Exploration of Functional Connectivity of Brain to Assess Cognitive and Physical Health Parameters using Brain-Computer Interface

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Abstract

The advancement of brain-computer interface (BCI) innovations has increasingly become an important field among researchers due to the numerous intriguing applications. BCI involves acquiring the neural activity, retrieving appropriate features from the raw electroencephalography (EEG), and translating this data into representations that can improve signal classification. The neural brain activations are triggered or stimulated by predetermined external influences, including music, videos, audio, meditation and several others. The impact of diverse stimuli on the brain is the core investigation purpose of this research. The response of the participants is evaluated in different frequency bands, such as beta, delta, alpha, and theta, and also in various brain regions like temporal, frontal, occipital, and parietal lobes, to better understand the impact. A total of 65 peer-reviewed publications were examined, with the articles being divided into six categories depending on stimuli: yoga and meditation, music, taste, scent, emotion, imagery and movement. The various types of stimuli, existing EEG databases, EEG equipment models, pre-processing techniques, feature extraction and classification approaches have been examined from the published literature on EEG-based investigations. Comprehensive research has been undertaken to describe stimuli and their effects on brain functional connectivity (FC). The proposed method describes the importance of the infinity walk, their effect on changes in humans' cognitive and physical health parameters. This study aims to investigate the impact

of the infinity walk and its effects on human mental health and perhaps to identify the active brain region in people who have practiced the infinity walk for months/years. This technique assists in the identification and justification of the truth behind the infinity walk.

Keywords: Brain-Computer Interface (BCI), Electroencephalography (EEG), Functional Connectivity (FC), Infinity walk, Figure-of-Eight walk.

1. Introduction

Brain-computer interface (BCI) is an approach that allows the brain and an external device to communicate directly [1]. This cutting-edge technology detects specific neurological patterns in real-time and bypasses the brain's conventional output channels. BCI devices can be classified as either non-invasive or invasive. Non-invasive BCI systems use sensors placed on or near the head to record brain wave information [2]. Invasive BCI systems often necessitate sophisticated surgery to implant electrodes in the patient's sensitive grey matter. One of the most important fields of neuroscience research has always been the study of the effects of various forms of external stimuli on the human sensory brain response [3]. A stimulus is anything or an event that causes the brain to direct a specific functional reaction in the organs. Different stimuli cause different reactions within an organism. Researchers have used several scanning tools to map brain reactions to stimuli and assess them according to the measuring technique's properties [4]. The effect of particular stimuli on the brain can now be researched with recent advances in neuroimaging technology. Large-scale connections between different brain regions within different oscillations can reveal information about brain function [5].

The manuscript contains numerous abbreviated words representing datasets/databases, methodologies, etc. The abbreviations used in this study with its expansion are described in Table 1.

Table 1. Abbreviations and their expansions

Abbreviation	Expansion	Abbreviation	Expansion
ADHD	Attention-Deficit/Hyperactivity Disorder	*LDA*	Linear Discriminant Analysis
AFBD	Average Frequency Band Division	*LR*	Logistic Regression

AFC	Artificial Food Colouring	*LSTM*	Long -Short-Term Memory
AISVM	Adaptive Integrated Support Vector Machine	*MARA*	Multiple Artefact Rejection Algorithm
ANN	Artificial Neural Network	*MCNN*	Multi-layer Convolutional Neural Networks
ANOVA	Analyses of variance	*MLP*	Multi-Layer Perceptron
ASMR	Autonomous Sensory Meridian Response	*MLPNN*	Multi-Layer Perceptron Neural Networks
BCI	Brain-Computer Interface	*MSCE*	Magnitude-Squared Coherence Estimation
CCA	Canonical Correlation Analysis	*MSFBCNN*	Multiscale Filter Bank Convolutional Neural Network
CCNN	Combined Convolutional Neural Networks	*NB*	Nave Bayes
DCNN	Deep Convolutional Neural Network	*OPPD*	Odor Pleasantness Perception Database
DCT	Discrete Cosine Transform	*PANAS*	Positive and Negative Affect Scale
DEAP	Database for Emotion Analysis using Physiological signals	*PCA*	Principal Component Analysis
DT	Decision Tree	*PM*	Preksha Meditation
DWT	Discrete Wavelet Transform	*PNN*	Probabilistic Neural Network
EEG	Electroencephalography	*PSD*	Power Spectral Density
EFAM	Emotion Fractal Analysis Method	*RF*	Random Forest
EMD	Empirical Mode Decomposition	*RMS*	Root Mean Square
ERP	Event related potential	*RNN*	Recurrent Neural Network
FAM	Focused Attention Meditation	*SAM*	Self-Assessment Manikin
FC	Functional Connectivity	*SD*	Standard Deviation
FFT	Fast Fourier Transform	*SKY*	Sudharshan Kriya Yoga
FIR	Finite Impulse Response	*SPSS*	Statistical Package for the Social Sciences
GRU	Gated Recurrent Unit	*SSVEP*	Steady State Visually Evoked Potentials
GUI	Graphical User Interface	*STFT*	Short Time Fourier Transform
HOC	Higher Order Crossings	*SVM*	Support Vector Machine
HSCNN	Hybrid Scale Convolutional Neural Network	*SWT*	Stationary Wavelet Transform
ICA	Independent Component Analysis	*TS*	Tratak Sadhana
IIR	Infinite Impulse Response	*VASS*	Visual Analog Scale for Stress
IMF	Intrinsic Mode Function	*VMD*	Variational Mode Decomposition
ISPC	Inter-Site Phase Clustering	*WSDF*	Wavelet Spatial Domain Feature
KNN	K Nearest Neighbour		

