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Feature Extraction and Classification of Meditation EEG Signals



Abstract: - The Meditation EEG signals are at the focus of scientific investigations due to the manifold benefits associated with it. The EEG signal analysis is implemented using wavelet decomposition and feature extraction. The Daubechies 'db4' wavelet is used for 6 level decomposition to obtain EEG sub bands. The statistical feature extraction based on wavelet coefficients is implemented. The combination of data set with inclusion of normalized coefficient band power values, as well, statistical features of wavelet coefficients such as maximum, minimum, average value, standard deviation, entropy, etc. are obtained. The ensemble subspace KNN classifier has a training accuracy 86.7 %. The testing accuracy has been 71.87 % to distinguish a EEG signal of a meditator before and after meditation.

Keywords: Meditation, Feature Extraction, Wavelet

1. INTRODUCTION

The brain EEG rhythms are the representative of every physical and mental activity the human being undertakes. The EEG rhythms in different activity hence shall be disparate. The exhaustive study of brain waves has shown that the EEG signals of meditators are distinct from the control subjects[1]. Though the EEG signals can be inspected for abnormalities or anomalies during clinical diagnosis, large amount of data available may make it tedious to resolve or interpret. Computational methods may be devised which can act as important tools in data interpretation and analysis. The dimensionality of EEG data can be managed by extracting specific statistical features from the data. But the EEG signal being a non-stationary signal do not have a fixed probability distribution function governing its generation, and the statistics continually vary[2]. In this case the signal is divided into small quasi-stationary segments and statistical analysis can be applied to these segments[3]. In this regard, researchers have different feature extraction techniques for reliable estimation of the interpretation of brain rhythms. In [2]the kurtosis value, which is a representative of the peakedness of the signal and entropies, which represents randomness in the signal are computed and are found to be higher in non-meditators than in meditators. Also, the relative band energy (RBE) is maximum in delta band only in case of meditators whereas in other bands the RBE is less in comparison to non-meditators.

During Zen meditation, alpha rhythm was considered as a primary index. Alpha activity was more prominent in parietal region in right hemisphere, and beta activity was more prominent in prefrontal region during Qi-Gong meditation, than in No thinking states[4]. EEG spectral analysis revealed a generalized increase in beta and theta EEG power during meditation compared to control. Alpha EEG power was also increased during meditation compared to control in the right lateral and posterior locations[5], [6].

Many researchers have used wavelet transform for analysis of EEG signals as it does not need to get a fixed window. It provides a short window for high frequency components and a long window for low frequency components, hence can be used for time-varying signals[7]. Wavelet transform provides time and frequency information together, therefore is known as the time-frequency representation of the signal[8].The Discrete Wavelet Transform coefficients obtained through the wavelet decomposition of the EEG signal represents the degree of correlation between the analyzed signal and the wavelet function at

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different instances of time hence, DWT coefficients carry useful temporal information about the transient activity of the analyzed signal[9].

Discrete Wavelet Transform (DWT) is performed by repeated filtering of the input signal using two filters. The filters are a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into different scales. The output co-efficient gained by the low pass filter is the approximation coefficient. Among different wavelets, daubechies wavelet has been chosen as they have a maximal number of vanishing moments and hence can represent higher degree polynomial functions. Among different wavelets, daubechies wavelet has been chosen as it has maximal number of vanishing moments and can represent higher degree polynomial functions[10]. It is assumed that the EEG channels of the Frontal region are important in cognitive workload classification. In [11], the subset of the frontal channels achieved the highest classification accuracy of 84.3% using 23 channels, which are the number of channels in the frontal region. In the present work, discrete wavelet transform of meditation EEG signal is implemented to obtain wavelet coefficients using daubechies 'db4' wavelet. The feature extraction and classification is performed.

2. METHODOLOGY

In this research work, the EEG signal is obtained from 15 participants (07M+08F) in the age group 20-35 years, before and after the 10-days Vipassana meditation retreat. The EEG data is acquired from the participants seated in the chair in relaxed posture. The data is acquired using a 32-channel, ENOBIO-32 device. It has a sampling frequency of 500 samples per second and a data resolution of 24 bits. This EEG device has a bandwidth of 0-250 Hz and, employs dry electrodes neoprene head cap. The written informed consent is obtained from the participants prior to the experimentation. The research work is approved from the ethical committee of the institution.

