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Article

Hybrid EEG Data Analysis for Diagnosis of Stress–Related Neurological Disorder: SKY as an Alternative Therapy

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Abstract: There are many reasons associated with stress, long term stress induces neurological and psychosomatic disorders like hypertension, hypothyroidism, diabetes, anxiety and depression which affect the lifestyle of human beings. Consequently, behavioural activity and action gradually changein their surrounding environment and also perceived by others. In general, stressful respiration is relatively different from normal. To release stress and control all the neuropsychologicalhormones, multiple activities like playing games, watching a movie, listening to songs and music, etc. or intake of medicine/drugs such as (Allopathic/Homeopathic/Ayurvedic)are used. Medicines can provide easy stress evasion, but relief isonly temporary. Thus, yoga and Sudarshan kriya (SK) meditation is a unique and alternate therapy identified by Gurudev Sri Sri Ravi Shankar by Art of living. It would be a healthy way to get rid of stress in peoples' lives. Study of long–term effects of (SKY) Sudarshan kriya Yoga before and after and response of the brain regions in experienced (10–15 yrs) practitioners, mediocre (3–5 yrs) and novice (non–practitioners) isthe main objective of this work. This study is planned in three phases, the first phase is an experiment on SKY practitioners formore than 10–15 years, in which their (EEG) Electroencephalogram is recorded just after a session of meditation and the common portion of excitation amongst the three subjects is mined and analysed, to draw inferences. This inference would help us draw a conclusion about (BLOC) base level of consciousness considered as benchmark. In the second phase, comparison of benchmark data with the Mediocre (3–5 yrs) measurement and in third phase, benchmark versus Novice data, is done. Next is the phase of interpretation of the response in the form of EEG spectral waves as Type I 10 to 15 years SKY Practitioners (Superconscious), Type II SKYpractitioners 3 to 5 years (mediocre/semiconscious) and Type III Non–practitioners (Novice/Un–conscious). Theunconsciousness here means a state of complete unawareness of the self, though conscious of the external, physical world. Thus, power spectrum analysis (PSA) is carried out and frequency of each electrode is computed through segment analysis, Power Spectrum Density (PSD), Correlation coefficient, Mean and Standard Deviation, for finding the level of consciousness. The spectral waveform of these recordings is analysed programmatically using machine learning techniques (used Python Language run on the Jupyter notebook, Spyder, Google colab environment). Frequency analysis results are obtained by placing 21 electrodes (Fz,C2,P2,FP1,FP2,F3,F4,C3,C4,P3,P4,O1,O2,F7,F8,T3,T4,T5,BP4,EK G,T6) those are frequency measuring electrodes/channels placed on the frontal lobe, temporal lobe, parietal lobe and occipital lobe over skull and brainwaves alpha (α)[8–12 Hz], beta (β)[12–16 Hz], delta (δ)[0.5–4 Hz], theta (Θ)[4–8 Hz], gamma(γ)[16–32 Hz] are synthesized. The interpretation of these analyses suggests alternative therapeutic techniques, to improveboth mentally and psychologically and thus become socially acceptable.

Keywords: SKY; ND; ML; meditation; stress; LTP; BLOC

1. Introduction

There are many reasons associated with stress, long term stress induces neurological and psychosomatic disorders like hypertension, hypothyroidism, diabetes, anxiety and depression which affect the lifestyle of human beings. Consequently, behavioural activity and action gradually change in their surrounding environment and also perceived by others. In general, stressful respiration is relatively different from normal. To release stress and control all the neuropsychological hormones, multiple activities like playing games, watching a movie, listening to songs and music, etc. or intake of medicine/drugs such as (Allopathic/Homeopathic/Ayurvedic) are used. Medicines can provide easy stress evasion, but relief is only temporary. Thus, yoga and Sudarshan kriya(SK) meditation is a unique and alternatetherapy identified by Gurudev Sri Sri Ravi Shankar by Art ofliving. It would be a healthy way to get rid of stress inpeoples' lives. Study of long term effects of (SKY) Sudarshankriya Yoga before and after and response of the brain regionsin experienced (10–15 yrs) practitioners, mediocre (3–5 yrs) and novice(non–practitioners) is the main objective of this work. This study is planned in three phases, the first phase is an experiment on SKY practitioners for more than 10–15 years, in which their (EEG) Electroencephalogram is recordedjust after a session of meditation and the common portion of excitation amongst the three subjects is mined and analyzed, to draw inferences. This inference would help us draw a conclusion about (BLOC) base level of consciousnessconsidered as benchmark. In the second phase, comparison of benchmark data with the Mediocre (3–5 yrs) measurement andin third phase, benchmark versus Novice data, is done. Next isthe phase of interpretation of the response in the form of EEGspectral waves as Type I 10 to 15 years SKY Practitioners(Superconscious), Type II SKY practitioners 3 to 5 years (mediocre/semiconscious) and Type III Non–practitioners (Novice/Un–conscious). The unconsciousness here means astate of complete unawareness of the self, though conscious ofthe external, physical world. Thus, power spectrum analysis(PSA) is carried out and frequency of each electrode iscomputed through segment analysis, Power Spectrum Density(PSD), Correlation coefficient, Mean and Standard Deviation,for finding the level of consciousness. The spectral waveformof these recordings is analysed programmatically usingmachine learning techniques (used Python Language run onthe Jupyter notebook, Spyder, Google colab environment).Frequency analysis results are obtained by placing 21 electrodes (Fz,C2,P2,FP1,FP2,F3,F4,C3,C4,P3,P4,O1,O2,F7,F8,T3,T4,T5,BP4,EKG,T6) those are frequency measuring electrodes/channels placed on the frontal lobe, temporal lobe, parietal lobe and occipital lobe over skull and brainwaves alpha (α)[8–12 Hz], beta (β)[12–16 Hz], delta (δ)[0.5–4 Hz], theta (Θ)[4–8 Hz], gamma (γ)[16–32 Hz] are synthesized. The interpretation of these analyses suggests alternative therapeutic techniques, to improve both mentally and psychologically and thus become socially acceptable.

1.1. Stress

Now the human way of life of a day is fast–paced and busy that causes stress among people. Stress can be defined as a mental tension state when someone goes under pressure. In day–to–day life everybody experienced stress to some degree. It contributes directly to the imbalance of physiological (endocrine/exocrine) and psychological (neurochemical) hormones that affects mental and physical health, decreasingquality of life. It may lead to lifestyle illnesses like mental illness, aggressive behavior, shallow breathing, reduced immunity, insomnia, weight loss, hypertension, hypotension, insomnia, drowsiness, thyroidism, diabetes, etc.