Stimuli, which can include pictures, videos, music, audio-video, meditation and yoga, walking, odour, taste, emotion and other forms of media, are used to initiate or stimulate brain activation [6]. The primary goal of this research is to discuss and critique the publications that included information on the type of stimuli, the stimuli's design, the presentation method, the participants' information and contributions. The changes in brain areas and physical factors that occurred as a result of the stimulus must also be investigated [7].

For this work, several reputable databases were reviewed exclusively between 2018 and 2022 in English, including the Open Science Framework repository, PubMed and IEEE Xplore. A wide range of keywords, including brain-computer interface, EEG analysis, stimuli+EEG analysis, stimuli+yoga, stimuli+scent, stimuli+taste, stimuli+music and others, were used to search in Google ScholarTM for potentially pertinent papers. The main goal was to choose papers that included the type of stimuli, the EEG apparatus used, the feature extraction approach, the classification method, the validation process, and the participant's detail. Ultimately, 65 relevant publications were selected and evaluated. The papers' selection of stimuli, equipment, presentation, and related elements, including subject count, dataset, and assessment variables, were closely examined. Furthermore, from this analysis, it can be observed that there are currently very few studies that have used walking as a research stimulus. The 8-shape walk or infinity walk technique is one of the best walking workouts, yet it is never used as a stimulus in any study. A general conceptual framework for the use of diverse stimuli has finally been offered. The suggestions made here are primarily directed at scientists working on studies to design and create a system that can recognise changes in the functional connectivity of the brain during infinity walking.

The paper is organized as follows: Section 1 elaborates on the need for EEG analysis and its application with BCI. Section 2 examines notable studies on various brain stimuli using EEG signals. Section 3 describes the use of BCI to detect changes in EEG signals for experienced infinity walk users. Section 4 concludes by emphasizing the significance of the paper.

2. Related works based on various stimulus

Various feature extraction techniques and classification approaches utilized by numerous researchers and their outcomes are also discussed in the literature survey section. The feature extraction techniques utilized by conventional researchers help in extracting the most appropriate features of the EEG brain signals [8]. The classification and the segmentation methods assist in classifying the EEG signals for distinct brain stimuli.

2.1 Meditation and Yoga as a Stimuli

Sharma *et al.* used brain waves to examine the combined effect of yoga and Sudharshan Kriya Yoga (SKY) meditation [9].[1] Before and after 3 months of regular practice, EEG signals from the control (non-meditators) and study (meditators) groups were recorded. The db4 kind DWT method divides the brain waves into six sub-bands, which are then assessed using Kruskal-Wallis statistical method. Then, using these statistical measures, an ANN was utilised to classify their data into meditators and non-meditators, with an accuracy of 87.2 percent. Using EEG signals, Kamthekar *et al.* investigate the effect of Tratak Sadhana (TS) meditation for reducing stress rapidly in humans [10].[2] Nonlinear metrics like approximation entropy, Higuchi's fractal dimensions and wavelet entropy are used to evaluate the oscillations in EEG signals during TS and rest. EPOC Emotive EEG sensor is used to record EEG signals from 6 subjects. In comparison to other meditation techniques, the results demonstrate that beginning practitioners can attain a rapid meditative state. The decreased entropies and lower complexity values result from TS, a type of concentrative meditation that gives brain signals more regularity and predictability while reducing complexity.

By analysing alpha and beta brain waves, Mariappan *et al.* explored the effect of Raja Yoga meditation on psychological health with the help of the Neurosky BCI mind wave kit [11].[3] The BCI GUI software programme is used to analyse the power levels and length of signals before and after meditation. After that, the data was evaluated using the IBM SPSS application. The results indicate that yoga meditation seems to have a significant influence on physical and mental health parameters like blood pressure, heart rate variability and cardiovascular health. Leng and Dai devised a classification system to assess how effectively the Taijiquan meditation practice aids in resolving mental issues, including depression, work pressure and anxiety [12].[4] The prominent characteristics are extracted

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[1] **Sudharshan Kriya [9]:** A rhythmic breathing method helps the mind-body complex get rid of pollutants and chronic stress.

[2] **Tratak Sadhana [10]:** It is described as keeping your eyes fixed steadily and without blinking on a single point or the flame of a lamp.

[3] **Raja Yoga [11]:** Yoga of control over the mind and body, emphasizing energy and meditation.

[4] **Taijiquan Meditation [12]:** Exercises done slowly with focused mind that help the body and mind work together.

using a discrete cosine transform, and the classification is carried out using an adaptive Integrated Support Vector Machine classifier. In comparison to other meditation techniques, the proposed methods' classification results inferred that this style of meditation would be useful in reducing the depression ratio of 18.5 percent.