2.1 Data Pre-processing: The acquired EEG signal is visually inspected for artefacts, and anomalies. The artifactual data is excluded completely from further analysis. The artefact free 07 seconds epoch is chosen for each participant. The power line frequency, 50 Hz is removed using the notch filter. The dc bias is removed, and each epoch is normalized so as to circumvent the differences in EEG magnitudes from different participants or from different electrodes. The pre-processing steps are implemented using EEGLab platform.

2.2 Wavelet decomposition: The pre-processed signal is imported to MATLAB for further processing. The zero-mean signal is decomposed using daubechies wavelet, 'db4'. The 06 level wavelet decomposition is implemented. The approximate coefficients are further divided into new approximate and detailed coefficients to obtain the EEG sub band signals, delta, theta, alpha, beta and gamma.

The DWT chooses subsets of scales (a) and positions (b) of mother wavelet $\varphi(t)$ based on powers of 2, known as dyadic scales and positions[12], such as

$$\{ a_j = 2^{-j}; \quad b_{j,k} = 2^{-j}k \}; \quad (j \text{ and } k \text{ are integers}). \quad (1)$$

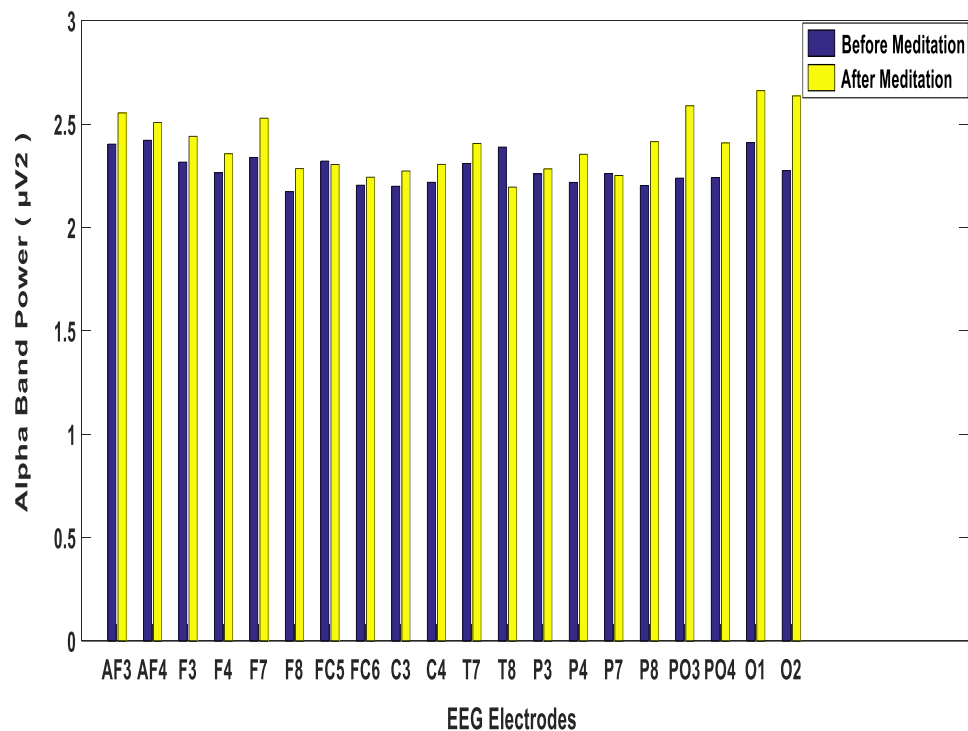
$$\varphi_{(a,b)}(t) = 2^{\frac{a}{2}} \varphi\left(2^{-\frac{a}{2}}(t - b)\right); \quad (2)$$

The equation shows that it is possible to build a wavelet for any function by dilating a function $\varphi(t)$ with a coefficient 2^j , and translating the resulting function on grid whose interval is proportional to 2^{-j} . The resulting 6 decomposition levels gives the EEG sub bands as shown in table(1).

Table1 : Wavelet Decomposition of EEG signals into sub bands

DWT (Decomposition Level)	Detail Coefficient (D) /Approximate Coefficient (A)	Frequency Band	EEG Sub band
1	D1	125 -250	High Frequency Noise
2	D2	62.5 - 125	High Frequency Noise
3	D3	31.25 – 62.5	Gamma (γ)
4	D4	15.625 – 31.25	Beta(β)
5	D5	7.8125 – 15.625	Alpha(α)
6	D6	3.90625 – 7.8125	Theta(θ)
6	A6	0 – 3.90625	Delta(δ)

The coefficient power in all the sub bands, and for each participant have been obtained before and after the Vipassana meditation retreat. The total power in each sub band have been obtained, as well, relative power in each sub band is computed. For estimation of the overall effect of the meditation retreat, a group average of all the participants is computed in alpha sub band power and beta sub band power, depicted in figure (1).