1.2. Stress Management

There may be several techniques or methods which involves likes Stress release therapy through drugs by intake Allopathy, Homoeopathy and Ayurvedic or by means of activity and action such as engage activities that promote relaxation including sleep, watching movies, listening music,dancing, playing games etc. or doing Yoga and Meditation such as Patanjali Yoga/Shad darshan, Karma Yoga, Bhakti Yoga, Jnana Yoga, Austang Yoga, Mindfulness meditation, Brahmakumaris Raja Yoga Meditation, Sudarshan kriya yoga (SKY).

1.3. Brain Computer Interface (BCI)

The brain controls and coordinates all the activities and actions of the human body. The brain–computer interface (BCI) plays a vital role in the research field of brain functionality. BCI is a brain imaging technology to study the brain, including magneto encephalography (MEG), functionalmagnetic resonance imaging (fMRI), position emissiontomography (PET), and electroencephalography (EEG). Among all of that technology, we used EEG since it allows for the extraction of information with higher resolution and greater relevance. Non–stationary EEG signals are present. Each EEG signal is therefore divided into 1–second segmentscalled epochs, each of which contains 256 samples. Onefeature set was recovered for each epoch by joining 21 channels, with each channel representing a different frequency band delta(0.5–4 Hz), theta(4–7 Hz), alpha(8–12 Hz), beta(12–16 Hz), and gamma(16–30 Hz) The 21 channels consist of the following: Frontal channels [‘FP1’, ‘FP2’, ‘F7’, ‘F3’, ‘Fz’, ‘F4’, ‘F8’], Central channels [‘C3’, ‘Cz’, ‘C4’], Temporal channels [‘T3’, ‘T4’, ‘T5’, ‘T6’], Parietal channels ['P3',‘Pz’,‘P4’], Occipital channel[‘O1’, ‘O2’], and Ear lobe [‘A1’, ‘A2’].

2. Related Works

The authors were observed Standard mean difference for the effect of SKY on depression was 0.02[– 0.02,0.24] in 6 studies having with 388 subjects whereas anxiety was – 0.5[– 0.63,0.52] based on the 5 studies with 428 subjects. There was also high heterogeneity observed for anxiety (l2=97%, p< 0.001) and depression (l2=93%,p<0.001)and suggested evaluate the short and medium term impact of SKY with larger samples for future studies [1].

In the United States, opioid use disorder (OUD) such as depression, anxiety is widely prevalent, and there are high levels of comorbidity between OUD and mental illnesses, Total 8 participants with opioid use disorder (OUD) received Sudarshan Kriya Yoga (SKY) alongside standard treatment. 87.5% completed SKY. Significant reductions in substance cravings (p = 0.04) and depression (p = 0.01) were observed compared to baseline. SKY, a breathing– based mind– body intervention, shows promise in addressing both physical and psychological aspects of OUD, suggesting potential for larger trials to validate its efficacy [2].

The authors analyzed EEG signals intervention of 25 subjects and infer the cognitive effects human brain for meditation proposed statistical, spectral, coherence and time frequency analysis and (SVM)Support Vector Machine, (KNN)k– Nearest Neighbors,(ANN)Artificial Neural Network classifier is used to comparethe accuracy and distinguish the subjects. SVM gives the better accuracy rather than ANN and KNN. It has been observed that the theta power is increased 88% of subjects where as alpha power is increased in post meditation and the coherence observed that pre– frontal channel pair is more in the meditators than in the control group [3].

Their pilot studied interpret the brain waves of post– COVID patients before and after SKY. Approximately two month after COVID– 19 patient enrolled in SKY programme and all subjects are conducted PCR test which was negative. Each examination ofone subject lasted about 15 mins and considered of two stage.First recording brain waves lasted 3 mins with eye closed. Second with eye open for 3 mins. Rest of the time wasconducted for calibration. The QEEG carried out first day before SKY, second After SKY[after the second long SKY i.e., the third(last)day of the course].It has shown changes in the result with less number of subjects and suggested for further research scope larger group of people. The EEG signal was quantitatively transformed with the Elmiko DigiTrack software (version 14, PL ELMIKO, Warsaw, poland). The study were conducteddelta, alpha, beta1, beta2 waves on the Fz, Cz, C3, C4, P3, P4, F3 and F4 electrodes. As a result the value of $p < 0.05$ indicated statistically significant and the amplitudes at Fz, Cz, C3, C4, P3, F3 and F4 increases significantly afterrelaxation [4].

Typical researcher developed machine learning model for three level classification (low stress [labels 1 and 2], medium stress [labels 3 and 4] and high stress[label5]) and feature extraction from ECG or EEG signals. Here the authors were explored two–fold, one for examine the EEG– PSD smoothing three level stress classification and two, to evaluate the practical viability of a two–level stress detector and found classification performance is directly to smoothing intensity (F1–score 0.61–0.94). Thus, combined (SPSL)Self perceived stress level survey reported into two classes, no stress [labels 1, 2 and 3] and stress [labels 4 and 5]. In SPSL survey, adapted perceived stress scale (PSS) to minimize the time required to answer. For that used stress level scale 1 to 5, 1 is for minimum and 5 for maximum. MIST (Montreal imaging stress task) designed to induce psychosocial stress is used for experimental purpose. MATLAB is used for implementation [5].

The authors were evaluated the degree of anxiety and stress brain network activated in high beta oscillation (22–30 Hz), during a resting, EC (Eye closed) basal condition of EEG 14 channels recording. Data collected from subjects total of 3 minutes of EC basal condition and Beta band frequency filtered and pre– processed by visual inspection using EEGLAB toolbox on MatLab2008AFrequency domain and correlation analysis were performed over EEG dataset with the mastoid system. Discussed characteristic transition differentiating between low beta and high beta waves, it is described a dynamic marker associated with a normal, moderately, activated, healthy oscillation network low beta at (13–21 Hz) vs a stressful, poorly–attentional, anxiety–related, and energy– consuming, high beta (22–30 Hz) activated network [6].

The authors look out the usefulness of the prefrontal relative gamma power (RG) for stress assessment. For the experimental analysis, EEG signal recorded six healthy subjects performed the Montreal Imaging Stress (MIST) at 540 Hz with the Miniature Data AcquisitionSystem. The MIST wasimplemented using MatLab (The Math Works, Inc., Natick, Massachusetts, USA) graphical user interface (GUI). Experiment was conducted first 3 mins corresponds training for MIST. After that 6 mins MIST test is performed. Then relaxation for last 10 mins. Based on that grey line indicates expected stress and found three level of stress (SL1, SL2, SL3) w.r.t period. In addition to that, Pearson's linear correlation coefficient was computed [7].