Using the Enobio-8 gadget, Ravikumar and Siddappa investigated the effects of pranayama and meditation on individual physical and mental health [13]. Pre- and post-pranayama and meditation data have been collected in four phases. Heart rate and blood pressure are also measured in addition to EEG data. The signals are preprocessed with a band-pass filter and then decomposed with a db4 DWT. Brain signals are analysed using both temporal and frequency analysis to extract characteristics. Diverse statistical quantifiable elements imply different signatures and can be used to improve pattern categorization of EEG data for various cognitive tasks. Yoshida *et al.* show that 56 days of FAM preparation for non-meditators can result in EEG alterations that are close to experienced meditators' EEG waves and can increase learning and memory performance [14]. Participants in the meditation group (n=17) had undergone an 8-week FAM programme, whereas control subjects (n=20) had undergone relaxation training for the same duration. A band-pass filter is used to reduce noise from EEG data. ERP strength during the activity immediately after FAM is correlated with frontal–occipital and frontal-parietal phase coherence during FAM, according to correlation analysis.

The EEG waves acquired from 23 subjects during Juingong meditation and mind wandering were studied by Kim *et al.* [15].[5] The EEG signal noise is removed in the pre-processing stage using an FIR band-pass filter and a Hanning window to taper the signal. Using FFT, the active brain lobes are identified by their power spectrum. The evidence reveals that the alpha wave dominated the temporal parietal region during the task immediately, as opposed to the theta wave. From EEG signals collected from 40 subjects, Edla *et al.* suggested a framework to classify meditation and concentration states [16]. The statistical parameters are used to identify and extract the most important features, and the random forest classifier executes the classification task with an average accuracy of 75%.

[5] **Juingong Meditation [15]:** The core mind that each of us possess naturally and that is intimately connected to everything.

Gholam *et al.* investigated the effects of Sudarshan Kriya Yoga (SKY) on three groups of subjects: those who have practised SKY for more than 3 years, those who have practised SKY for less than 3 years, and those who have not practised any yoga [17]. The statistical measures of the data were handled by SPSS programme. The significant difference in peak amplitude and latency between the three datasets was determined using post hoc testing and ANOVA. As a result of the findings, it can be concluded that SKY practise aids in improving cognitive function and preventing premature ageing. Dol investigates the impact of Yoga Nidra on university students' dignity and stress [18].[6] Data is collected from 20 subjects in each of the control groups and yoga nidra. Before and after yoga practice, demographic data, self-esteem scores, and the VASS intensity are calculated. The t or χ^2 test statistics are used to analyse the data. The yoga nidra group had significantly lower levels of stress and greater levels of self-esteem than the control group.

Ajjimaporn *et al.* tested the influence of Hatha yoga on ERP and EEG in individuals with physical disorder-related anxiety [19].[7] Data were acquired from 18 subjects who were separated into two groups: trained and untrained. The absolute power for each frequency band was measured in the EEG analysis, and ERP was obtained using an auditory oddball paradigm. ANOVA was used to evaluate the ERP and EEG features. There was a considerable rise in alpha EEG activity over the central, parietal, and frontal electrodes, as well as delta EEG frequency over the centroparietal electrode, in the trained group from pre- to post-training. In 52 young novice students, Pragya *et al.* demonstrated changes in alpha wave frequency as a result of Preksha meditation (PM). The data was analyzed using the EEG machine's frequency analysis application software [20].[8] The difference between the before and after durations in the experimental and control groups was determined using the paired sample t-test separately. Four months of PM practice resulted in a considerable rise in alpha waves in young novice students. This improvement was noticed at 4 months but not at 2 months, implying that longer meditation practice is required to get substantial results.

[6] **Yoga Nidra [18]:** Known as yogic sleep, is a state of consciousness that can be set on by guided meditation.

[7] **Hatha Yoga [19]:** Promotes control of the body as a means of achieving a condition of spiritual perfection in which the mind is detached from outside objects.

[8] **Preksha Meditation [20]:** Integration in one's existential existence through altering one's mindset and actions.

Phutke *et al.* used the EMOTIV EPOC EEG device to collect data to identify the effects of meditation on 11 participants [21]. The data were pre-processed with a Butterworth band-pass filter. Pre- and post-meditation Higher Order Crossings (HOC) and Functional Connectivity (FC) are investigated. Magnitude-Squared Coherence Estimation (MSCE) can be used to examine FC. The increase in interhemispheric connectivity as an outcome of FC suggests that meditation aids in being peaceful and focusing attention on the intended goal. EEG recordings of 18 Buddhist monks were used by Marasinghe *et al.* to investigate the effects of Vipassana meditation [22].[9] The mean amplitudes of signals examined using the paired t-test are measured using FFT. For spectrum analysis, parametric T statistics are used. As a result, the left occipital area of the brain shows alpha and theta activations. Both sides of the occipital, temporal, central and frontal areas show gamma activation. Shinde *et al.* examined how yoga affected concentration levels in ten engineering students [23]. Features are retrieved using the Symlet Discrete wavelet transform. The features are classified before and after yoga sessions using three distinct classification algorithms: SVM, KNN, and probabilistic neural network (PNN). PNN is one of them, with a classification accuracy of 95%.