**Figure 1: Group Average : Alpha Band Power**

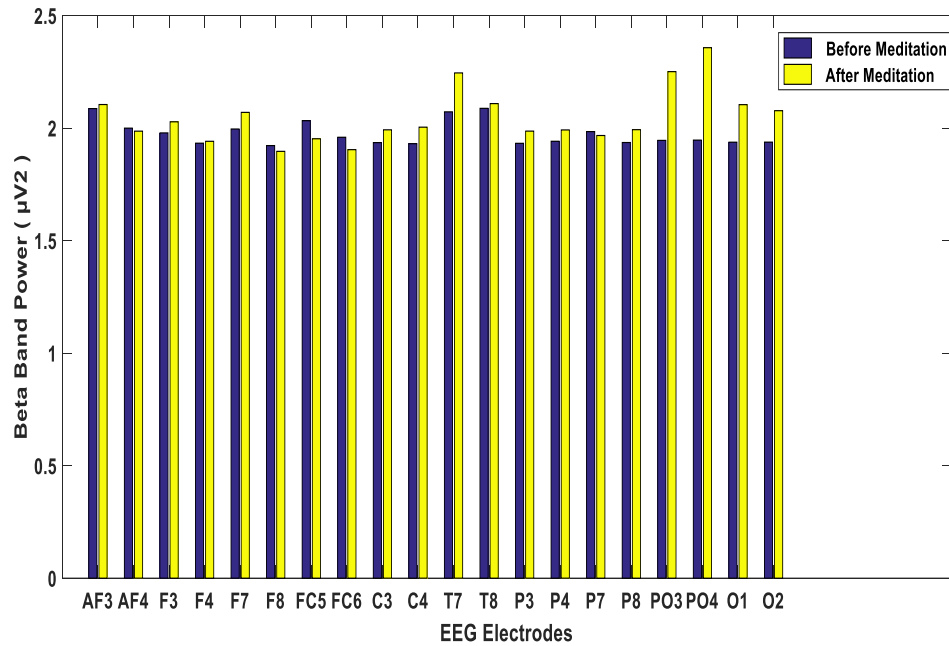


Figure 2 : Group Average : Beta Band Power

Though individually, there are wider variations in the amplitude changes in sub band power in different brain lobes, the average values shall signify trait effect. It can be observed that there is a generalized increase in the sub band power. The maximum increase is in alpha band in 17 electrodes, and in beta band in 15 electrodes as compared to other sub bands after the meditation retreat.

2.3 Cerebral Asymmetry: The cerebral asymmetry is a parameter computed in alpha, beta sub band is indicative of the positive affect, approach behaviour if the left-sided activation is higher, and an indicative of negative affect, withdrawal or avoidance behaviour if the right-sided activation is higher[13],[14].Cerebral asymmetry hence is a parameter of personality trait, computed at frontal lobe electrodes, such as (F3,F4), (F7,F8) [15].

Cerebral Asymmetry=(Left Power–Right power)/(Left Power+Right Power); (3)

It is observed that the Cerebral asymmetry increases in 42% participants at (F3,F4) electrodes and in 64 % participants at (F7,F8) electrodes, in alpha band. The cerebral asymmetry increases in 71% meditators at (F3,F4) electrodes and in 78 % meditators at (F7,F8) electrodes, in beta band. The average cerebral asymmetry for the group in alpha and beta band is observed as given in table (2).

Table 2 : Cerebral Asymmetry : Before and After Meditation

Cerebral Asymmetry (Average)	Electrode Pair (F3,F4)		Electrode Pair (F7,F8)	
EEG Sub band	Before	After	Before	After
Alpha	0.0596	0.0969	0.1882	0.2740
Beta	0.0525	0.0994	0.0845	0.1967

It is observed that the average asymmetry increases after the meditation, in alpha and beta bands indicating a rise in the positive affect, approach behaviour.