The authors were proposed a model for realtime detection system of stress level. They were provided experiment's information sheet and informed consent which were approved by the Bioethics Committee of the University,Granada. The total duration was around 30 mins, including (MVC) Maximum voluntary contraction, (RS) Resting state block and (MIST) Montreal imaging stress task. Thegrand– average across participants of the time evolution processed stress markers in the regions of interest i.e., set of values RG, HR, TA and SC was computed and 86% accuracyand suggested this model could have a relevant impact on people's lives. It can be used to prevent stress in many situation [8].

The authors exposed brain network state in stress. Applied Compensation Distance Evaluation Technique (CDET) for select the sensitive optimal features from EEG dataset. Then Multiclass (SVM) Support Vector Machine was trained to classify the brain network. As a result,SVM model showed that the features based on the original EEG, α and β better performance. For the brain networkmeasurement, transitivity, modularity, characteristic path length and global efficiency have been calculated [9].

The authors were explored that Sudarshankriya Yoga (SKY) is one which peoples can get relax or stress less life. The obtained result has been validated by statistical test like Kruskal– wallis. Further, (ANN) Artificial Neural Network has been applied to classify subjects as meditators and non– meditators. This proposed method achieved 87.2% accuracy for classification and suggested a construct better accuracy system for detection of meditates and non– meditators [10].

The authors were proposed real time EEG based systemfor mental stress detection (MSD)model using machinelearning (ML) techniques to prevent illness and health problem. The MSD system consisted of four phases. In phase1– Feature set 3 is formed by fusing feature set1 and 2. In phase2– the select the appropriate electrode location for determine higher influence on stress detection rate. In phase3– investigatethe optimal number of principal components to reduce the dimension of the feature space. In case of phase4, examine theimpact of each frontal electrode in order to build a portable MSD system. By this process, it was achieved 99.9% (sd=0.015) and 99.2%(sd=0.08) accuracy for identifying stress and non– stress states [11].

The effect of music tracks in English and Urdu language on human stress level using brain signals is examined in this study. Twenty– seven subjects, including 14 males and 13 females having Urdu as their first language, with ages ranging from 20 to 35 years, voluntarily participated in the study. Five groups of features including absolute power, relative power, coherence, phase lag, and amplitude asymmetry were extracted from the preprocessed EEG signals of four channels and five bands, which were utilized by the classifier for stress classification. Four classifier algorithms, namely sequential minimal optimization, stochastic decent gradient, logistic regression (LR), and multilayer perceptron, were employed to classify the subject's stress level into two and three classes. It was observed that LR performed well in identifying stress, with the highest reported accuracy of 98.76% and 95.06% for two– and three– level classification, respectively. For understanding gender, language, and genre– related discriminations in stress, a t– test and one– way analysis of variance were used. It was evident from the results that English music tracks had more influence on stress level reduction compared to Urdu music tracks [12].

In today's fast– paced life, stress is reported among people at such levels that it may lead to various psychological and physical illnesses. Yoga and meditation are regarded as the best strategies to reduce the effects of stress on the physical and mental levels without any side– effects. In this study, combined yoga and Sudarshan Kriya (SK) have been utilized as alternative and complementary therapy for stress management. The aim of the study is to find a method to classify the states of meditator and non– meditator with the best accuracy. Fifty subjects participated in this study and were divided into two groups, namely the study and control groups. Subjects with regular practice of Yoga and SK were designated as meditators, while those without any practice of yoga and meditation were labeled as non– meditators. Electroencephalogram (EEG) signals were acquired from both groups before and after 3 months. Statistical parameters were computed from these acquired EEG signals using Discrete Wavelet Transform (DWT). These extracted statistical parameters were used as input for the classifiers. The classifiers including decision tree, discriminant analysis, logistic regression, Support Vector Machine (SVM), Weighted K– Nearest Neighbor (KNN), and ensemble classifiers were employed for the classification of meditator and non– meditator states from the acquired EEG signals. The results have shown that the SVM method yields the highest classification accuracy compared to other classifiers. The proposed method can be utilized as a diagnostic system in clinical practices [13].

Stress, recognized as one of the most significant health problems in the 21st century, necessitates attention due to the costs associated with primary and secondary cares for stress– related psychological and psychiatric issues. In this study, brain network states exposed to stress were monitored through electroencephalography (EEG) measures extracted via complex network analysis. Twenty– three healthy male participants aged 18–28 was subjected to a stress test. EEG data and salivary cortisol levels were recorded for three different conditions: before, immediately after, and 20 minutes after exposure to stress. Synchronization likelihood (SL) was calculated for the EEG data to construct complex networks, which are scale– reduced datasets acquired from multi– channel signals. These networks, with weighted connectivity matrices, were constructed based on the original EEG data and also by utilizing four different waves of the recorded signals: δ, θ, α, and β. Additionally, networks with binary connectivity matrices were derived using a threshold T. For each constructed network, four measures including transitivity, modularity, characteristic path length, and global efficiency were calculated. The compensation distance evaluation technique (CDET) was applied to select the sensitive optimal features from the set of calculated measures. Finally, multi– class support vector machine (SVM) models were trained to classify the brain network states. The results of testing the SVM models indicated that features based on the original EEG, α, and β waves exhibited better performances in monitoring the brain network states [14].

3. Data Acquisition and Processing

All the subjects were seated comfortably in a relaxed state in aarm chair within a air conditioned room. All the participants were consumed normal diet while performing EEG. The EEGexperiment were conducted afternoon session as per the guidelines of the Institutional ethics committee of Jadavpur University.EEG signals were acquired from three long term practitioners (10–15 yrs SKY practitioners), one Mediocre (3–5 yrs SKY practitioners) and one Novice (Non–SKY practitioner) using recoders medicare International 10/20 system consisting of 21 electrodes (Silver chloride sintered ring electrodes). The EEG recording system was operated at 256 samples customized RMS software. The brain waves were filtered using low pass and high pass filtered with cut–offfrequencies 0.5–32 Hz. The electrical inference noise (50 HZ) was eliminated using notch filter and artifacts were removed through EMG filter. After initialization, total 25 min period of recording was started for long term, mediocre and novice. First 5 min control (Pre–SKY meditation), second 15 min (SKY meditation). In this state, all 3 subjects were followed three steps. i.e., Ujjayi, Bhastrika and Om chant. Theprocess involved during Ujjayi, the slow 2 to 4 breaths/min increase airways resistance while inspiration where as inBhastrika, air is rapidly inhaled and forcefully exhaled at the rate of 30 breath/min. After that Om is chanted three times with very prolonged expiration and this cyclic motion iscontinued for slow ,medium and faster way. Finally 5 min rest (Post–SKY meditation). The following protocols wasobserved for the five subjects such as 3 subjects [1, 2 and 3] are the long term practitioners, one subject is mediocre and one subject is novice. The EEG of 25 min was acquired from thesefour subjects (3 long term practitioners (LTP) and 1 mediocre) and 15 min from novice from one subject. The following Table 1 as given below,

Table 1. Subject Information (LTPs, Mediocres and Novices).