2.2 Music as a stimuli

With the use of DEAP, a multichannel standard emotion database, Xue employed music stimulation to classify emotions [24]. Beta, theta and alpha waves are extracted using the wavelet transform. EMD is used to extract the IMF component from signals. IMF is used to estimate the average energy and amplitude difference eigenvalues. A Support vector machine is used to classify features. When compared to generic feature extraction, EEG feature extraction has a classification accuracy of more than 70%. When music is used as a stimulus, Mahmood *et al.* investigated the changes in the FC of the brain [25]. Non-musicians are stimulated by listening to their favourite music and relaxing alpha-beat music. Inter-Site Phase Clustering (ISPC) was used to construct grand-averaged connection matrices from EEG data divided into multiple frequencies. Statistical analysis such as

[9] **Vipassana Meditation [22]:** It involves accepting your ideas and feelings as they are and not passing judgement or giving them too much attention.

ANOVA and t-test, are utilised to detect the significant alterations in FC of the brain. While listening to favourite music, there is a decrease in the beta band and an increase in the alpha and theta band when listening to relaxing music.

Zainab and Majid used a muse headset to analyse 27 respondents' emotions using bilingual music as a stimulus [26]. The time domain and frequency domain features are extracted and classified as unhappy, calm, cheerful and rage. Hyper Pipes, Multilayer Perceptron and Random Forest are utilised for classification. Hyper Pipes surpassed the rest of the classifiers, with an average accuracy of 83.95%. The brain's cortical activity patterns in reaction to music were studied by Kumagai *et al.* A total of 64 scalp electrodes were used to capture EEG data from 15 participants [27]. The spectro-temporal properties of brain signals were evaluated using cross-correlation functions and were verified with the help of t-test and ANOVA statistical measures. As a result of SVM classification, when listening to unknown music, the FC of the brain is stronger than when listening to familiar music. Even when the individual is not paying attention, novel information reaches the brain more easily than familiar knowledge.

Using Emotiv EPOC+ EEG equipment, Paszkiel *et al.* analysed the impact of music stimulation on the stress levels of 9 participants [28]. Silence/no music, music-producing ASMR, calming music, and rap are employed as music stimuli. The difference between the stressor stage and the listening to music stage is compared with the reference value to evaluate how quickly one may relax in any particular situation. Statistical analysis is used to determine how different music genres affect stress perception. As a result, rap music has a negative effect on stress reduction. Relaxing music and ASMR music are more peaceful than silence. Wang *et al.* looked into the effects of music on fatigued drivers with more than three years of driving experience were surveyed. Independent component analysis (ICA) and Variational Mode Decomposition (VMD) are used to reduce noise from data [29]. Power spectrum features are extracted using frequency domain analysis. The changes in driver weariness are studied using a statistical linear regression model. As a result, when a driver listens to music, his brain waves are active for an additional 30 minutes compared to when he is not listening to music.

Wang *et al.* examined the effect of various music rhythms on human psychology tested on 47 participants who are categorized into two groups, one listening to slow-rhythm music and the other listening to fast-rhythm music [30]. In contrast to slow-rhythm music, fast-rhythm music raises variance and decreases synchronism, causing psychological stress and disorder by monitoring EEG variance and synchronism features in distinct brain regions. Balasubramanian *et al.* analyzed the emotions elicited by self-selected music stimuli noted using RMS EEG-32 Super Spec on 12 participants [31]. The wavelet packet decomposition method is used to extract theta, alpha and theta frequencies from raw EEG signals. The Friedman test examines the total differences of three frequency bands at three perceptions: disliked music listening, liked music listening and silence. As a result, in the frontal portion of the brain, the theta band increases while listening to liked music, and when beta band increases while hearing disliked music.

Using the DEAP dataset, Naser *et al.* explored the impact of enjoying music on human moods [32]. The wavelet decomposition approach extracts features from a single electrode, pairwise FC extracts characteristics between two electrodes, and the graph theoretic method extracts features from a certain brain network architecture. When these features are combined, the categorization increases by 5% when compared to individual features. Cross-validation on a k-fold scale classification measures of dominance, arousal, and valence of brain waves are 19.44 %, 22.50 %, and 14.87 %, respectively. On experimenting with 16 volunteers, Geethanjali *et al.* investigated the effect of Indian music Dharmavathi Raga and Bhairav Raga on FC in the brain [33].[10] Wavelet packet decomposition is used to extract features. PANAS was utilised to assess each participant's mood before and after listening to the chosen raga. Subjects' arousal and valence are evaluated using a SAM. Consequently, listening to the Dharmavathi raga elevated the frontal theta band more than quiet.

Using positive, negative and neutral auditory input, Cai *et al.* created a depression identification system [34]. EEG data were acquired from 92 healthy people and 86 people who were depressed. Using the feature-level fusion technique, linear and non-linear EEG information from three states are combined. KNN, DT, and SVM are utilised for

[10] **Dharmavathi Raga and Bhairav Raga [33]:** Dharmavati is the 59th melakartha ragam in Carnatic music. It is a sampurna raga that is typically played early in the day and as the opening song at events.

classification and achieved 86.98% accuracy for KNN. Based on aural visual cues, Ahirwal and Kose categorised emotions, such as angry, joyful, relaxed and sad [35]. Three types of characteristics are extracted: frequency domain, time domain, and entropy-based features. The DEAP dataset is used to identify emotions using three types of classifiers: nave bayes (NB), SVM and ANN. Entropy-based features and ANN classifiers are the most accurate, with 90.73 % and 97.74 %, respectively.