Table 3 : EEG Data Feature Extraction

S.No.	Feature Name	Representation
1	Delta Band power	$P = \frac{1}{N} \sum_{j=1}^N D_{ij} ^2 ;$ $i = 1, 2, \dots, 1 ;$
2	Theta Band power	
3	Alpha Band power	
4	Beta Band Power	
5	Gamma Band Power	
6	Delta Maximum	$\delta_{\max}$
7	Delta Minimum	$\delta_{\min}$
8	Theta Maximum	$\Theta_{\max}$
9	Theta Minimum	$\Theta_{\min}$
10	Alpha Maximum	$\alpha_{\max}$
11	Alpha Minimum	$\alpha_{\min}$
12	Beta Maximum	$\beta_{\max}$
13	Beta Minimum	$\beta_{\min}$
14	Gamma Maximum	$\gamma_{\max}$
15	Gamma Minimum	$\gamma_{\min}$
16	Delta Standard Deviation	$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \psi_i)^2} ;$ $i = 1, 2, \dots, 1 ;$
17	Theta Standard Deviation	
18	Alpha Standard Deviation	
19	Beta Standard Deviation	
20	Gamma Standard Deviation	
21	Delta Entropy	$EN = \sum_{j=1}^N D_{ij}^2 \log(D_{ij}^2) ;$ $i = 1, 2, \dots, 1 ;$
22	Theta Entropy	
23	Alpha Entropy	
24	Beta Entropy	
25	Gamma Entropy	

2.4 Arousal Ratio: The Beta waves are indicative of an alert state of mind, and alpha waves are dominant in relaxed state. Research has shown an association between alpha activity and brain inactivation, which also points out to the similar conclusion[16]. The beta/alpha power ratio hence can become an interesting indicator of the state of arousal of a person. As the prefrontal lobe plays a crucial role in conscious experience of an individual, the arousal ratio may be computed at frontal lobe electrodes. The arousal ratio is computed at various electrodes is shown in figure (3).

$$\text{Arousal Ratio} = \text{Beta Band Power} / \text{Alpha Band Power} \quad (4)$$

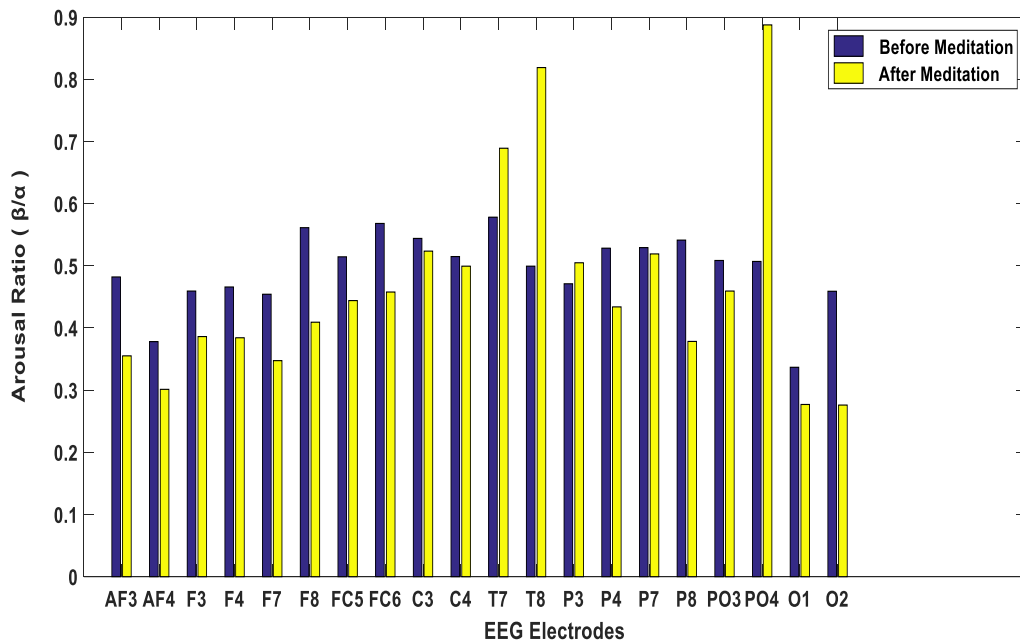


Figure 3 : Arousal Ratio (β/α) Band Power

It may be observed from figure (3) that the arousal ratio has reduced in all the frontal electrodes after meditation. This may be because a person has become more calm after the meditation retreat.

3. **Feature Extraction and Classification:** The feature extraction is implemented for all the EEG sub bands for each participant and before and after the meditation retreat. The objective of the feature extraction and classification paradigm is to distinguish a participant's EEG dataset before and after the meditation retreat. The outcome of feature extraction process is a set of feature vectors that represent the EEG data. The features are extracted for 20 EEG electrodes covering the whole scalp. A total of 25 features are extracted. A feature dataset matrix for training is formed. Following table (3) gives different features extracted from this data.