Session	Subject [LTPs, Mediocre, Novices]	Time [12 Hr]
1	Pre–Meditation	00:00:30–00:05:00
2	In–Meditation	00:05:10–00:20:00
3	Post–Meditation	00:20:30–00:25:00

This study involves an EEG experiment to analyze brain wave patterns during SKY meditation practices among three groups: long–term practitioners (10–15 years), mediocre practitioners (3–5 years), and a novice. The experiment was conducted in an air–conditioned room following the ethical guidelines of Jadavpur University. EEG signals were acquired from 60 subjects using a 21–electrode system and were recorded at a sampling rate of 256 samples per second, filtered to remove noise and artifacts. Each session lasted 25 minutes for practitioners and 15 minutes for the novice, divided into pre–meditation, in–meditation, and post–meditation periods.

During the in–meditation phase, subjects followed three steps: Ujjayi breathing, Bhastrika breathing, and Om chanting. The EEG data was filtered and analyzed to extract brain waves in different frequency ranges (delta, theta, alpha and beta) using wavelet transform and machine learning techniques. The power spectral density (PSD) of these frequencies was calculated, particularly focusing on the frontal and occipital electrodes, to evaluate cognitive processing.

The following flowchart shows the steps taken in this present work to perform theanalysis (Figure 1).

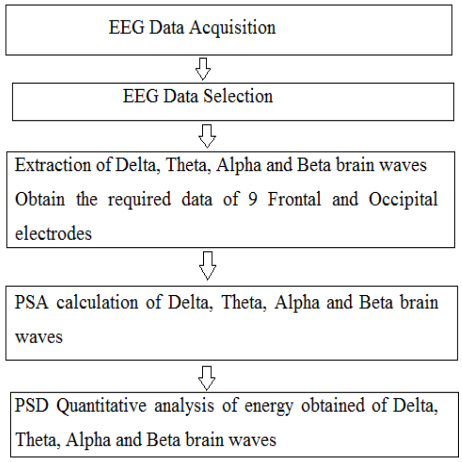


Figure 1. EEG signal steps.

4. Contributory Work

By applying the machine learning techniques (ML) usingpython running in Google CoLab, Spyder and Jupyter notebook environment, we synthesized the datasets subjectslikes experienced, mediocre, novice SKY. Importing the pandas, numpy, scipy, mne, libraries to read the .csv files and exploratory analysis (EDA) is obtained for EEG time series signal. In EDA, framing and filtering are included. As a result, differential analysis and superimposition is an experimental work has been carried out of (Base Level of Consciousness) BLOC vs. Mediocre and BLOC vs. Novice over 21 electrodes placed at occipital, temporal, frontal, parietal lobes. In order to calculate the PSD and variance of delta, theta, alpha, beta and gamma waveforms, the *t*–test, *p*–value, mean, median, standard deviation will be calculated.To achieve the property of BLOC, we divided whole 15 min periods of meditative state into 9 segments in eachexperienced 10–15 yrs subjects and comparison bring out optimal phase which referred as BLOC. Libraries in python like Matplotlib and Seaborn is imported for showcase gaps among them.

EEG of novices (00:00:30–00:15:00) 15 min has beenrecorded. All the study subjects were free from psychiatricillness, neurological illness, high blood pressure, diabetesmellitus, tuberculosis, lungs infection, bronchial asthma andchronic medication. The brain waves have been extracted indifferent frequency range delta (0.5–4 Hz), theta(4–8 Hz), alpha(8–12 Hz), beta(12–16 Hz) and gamma(16–32 Hz) using wavelet transform machine learningtechniques. The amplitude envelope of different frequency rhythm were obtained for pre, mid and post session. A number of studies validated the importance of frontal and occipitalelectrodes in case of cognitive processing. So we havechosen to study the variation of scaling exponent corresponding to various frequency rhythms and PSD of 7 frontal electrodes [‘FP1’, ‘FP2’, ‘F7’, ‘F3’, ‘Fz’, ‘F4’, ‘F8’] and 2 occipital electrodes [‘O1’, ‘O2’] also all 21 electrodes offrontal, occipital, temporal and parietal is computed whilelistening to meditation. Therefore eliminate all thefrequencies outside the range of interest, data was band passfiltered with 0.5–32 Hz FIR filter. Though it is a time seriesdata, we performed the Fast Fourier transform (FFT) using fft method. A continuous frequency band from f_{low} to f_{up} is sliced into k bins, which can be equal width or not. The bins usedsuch as α *bin* (8–12 Hz), β *bin*(12–16 Hz), δ *bin*(0.5–4 Hz), Θ *bin*(4–8 Hz), γ *bin*(16–32 Hz). The PSD of K^{th} binis evaluated and the alpha and theta power values are computed. Theaverage power corresponding to each experimental condition was computed for all frontal and occipital. The following flow chart shows the steps taken in this present work to perform the analysis.