2.3 Taste as a stimuli

According to Wallroth *et al.*, the taste stimuli caused changes in cortical patterns in the brain [36]. Using 64-channel EEG equipment, the experiment is conducted on 16 people based on four types of tastes: salty, sour, bitter, and sweet. Within 130 milliseconds of tasting, the changes in the delta frequency activity are detected in the brain. The effect of taste stimuli on brain waves was studied and categorised by Chandran and Perumalsamy [37]. The EEG signals are preprocessed using an infinite impulse response filter. The features, such as the root mean square value, mean, power spectral density, median, kurtosis and standard deviation, are extracted and classified using SVM to categorise sour, sweet, bitter and salty tastes with a 95% accuracy. Songsamoe *et al.* used EEG recordings to study customers' emotional responses to food products in order to improve food design [38]. To examine the consumers' culinary preferences, EEG spectral data is collected from both the left and right hemispheres of the brain. A larger EEG power spectrum in the left and right lobe indicates food acceptance and rejection, respectively.

Kirkland *et al.* acquired EEG data with the help of g.tec device to study the impact of artificial food colouring (AFC) in young adults with (18 subjects) and without Attention-Deficit/Hyperactivity Disorder (ADHD) (41 subjects) [39]. ICA with a multiple artefact rejection algorithm (MARA) approach is used to remove artefacts. The power spectral density values are obtained using FFT with a Hanning window, and statistical analysis is performed using SPSS software. In the ADHD group, AFC led to a rise in gamma and a decrease in alpha mean power, as well as an increase in inattentive symptoms. Chandran and Perumalsamy classified EEG signals based on human gustation [40]. EEG signals are preprocessed using an IIR band pass filter. Features are extracted using Stationary

Wavelet Transform (SWT). Based on mean, power spectral density, and standard deviation features, sour, sweet and bitter tastes are classified. Preprocessing and feature extraction are done using Spartan—6 FPGA kit, increasing computational speed. Figure 1 depicts the various stimuli used by numerous researchers for EEG signal classification.

2.4 Odour as a stimuli

With the help of nine volunteers, Ko *et al.* investigated the effects of essential oils' aroma on human sleep quality [41]. Power spectral density is determined using STFT with hamming window to analyse the spectrum changes generated by lavender stimuli. The Wilcoxon signed-rank test was used to compare sleep quality. Following the emission of scent, participants' alpha activity reduced, and delta activity increased.

Hou *et al.* created an odour-based emotion identification system [42]. The average frequency band division (AFBD) approach is used to extract power spectral density information from EEG data using a support vector machine (SVM). For two- and five-emotion recognition, the suggested AFBD-based SVM technique has attained average accuracy of 98.9% and 88.5%, respectively, compared to existing methods. Using EEG data from 30 individuals and the Nihon Kohden gadget, Sadik *et al.* investigated the influence of rosemary scent during mental workload [43]. To extract features, the Welch approach is employed. With an accuracy of 96.88%, a classification and regression tree technique is utilised to identify people depending on whether or not they breathed scent.

Using the QEEG-8 EEG system, Kim *et al.* examined the reaction of aromatic chemicals on 20 subjects [44]. The variations in EEG power spectrum values were investigated during nonanal (C9), decanal (C10), and no odour aldehyde odour circumstances. It is observed that the C10 odour primarily affected the left parietal region rather than other regions of the brain. Zhang *et al.* classified olfactory signals using publicly available own and OPPD datasets [45]. The olfactory EEG signals are decoded using the WSDF approach. The proposed technique used several classifiers and attained the best mean accuracy of 99.50 % and 100% for the own and OPPD datasets, respectively, for WSDF.

2.5 Imagery and movement as a stimuli

Using motor Imagery EEG, Amin *et al.* compared the performance of the new classification approach to that of established methods [46]. To extract spatio-temporal characteristics for classification, multi-layer convolutional neural networks (MCNN) and combined convolutional neural networks (CCNN) are utilised. For the High Gamma Dataset and BCI Competition IV dataset 2a (BCID), MCNN achieves 95.4% and 75.7% accuracy, respectively. For motor imagery EEG, Dai *et al.* compare the Hybrid scale convolutional neural network approach (HSCNN) to the classic single scale CNN [47]. The average classification accuracy of the proposed technique when applied to the 2008 BCI Competition IV 2a and 2b datasets is 91.57% and 87.6%, respectively.

Masood *et al.* used the Emotiv EPOC EEG Headset to analyse the neural signatures of 15 participants [48]. Data is collected using self-induced visuals and videos as stimuli. Band-pass filters are used to get 7 frequency bands from each subject. To extract features, a common spatial pattern approach is utilised. The LDA classifier performs better in gamma bands than in other bands. The findings show that both stimuli exhibit subject-independent EEG at significant frequency bands and brain areas. Asif *et al.* used music stimuli to classify stress on humans using EEG signals with the help of a MUSE headset [49]. Relative power, absolute power, phase lag, coherence and amplitude asymmetry features are extracted and classified using LR, sequential minimal optimization, MLP and stochastic decent gradient classifiers. Among them, LR reported an accuracy of 98.76%.