As a general practice, a randomly selected 90% of the data is used in the training phase; the remaining 10% of the data is used for testing. To ensure that the different feature variables are on similar scales, the z-score normalization is employed. For a feature variable X the z-score of data point is defined as:

$$z_i = (x_i - \mu_X) / \sigma_X. \quad (5)$$

The z- score normalization of all the features is implemented before inclusion for classification[11]. A balanced test data set has been prepared so as to have equal number of cases of each category. Hence, the number of cases of EEG features with EEG data before meditation are approximately equal to the no. of cases of EEG feature after the meditation, to avoid any bias in the dataset. A variety of feature inclusion/exclusion criteria have been adopted so as to obtain the better accuracy. All the features listed in table (3) are included.

3.1 K-NN Classifier: -Nearest Neighbor is a non-linear efficient classifier based on feature similarity. It consists of assigning a feature vector to a class according to its nearest neighbor. It finds the distances between a given sample and examples in the data by selecting the specified number of examples(k) closest to the given sample and assigns the most frequent label based on the minimum distance. It is a supervised classification method as it uses the class labels of the training data. An ensemble of models are employed with an individual model selecting a subset of features, while the total accuracy is the average of the individual models[17].

Following parameters are computed to evaluate the performance of the classifier :

$$\text{Sensitivity (TPR)} = \text{TP} / \text{TP} + \text{FN} \quad (6)$$

$$\text{Specificity (TNR)} = \text{TN} / \text{TN} + \text{FP} \quad (7)$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (8)$$

Amongst the number of classifiers which have been used for the training of the data set, the highest classification accuracy is obtained with the ensemble subspace KNN classifier as 86.7 %. The ensemble subspace KNN classifier has a training accuracy 86.7 % with five-fold cross-validation. The testing accuracy has been 76.92 % to distinguish an EEG signal before and after meditation.

The five-fold cross validation scheme is used. The Receiver Operating Characteristics (ROC) for the classifier is shown in figure (4)