5. Result and Graph Analysis

Importing of three subjects long term SKY practitioner EEG meditative period (Session 2) datasets using pd.read_csv method and storing them into twenty different variables as eeg_data1, eeg_data2, eeg_data3 respectively. In order to achieve the Base level consciousness(BLOC), we installed anenhanced Interactive Python tools version 3.9.13 [MSCv.1916 64 bit (AMD64)], IPython 7.31.1, MNE–Python run with Spyder v–5.2.2, IDLE Shell v–3.10.2, Jupyter Notebook v–6.4.12, Google Colab Notebook and hardware specification: Processor–Intel(R) Core(TM) i5–8250U CPU @ 1.60GHz 1.80GHz,RAM–8.00 GB, System type–64–bit OS, x64–based processor. Creating MNE info objectsfor each dataset using mne.create_info function, specifying the channel names FZ1, FZ2, F7, F3, F4..., sampling rate and channel types. After that RawArray object are created for each dataset using MNE RawArrayclass, passing the EEG data and corresponding info objects (raw1, raw2, raw3) using mne.io.RawArrayby passing the transpose of EEG data and the corresponding info objects. After that segment analysis bring out for BLOC after convolution of 3 EEG data files. Splitting 15 min recorded signal of each EEG dataset into 9 segments over 9 electrodes using np.array_split and storingthem into eeg_segments1, eeg_segments2 and eeg_segments3 respectively. Figure 2 is visualized the Segments7 will be effectiveness as an experimental analysis. PSD is calculated to compare BLOC with Mediocre and Novice. We found that the long–term practitioners describe more cognitive rather than mediocre but not in novice. Figure 3 is calculated PSD pre, mid and post SKY meditation over 20 subjects splitting into 9 segments to achieved base level referred to bench mark. In Figure 4, Power Spectrum Density (PSD) is calculated and comparison is done with a bench mark data vs no voice of 15 minutes recorder signals brain waves during the mediation. In Figure 5, PSD comparison is done the subject1, subject2 & subject3 are the SKY trainers and Medicores are having 3–5 years' experience and no SKY meditation experienced belongs to novices.

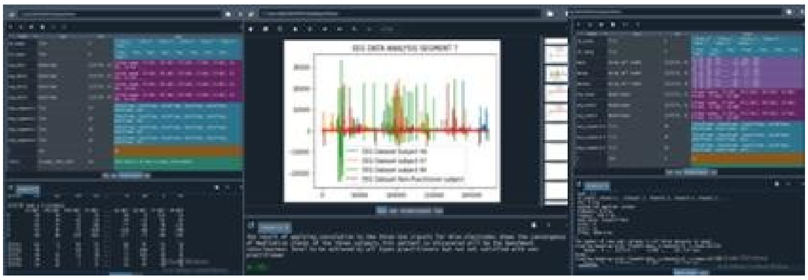


Figure 2. Segment 7 achieved high degree of BLOC.

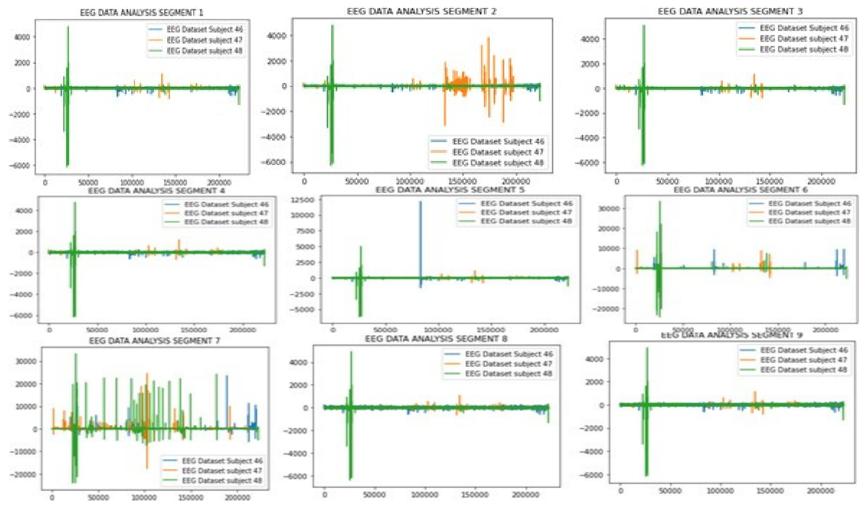


Figure 3. PSD of combining 20 subjects EEG datasets splitting to 9 segments for achieve SKY BLOC.

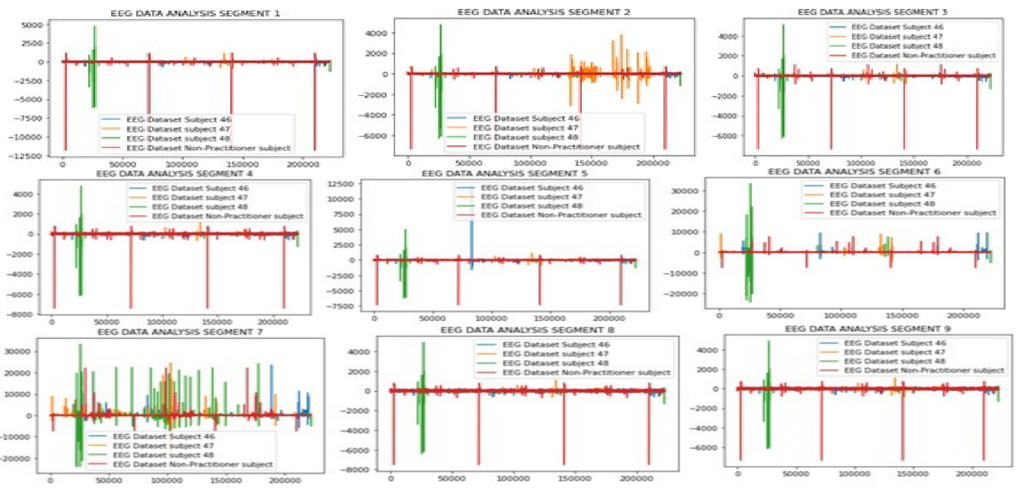


Figure 4. PSD of 9 segments, 10–15 yrs LTP–SKY vs. Novice total 15 min meditation.