EEG signals of 13 participants who have imagined 26 alphabets were classified by Agarwal *et al.* DWT is used to denoise the raw EEG data, while support vector machine and random forest classifiers are used to extract and classify spatial and time domain features, respectively [50]. As a result, the alpha, theta, and beta bands are mostly generated than the other bands during alphabet classification. Ullah *et al.* built a model to recognise EEG patterns obtained by visual imagining the alphabet, allowing for brainwave typing [51]. The Morlet wavelet transformation is used to convert the raw EEG signals into band powers. A deep convolutional neural network (DCNN) is utilised to extract spatial information to categorise alphabets. On two public motor imagery datasets, DCNN outperforms classical classification with an accuracy of 99.45% and an average recognition rate of 95.2%.

Figure 1 shows the different stimuli that traditional researchers have used in BCI applications. The most recent articles on the various stimuli are found and reviewed. The reviewed papers are also shown in Figure 1, along with information on the authors and the years of publications.

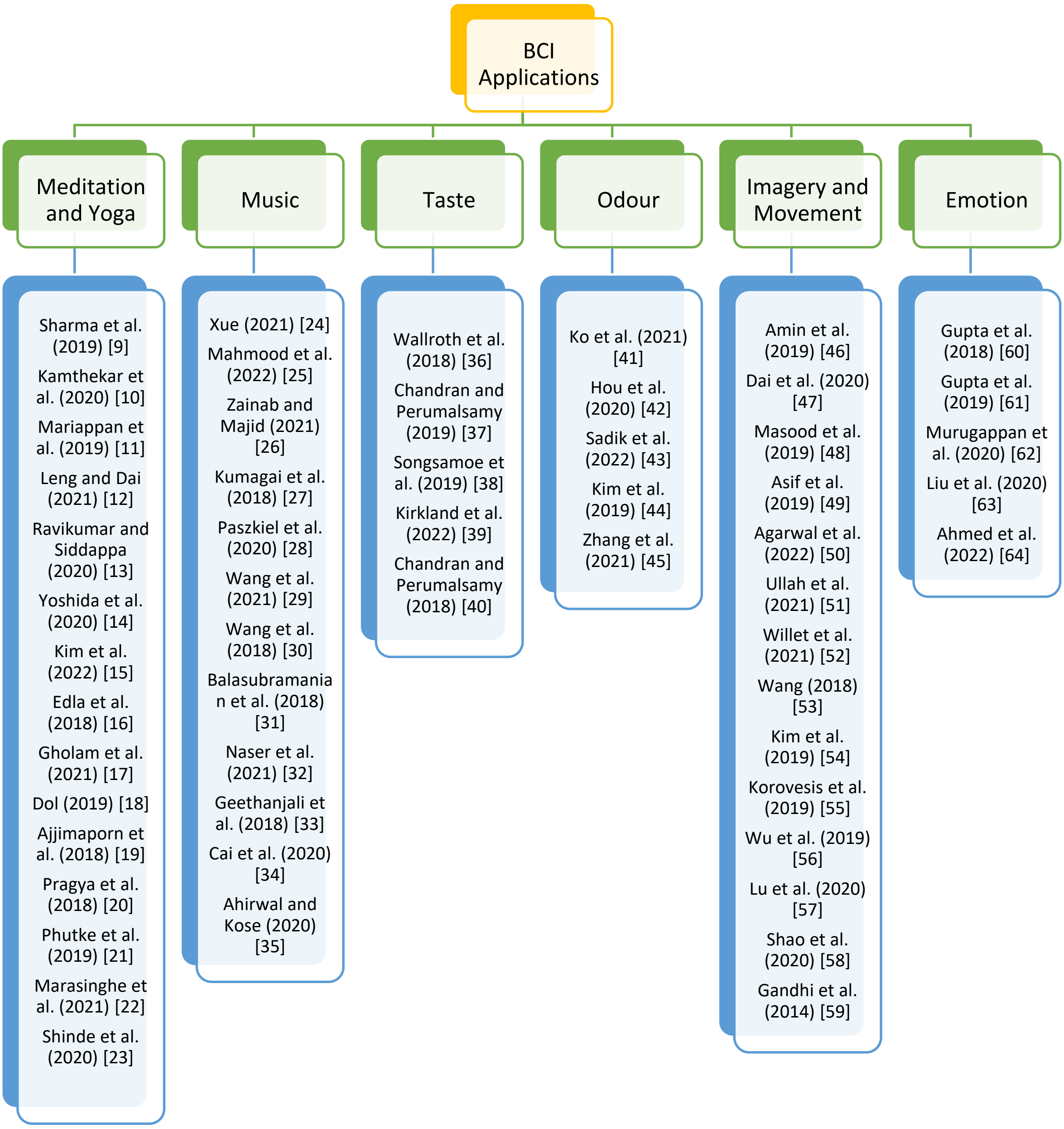

Figure 1. Researches based on various stimuli

Willet *et al.* used an invasive microelectrode array to acquire brain signals to construct a brain-to-text communication model to assist disabled patients [52]. The brain activity from attempted handwriting is translated into alphabetic characters using a recurrent neural network. As a result, 90 characters per minute may be typed online with 94.1% and 99% accuracy offline with auto-correct.