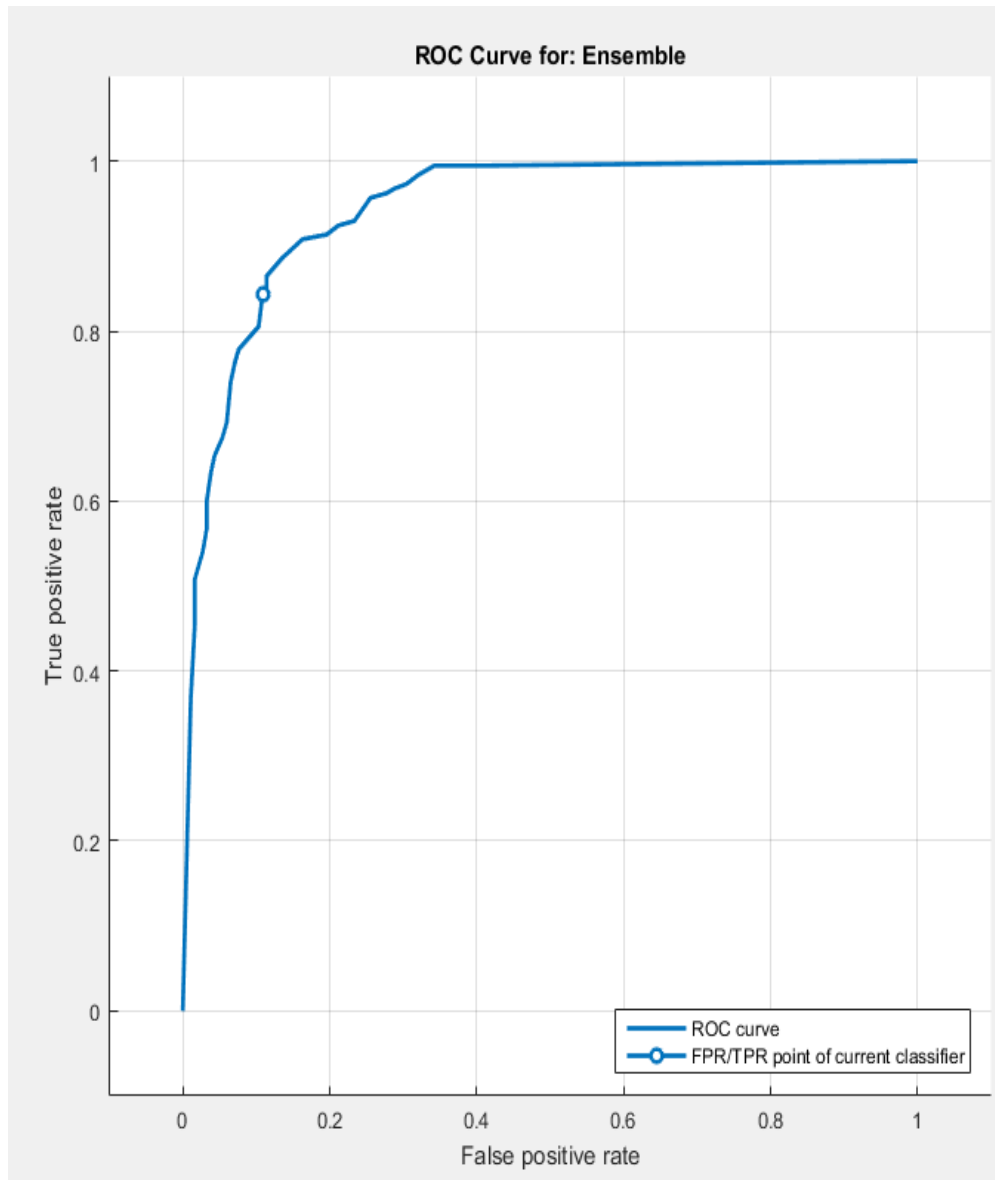


Figure 4 : Ensemble subspace KNN Classifier : ROC Curve

The part of the dataset has been used for the testing purpose. The highest classification accuracy with combination of before and after meditation EEG test dataset using the ensemble subspace KNN classifier

is obtained as 76.92 %. It is found that the accuracy of identifying the EEG dataset ‘after’ meditation has been always high, reaching up to 93.75 %.

Table 4 : Performance Parameters of Ensemble Subspace KNN Classifier

Performance Evaluation of Ensemble Subspace KNN classifier	Linear features obtained from wavelet decomposition
Sensitivity	93.75 %
Specificity	50 %
Accuracy	76.92 %

In future, the availability of larger dataset may help improve the accuracy, further.

The discrete wavelet transform of the EEG signals is implemented by decomposition upto 6 levels. The delta, theta, alpha, beta, and gamma sub band coefficient power have been obtained before and after the Vipassana meditation retreat. The total power, average power, relative power in each sub band is computed. For estimation of the overall effect of the meditation retreat, a group average of all the participants is computed in alpha and beta sub band power. For estimation of the overall effect of the meditation retreat, a group average of all the participants is computed in alpha sub band power and beta sub band power. It is clear from the above figure that the alpha and beta band power increases in almost all the electrodes after the meditation retreat. Greater levels of alpha power are found to be correlated with lower levels of anxiety and feelings of calm and positive effect[18]. Hence, increase in alpha power in these novice meditators is a trait effect, indicates relaxed state after the meditation retreat. The higher beta power indicates an alert state of mind[13]. The increase in beta power, hence, points out to an affirmative change after meditation.

The higher and lower value of asymmetry are indicative of approach and withdrawal behaviour respectively. The average cerebral asymmetry at EEG electrodes (F3,F4) and (F7,F8) is found to be increased after the meditation retreat.

It may be observed from figure (3) that the arousal ratio has reduced in all the frontal electrodes after meditation. The computation of arousal ratio is normally taken up for frontal electrodes[13]. The reduction in arousal ratio may indicate that the person has become more calm after the meditation retreat.

In order to distinguish an EEG signal before and after meditation feature extraction an classification of EEG dataset is implemented. The KNN classifier has been used for feature classification of meditation EEG signals[17].The ensemble sub space KNN classifier gives the highest training accuracy as 86.7 %. The classification of an EEG dataset before and after the meditation is obtained with an accuracy of 76.92 %.

The classification accuracy is possible to improve by inclusion of larger dataset.

4. **Conclusion:** The alpha and beta band power increases in almost all the electrodes after the meditation retreat. There is an enhancement in approach, positive affect after the meditation retreat. The arousal ratio is reduced may indicate the attainment of calmness. The trait effects of meditation have been established by distinguishing the EEG dataset before and after the meditation.

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