentage of correct classifications made by the model. Table 9 gives the accuracy values for all the models. As can be seen, there is no one such metric that gives the best performance in all the models. Different metrics perform differently with each model. The best accuracy for Logistic Regression and SVM was obtained with RRC metric, Decision Tree, Random Forest, and GBT with wRRC metric. But when we compare the metric's performance over all the models, RRC does best with SVM, wRRC with Random Forest, mRRC with Random Forest & GBT, gPPI with SVM. The highest accuracy obtained is 59% for Random Forest Classifier with wRRC metric and SVM with RRC metric.

Table 9. Accuracy of Machine Learning Models for Individual FC metrics

FC metric	LR	SVM	DT	RF	GBT
RRC	0.56	0.59	0.54	0.58	0.57
wRRC	0.54	0.58	0.55	0.59	0.58
mRRC	0.52	0.54	0.54	0.58	0.58
gPPI	0.55	0.58	0.53	0.57	0.55

4.3. Comparison of Performance Measures for Combination of all Functional Connectivity metrics

The results obtained using individual FC metrics were not very encouraging. Hence, we used all the FC metrics together as features and trained the Models. Improvement in accuracy was seen in some of the Machine Learning models like Logistic Regression, Random Forest, and GBT. Random Forest and GBT performed best among the models with an accuracy of 62%. Table 10 gives the accuracy obtained for all the models. Table 11 and 12 gives the other performance measures of the classifiers.

Table10. Accuracy of Machine Learning Models for a Combination of all FC metrics

Machine Learning Model	Accuracy
Logistic Regression	0.58
Support Vector Machine	0.57
Decision Tree	0.55
Random Forest	0.62
Gradient Boosted Tree	0.62

Table 11. Performance measures of Logistic Regression and Support Vector Machine for Combination of all FC metrics

Class	Logistic Regression			Support Vector Machine		
	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.60	0.55	0.57	0.59	0.51	0.55
1(STP)	0.57	0.61	0.59	0.56	0.64	0.60

Table 12. Performance measures of Decision Tree, Random Forest and Gradient Boosted Tree for a Combination of all FC metrics

Class	Decision Tree			Random Forest			Gradient Boosted Tree		
	Pre	Rec	Fs	Pre	Rec	Fs	Pre	Rec	Fs
0(LTP	0.56	0.53	0.54	0.63	0.60	0.61	0.63	0.61	0.62
1(STP)	0.54	0.57	0.56	0.61	0.64	0.62	0.61	0.63	0.62

The ROC curve for all the five Machine Learning models when all the metrics were used as features is shown in Figure 1.

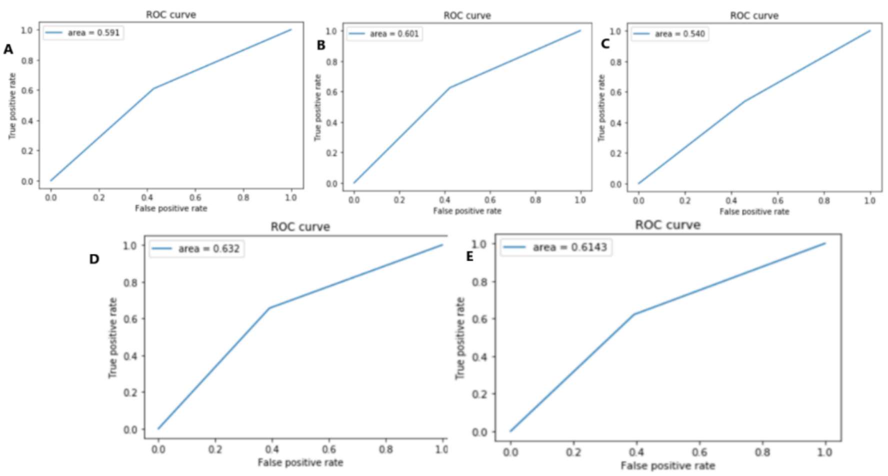

Figure 1. The ROC curve for the case where all the functional connectivity metrics were used as features for the classifier (A) Logistic Regression (B) Support Vector Machine (C) Decision Tree (D) Random Forest (E) Gradient Boosted Tree

5. CONCLUSION

In meditation-related studies, it is common to use rs-fMRI to conduct the functional activation and connectivity analysis. In this study, we used features derived from task-based fMRI to train Machine Learning Models so that they can distinguish between Long-term and Short-term Rajayoga Practitioners. The ensemble learning algorithms Random Forest and Gradient Boosted Tree performed well with an accuracy of 62% when all the four Functional Connectivity metrics namely RRC, mRRC, wRRC, and gPPI were used as features. The performance measures of these two classifiers were also best when compared to others. When individual features were used to train the models, the highest accuracy obtained was 59% for Random Forest Classifier with wRRC metric and SVM with RRC metric. Such a classification proves that there should be a difference in functional connectivity between the two groups of mediators that were effectively represented by the four FC metrics. As a further study, other measures of functional connectivity like Graph measures, Amplitude of Low Frequency Fluctuations (ALFF) can be used as features to train the classifiers. Similar studies can be carried out with other meditation techniques, to contribute to the study of well-being.

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