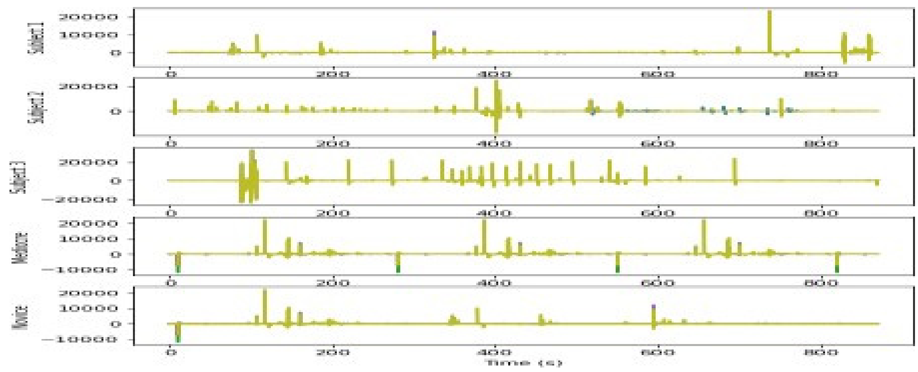
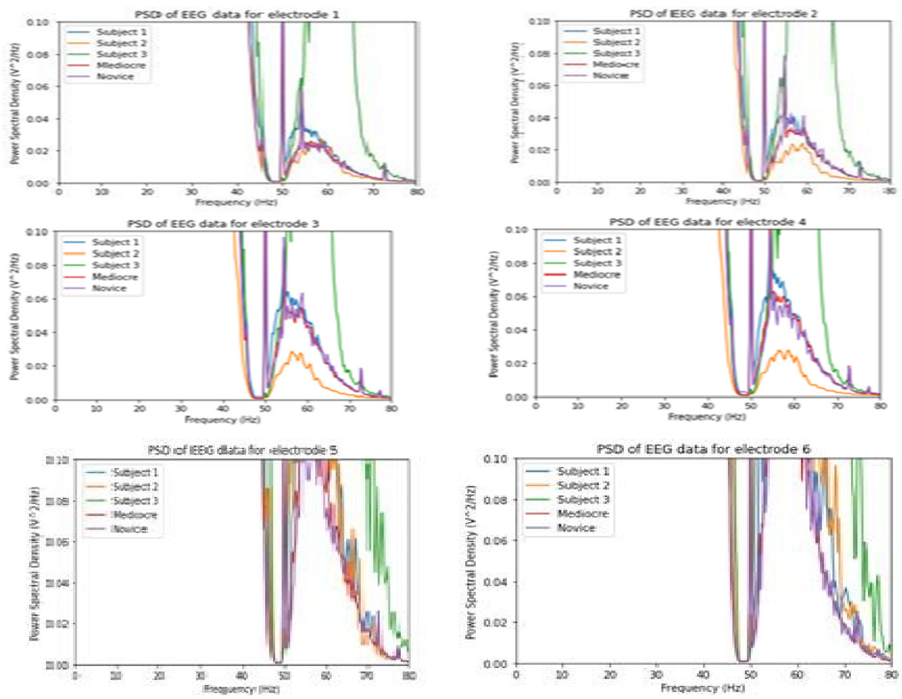


Figure 5. Comparisons of EEG signals (LTPs,Mediocres and Novices).

Now we calculated PSD of the EEG signals across different datasets (10–15 yrs experienced of 3 subject, mediocre and novice)electrodes and provided a visual representation of thedistribution of power at different frequency ranges, allowingfor comparisons between subjects and groups(mediocre and novice). Hence we import necessary libraries including pandas, numpy, matplotlib, seaborn and scipy.signal for (PSD) power spectrum density. The EEG signal are extractedfrom the loaded data by selecting the appropriate column using the .iloc attribute. The extracted data is stored in different variables eeg1, eeg2, eeg3, eeg4, eeg5 respectively. The sampling frequency fs is defined, that is 250 Hz in this case. A time vector t is also defined using the number of samples and the sampling frequency. The frequency range for the PSD calculation is define using the signal.Welch() function fromscipy library. The PSD calculation is performed for each electrode in the EEG data, using a window length of 1024 samples (nperseg = 1024). The PSD values and corresponding frequencies are stored in Pxx1, Pxx2, Pxx3, Pxx4, Pxx5 and ‘f ', respectively. The code then proceeds to plot the PSD of each electrode in separate figures. A loop is used to iterate over the electrodes. Inside the loop , the Plt.plot()function is used to plot the PSD valuesfor each subject or the dataset. The plt.title(), plt.x–label(), plt.y–label(), plt.xlim() functios are used to set the appropriate labels and limits for each plot. The plt.legend() function is used to add a legend to distinguish betweendifferent subjects. Finally, the plt.show()function is called todisplay all the plots (Figure 6).



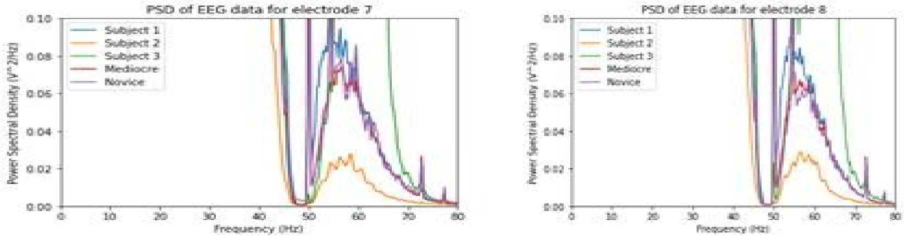
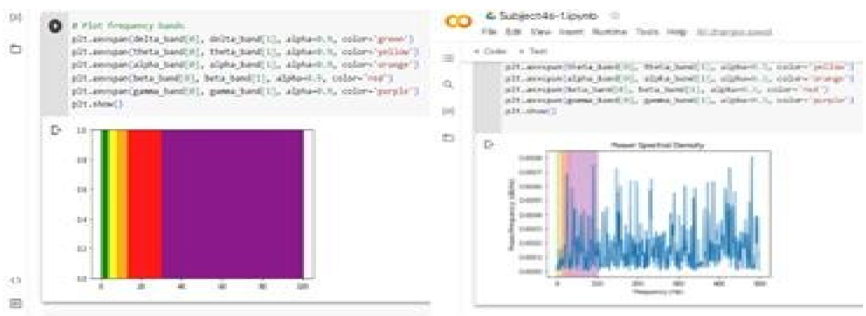


Figure 6. PSD of each electrode (Frontal/Occipital) of 10–15 yrs LTP SKY subjects, 3–5 yrs. Mediocre and Novice.