Wang created a model to compare predicted cursor movement velocity to actual cursor movement velocity [53]. For 34 participants, EEG data was collected using an Emotiv EPOC headset. The Butterworth filter is used to process the signals. For EEG decoding, a recurrent neural network containing LSTM and GRU is used. Both models' performance has vastly improved.

Kim *et al.* used 60 individuals' EEGs to establish online home appliance control [54]. A two-sample t-test is used to extract distinctive amplitude characteristics between the non-target and target ERPs from EEG data. PCA reduces computational complexity. The target is identified using an SVM classifier. On average, BCI users were able to manage light, television channels and digital door lock with an accuracy of 83.0% ± 17.9%, 78.7% ± 16.2%, and 80.0% ± 15.6%, respectively. With the help of the OpenBCI Ganglion device, Korovesis *et al.* created a robotic motion control model using EEG data from 12 subjects. For feature extraction and classification, DFT and multilayer perceptron neural networks are used [55]. The devised system can operate the robotic vehicle left, right, forward and backwards in response to the operator's alpha brainwaves, with an overall accuracy of 92.1%.

Using BCI Competition IV datasets 2a, 2b, and high gamma datasets, Wu *et al.* suggested a parallel multiscale filter bank convolutional neural network (MSFBCNN) for MI categorization [56]. Using a feature-extraction network, spatial and temporal features are retrieved and categorised using MSFBCNN. According to the findings, the suggested network has outstanding quality, resilience, and transfer learning ability when compared with conventional methods.

Using the EEG of 15 tractor drivers, Lu *et al.* built a tractor-assistance driving control model [57]. Wavelet packets are used to denoise EEG signals, and the retrieved spectral characteristics are sent to RNN. In the end, the EEG-assisted RNN driving system was built with robot control operations, including straight moving, halt, right moving, and left moving and achieved in a time cost of 0.61 milliseconds with a control accuracy of 94.5%.

EEG data was used by Shao *et al.* to drive a wall-crawling cleaning robot. EEG data from seven subjects were used to obtain SSVEP [58]. Data are analysed using the Canonical

Correlation Analysis method. The threshold of each subject can be determined by comparing the CCA correlation coefficient of the subject in the idle and the task state. The suggested system performed well in the control and classification stages, with a response speed of 22.23 bits/min and an accuracy of 89.92 %, respectively.

An innovative intelligent adaptive user interface (iAUI) design for a mobile robot control task was given by Gandhi *et al.* in real-time [59]. The user-centric iAUI for increasing the bandwidth and the recurrent quantum neural network (RQNN) approach for filtering was implemented for the robot control task in the external surroundings. Most participants hit the goals on their first or second try, and as the sessions went on, they easily became familiar with the adaptive interface. With additional training on the subject, it is possible to achieve better control with 100% accuracy.

2.6 Emotion as a stimuli

A novel technique for the cross-subject categorization of emotion EEG data was given by Gupta *et al.* The EEG signal is divided into many subband signals using flexible analytic wavelet transform [60]. In order to classify the emotions, the retrieved feature values were smoothed before being input to the random forest and support vector machine classifiers. In comparison to conventional methods, the proposed methodology exceeds them, providing average classification accuracy rates of 83.33 % on the SEED database and 59.06 % on the DEAP database.

An end-to-end system that seeks to improve user-input sentences in accordance with their present emotional state was proposed by Gupta *et al.* EEG signals from the brain are analysed to determine the user's emotional state [61]. By identifying the user's emotional state, adding adjectives and adverbs, and testing for coherence with Language Models using a correlation finder technique, the system transforms a sentence. Next, a language modelling framework built on Long Short-term Memory (LSTM) Networks was used to verify the accuracy of the sentences. The classification of five emotional states has a documented accuracy of 74.95 %.

The proposed method by Murugappan *et al.* for the categorization of emotions in Parkinson’s disease (PD) and normal controls (NC) makes use of the tunable Q wavelet transform (TQWT) [62]. Six emotional states' EEG signals are investigated. From the high pass and low pass sub-bands of TQWT, characteristics based on power, entropy, and statistical moments are extracted. Using a k-nearest neighbour, probabilistic neural network, random forest, decision tree, and extreme learning machine, six features chosen by statistical analysis are categorised. With a probabilistic neural network, it is possible to attain maximum mean accuracy, sensitivity and specificity of 96.16 %, 97.59 %, and 88.51 % for NC and 93.88 %, 96.33 %, and 81.67 % for PD.

Convolutional Neural Networks (CNN), Sparse Autoencoder (SAE) and Deep Neural Networks (DNN) are three new deep neural networks that Liu *et al.* proposed for emotion classification using EEG [63]. First, SAE receives the characteristics that CNN has extracted for encoding and decoding. Then, for a classification task, the data with less redundancy is used as the input characteristics of a DNN. Testing is conducted using the DEAP and SEED public databases. According to experimental findings, the suggested network performs emotion recognition better than traditional CNN approaches. The greatest recognition accuracy for valence and arousal for the DEAP dataset is 89.49 % and 92.86 %, respectively. The best recognition accuracy for the SEED dataset, however, is 96.77 %.