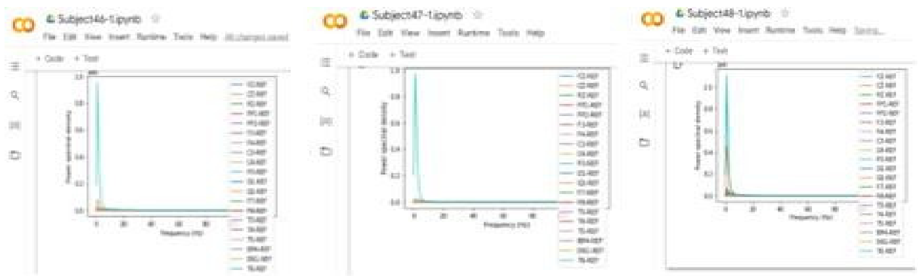
Now the Power spectral density (PSD) is calculated using theWelch method from SciPy's signal module. The PSD is then used to calculate the power in each frequency band using the trapezoidal rule from NumPy's trapz function. Finally, the frequency with the maximum power is determined using NumPy's argmax function. plt.axvspan() function is used to create shaded rectangles that represent each frequency band ofinterest. there are five frequency bands specified: delta, theta,alpha, beta, and gamma. For each band, a rectangle is plottedusing the plt.axvspan() function with the appropriate lower and upper frequency bounds for that band.The alphaparameter specifies the opacity of the rectangle, with a value of 0.9 meaning the rectangle is 90% transparent. The color parameter specifies the color of the rectangle, with green for delta, yellow for theta, orange for alpha, red for beta, and purple for gamma.Finally, the plt.show() function is used to display the PSD plot with the shaded rectangles indicating thefrequency bands of interest. This helps to visually identify the power within each frequency band for each electrode.These lines of code plot shaded rectangles over the frequency bandsfor each electrode's power spectral density plot. The plt.axvspan() function is used to create these rectangles, withthe x–limits of the rectangle specified by the lower and upper bounds of each frequency band. For example, plt.axvspan(delta_band[0], delta_band[1], alpha = 0.3, color = 'green') creates a shaded rectangle for the delta frequency band (0.5–4 Hz) with an opacity of 0.3 (i.e., 30% transparent) and a green color. Similarly, plt.axvspan (alpha_band[0], alpha_band[1], alpha = 0.3, color = 'orange') creates a shaded rectangle for the alpha frequency band (8–13 Hz) with an opacity of 0.3 and an orange color. These rectangles make it easier to visuallyidentify the power within each frequency band for each electrode.

In the above (Figure 7), EEG data for each electrode is extracted into numpyarrary using eeg_data.iloc[: ,1 :].values.T. which was selecting all the rows. The sampling frequency f_s and window length(win_len) are set to 1 second,which corresponds to 1 *f_s and loop is calculated PSD (Pxx) for each electrode using signal.welch() function and nperseg is set to win_leg to define window length and stored in psd. Finally, itis converted numpy array using np.array(psd). It shown x–axis frequency (f) and y–axis PSD of each eletrode (psd.T) of 3 experienced SKY practitioner (Figure 8).



(**a**) (**b**)

Figure 7. (**a**) Color rectangle frequency band green representdelta, yellow for theta, orange for alpha, red for beta and purple for gamma. (**b**) The alpha parameterspecifies the opacity of the rectangle, with a value of 0.9 meaning the rectangle is 90% transparent.

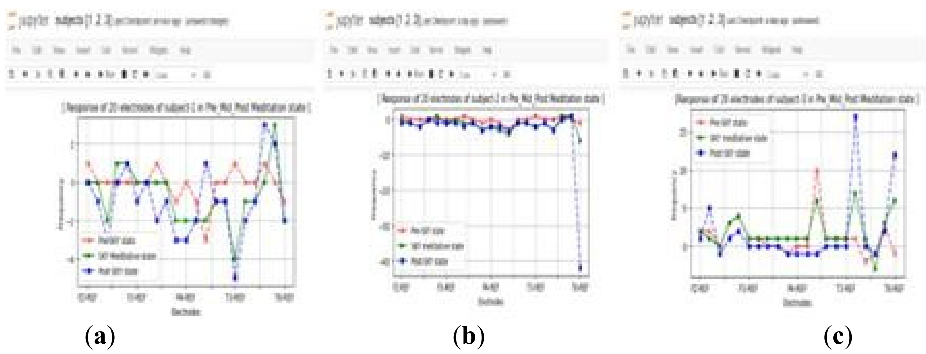


(**a**) (**b**) (**c**)

Figure 8. (**a**–**c**) PSD of subjects LTP SKY practitioner over 19 electrodes placed in frontal, occipital, parietal and temporal channels.

To find the correlation, behavior or cognitive measure has been determined the relationship or association between different EEG signals or channels. It helps to measure the electrical activity, identity pattern, connectivity or synchronization between different brain regions or specific frequency bands. Correlations between EEG features and reaction times, accuracy rates or other performance measurescan provide insights into the neural processes underlying thespecific cognitive tasks. This analysis can reveal brain responses that are time–locked to represent the stimuli, helping to understand how the brain processes and responds to external events. We observed and draw a conclusion that how each electrode was associated among different EEG brain waves and records the voltage fluctuation over time. Electrodes were placed in frontal, temporal, occipital and parietal different positioning vectors. Graph shown the correlation of Pre meditation, meditation and post meditationstate over all twenty long term practitioners. For Statistical analysis we have drawn differential analysis by calculatig mean,median, standard deviation,t–statistics and p–value for the datasets. So we import the necessary libraries scipy.stats,numpy and matplotlib.pyplot and load EEG datasets from .csv files using pd.read_csv function and assigned eeg_data1,eeg_data2, eeg_data3, eeg_data4 and eeg_data_new. Calculating the mean of each dataset using the np.meanfunction assigned the variable mean1(subject1), mean2(subject2), mean3(subject3), mean4(mediocre) and mean_new(novice).Then calculated averaging the means and assigned to mean_all. Calculated the standard deviation of allthree datasets using np.std function and thatassigned to std_all. The calculation takes into account the size of each dataset. The t–statistic and p–value using the formulas for an independent samples t–test. The t–statistic measures the differenece between the mean of the new dataset(mean_new)and the mean of all three dataset (meal all) in relation to the variability within the datasets. The *p*–value represents the probability of obtaining a t–statistic as extreme as the observed value, assuming the nullhypothesis(no difference between the mean) is true.plt.plot, plt.show and legend function used to diffrentiate between the datasets.

Calculate the Pre meditative, meditative and post meditative central tendency of the 20 subjects long term partitioners at different time point in different location on the brain (Figure 9).



(**a**) (**b**) (**c**)

Figure 9. (**a**–**c**) Insight into the central tendency of the EEGbrain waves at different time point in location on the brain (Twenty subjects with long term SKY practitioners) Prestate, mid–state and post state.

Comparison is done SKY trainers knowns as LTP, 10–15 years partitioners versus mediocres. X–axis represents all the 7 frontal and 2 occipital electrodes and the y–axis represents frequency amplitude. Also, comparison with 10–15 years SKY partitioners versus novices. Finally differential analysis is carried out 10–15 years partitioners with mediocre versus 10–15 years partitioners with novices. The statistical analysis *t*–test and *p*–value will be calculated for validation (Figure 10).

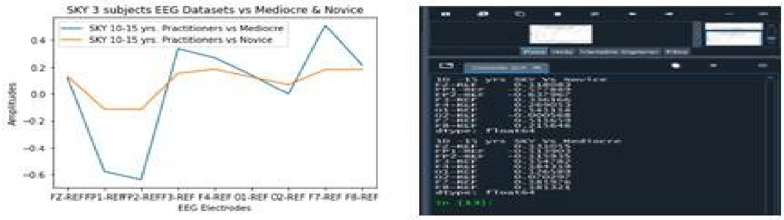


Figure 10. Comparisons and output of 10–15 years SKY practitioners vs mediocre and 10–15 years SKY practitioners vs Novices, *t*–test and *p*–value.

Differential analysis is obtained by comparison 10–15 years partitioners versus mediocre versus novices and t–statistical test and P–value is calculated. X–axis represent denoted all electrodes and the Y–axis represent the amplitude (Figure 11).

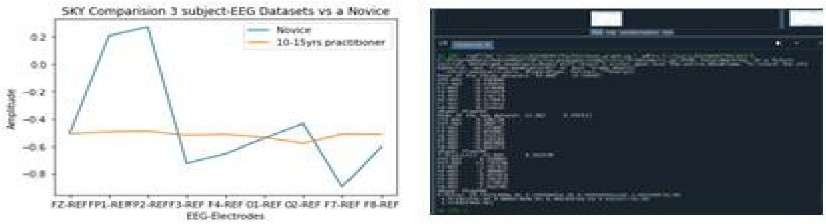


Figure 11. Comparisons and output of 10–15 years SKY practitioners vs. Novices, t–statistic and *p*–value.

Differential analysis is carried out analysis of 10–15 years versus mediocres also compared with novices SKY meditation. X–axis is denoted all frontal and occipital electrodes of EEG and Y–axis represent frequency amplitude (Figure 12).

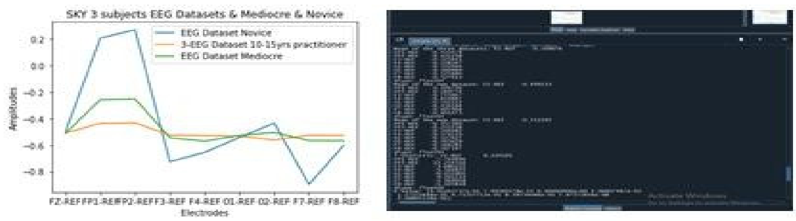


Figure 12. Comparisons and output of 10–15 years SKYpractitioners, Meddiocres and Novices.

In Figure 13, the time–domain amplitude analysis is required for powerspectral maps, electrodes were average re–referenced. Frequency domain and correlation analysis were performed over EEG data.

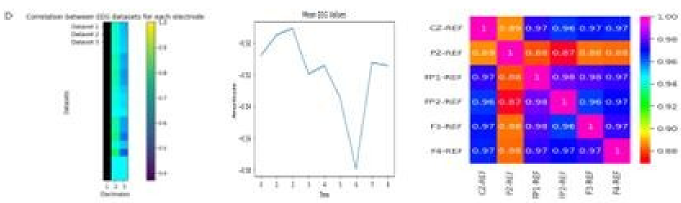


Figure 13. Correlation, mean of 3 EEG LTP dataset

6. Conclusions and Feature Work

Wavelet Transform proves out to be the best method for the time–frequency analysis of EEG signals as it gives the required frequency information along with the time instance at which it occurs. Research involves analysis of EEG brain waves those were recorded for the Experienced, Mediocre andNovice subjects while performing Sudarshan Kriya Yoga. The mean of EEG power at different frequency bands and locations was computed over time periods corresponding to Subject1, 2 and 3. Mean on Mediocre and Novice were also calculated over the same period of time. The Welch's methodis applied for showcasing the power spectrum density of eachelectrode and also amplitude variance is calculated for the significance of consciousness. Moreover, the performancewas achieved with the t–test across every level and p–value hasbeen calculated. The t–test is a valuable statistical tool and Machine learning(ML) using Python is introduced to EEG data analysis, allowing us to determine the significance of observed difference between condition or group. It helps the findings of statistical validity and supports the interpretation of EEG data in the context of neurocognition. In addition, correlation of EEG band power and insight into the central tendency of the EEG brain waves at different time points or locations on brain is computed. We found the result of differentiation in each electrode over subjects 10–15 years SKY versus Mediocre Fz–REF:0.131055, Fp1–REF:–0.113903, Fp2–REF:–0.115935, F3–REF :0.154782,F4–REF :0.184319, F7–REF :0.181976, F8–REF :0.181321,O1–REF :0.126589, O2–REF :0.070297 and subjects 10–15years SKY versus Novice Fz–REF :0.0118083, Fp1–REF:—0.577889, Fp2–REF :–0.637967, F3–REF: 0.336166,F4–REF: 0.269053,F7–REF:0.511659,F8–REF :0.215646,O1–REF :0.141114, O2–REF :–0.000568 respectively. Our proposed system could be used as a reliable tool for real timestress monitoring likes prevention of job stress in periods of high level of work intensity, stress monitoring on children's tasks at school, relationships or diversity of new stressors. Finally, SKY could help substantially improve people's health and quality of life and we recommend SKY practice asan alternative therapy to be prescribed by Psychiatrists to their patients.

Author Contributions

H.B.M. developed the theoretical framework and perform the experiment also an encourage to B.R. to aided in the analysis. B.R. is working under the supervision of H.B.M. Both the authors discussed the result and contributed to the final manuscript. B.R. performed the experiments, calculations and analyzed the data. H.B.M. contributed to the final version of the manuscript and supervised the project. Both the authors conceived, plan, carried out the experiment, designed the model and implementation of the computational framework of the research work. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The author M. Hima Bindu as she led her life, went through it's ups and downs only to become a more emotionally stable and stoical person, transforming from a very happy and fulfilled child to an insecure young adult struggling to have an identity, other emotional upheavals and shocks to a spiritually oriented, detached and serene individual. During this time, in addition to other activities like social problem solving, organizing social functions & gatherings and fighting for others, Learning Hindustani Classical Music, which had its own positive effects like expression of emotions in a subtle manner and a soothing effect on the psyche. With these self–observed changes in the level of consciousness, the motivation to start studying the effects of yoga and meditation experimentally proving the hypothesis that originated because of the experience, has come. Also, Yoga and Meditation techniques taught by teachers of Art of Living(AOL), comprising of musical therapies through Satsangs have helped a lot in the positive change of consciousness.

Data Availability Statement

All datasets are newly created in experimental laboratory at Jadavpur University and all experiments were performed as per the guidelines of the Institutional ethics committee of Jadavpur Univsity.

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