AsMaps was used by Ahmed *et al.* to automatically extract features using a CNN model [64]. The differential entropy and various feature extraction techniques, including relative asymmetry, differential asymmetry, and differential caudality, have been compared to the suggested feature extraction method. The DEAP dataset and the SJTU emotion EEG dataset are used in experiments. The collected findings show that the suggested feature extraction method outperforms the other feature extraction methods in terms of classification accuracy. Using the SJTU emotion EEG dataset, the highest classification accuracy of 97.10 % is attained on a three-class classification problem.

The study gives insight into the utilization of various deep learning methods for EEG classification. The evaluation exertion was chiefly focused on various stimuli for EEG detection and deep learning techniques for classification. The investigation also unveils different databases, dataset descriptions, available EEG equipment and evaluation factors that can assist researchers in this field. Although previous deep learning approaches trying to assess EEG signals had drawbacks such as lower accuracy and classification rate.

A wide range of machine/deep learning methods are currently being used in a number of scientific fields. Advances in hardware and software are being seen in daily life, especially in medicine and healthcare. These can be used for automatic interpretation, illness classification and prognosis, customized treatment, and drug development.

The various conventional types of research and their findings, description of the stimuli and dataset used in their study are explained in Table 2. The number of subjects employed for their research is revealed during live data gathering. They discuss the EEG equipment they utilised, feature extraction, classification, and validation techniques, as well as the results of their study.

Table 2. Comparison of outcomes of conventional research

Author	Dataset	No. of Subjects	Equipment	Feature Extraction	Classification	Validation method	Outcome
Sharma *et al.* (2009) [9]	Yoga and Sudharshan Kriya yoga (SKY) Meditation	50	-	DWT	ANN	Kruskal-Wallis statistical test	Accuracy = 87.2%.
Kamthekar *et al.* (2020) [10]	Tratak Sadhana Meditation	6	EPOC Emotive EEG sensor	Entropy, wavelet entropy, and Higuchi' fractal dimensions.	-	-	Decreased entropies and lower complexity values.
Mariappan *et al.* (2019) [11]	Raja Yoga Meditation	-	Neurosky BCI mind wave kit	-	-	SPSS	Impact on physical and mental health.
Leng and Dai. (2021) [12]	Taijiquan Meditation	-	-	DCT	AISVM	ANOVA	Reduces the depression ratio to 18.5%.
Ravikumar and Siddappa. (2020) [13]	Pranayama and meditation		Enobio-8 device	DWT	-	-	Improved cognitive performance.
Yoshida *et al.* (2020) [14]	Focused attention Meditation	49	Easycap GmbH	Phase synchrony index	-	Correlation Analysis, ANOVA	Frontal–parietal and frontal–occupital activation
Kim *et al.* (2022) [15]	Juingong Meditation	23	MUSE headset	Power spectrum	-	t-test	Alpha wave dominated the temporal-parietal region.

Edla *et al.* (2018) [16]	Meditation and Concentration	40	Neurosky Mindwave Mobile	Mean, SD, Min and Max amplitude.	Random forest classifier with ensemble learning	-	Accuracy = 75%.
Gholam *et al.* (2021) [17]	SudarsanKriya Yoga	20	Electrical Geodesics Inc 64 channel system	Peak amplitude and latency.	-	ANOVA	Improving cognitive function and preventing premature ageing.
Dol (2019) [18]	Yoga Nidra	40	-	Demographic data, self-esteem scores, VASS.	-	t or χ2 test	lower stress and high self-esteem.
Ajjimaporn *et al.* (2018) [19]	Hatha Yoga	18	Quik-Cap 10–20 placement system	ERP	-	ANOVA	Increase in alpha EEG activity across the frontal, central, and parietal electrodes, as well as delta EEG activity over the centroparietal electrode.
Pragya *et al.* (2018) [20]	Preksha Meditation	52	32 channels recorder medicare system	-	-	Paired sample t-test	Rise in alpha waves in young novice students.
Phutke *et al.* (2019) [21]	Meditation	11	EMOTIV EPOC EEG	Higher Order Crossings	-	Magnitude-Squared Coherence Estimation	Increase in interhemispheric connectivity.
Marasinghe *et al.* (2021) [22]	Vipassana Meditation	18	Neurovirtual Brain Wave III EEG unit	Mean amplitude and spectral analysis.	-	Paired t-test, parametric T statistics	Alpha and theta activations in left occipital area and both sides of the occipital, temporal, central, and frontal areas show gamma activation.
Shinde *et al.* (2020) [23]	Yoga	10	Brain Vision Recorder	Symlet Discrete wavelet transform	Probabilistic neural network	-	Accuracy = 95%
Xue (2021) [24]	DEAP	-	-	IMF and EMD	SVM	-	Accuracy >= 70

Mahmood *et al.* (2022) [25]	Favourite and Relaxing Music	32	Emotiv EPOC headset	ISPC	-	ANOVA, t-test	When compared to listening to favourite music, there is a decrease in beta band and an increase in alpha and theta band when listening to relaxing music.
Zainab and Majid (2021) [26]	Bilingual Music	27	muse headset	Time and frequency domain features	Hyper Pipes classifier	t-test	Average accuracy = 83.95%.
Kumagai *et al.* (2018) [27]	Familiar and Unfamiliar Music	15	64 scalp electrodes	CCF	SVM	t-test and ANOVA	When listening to unknown music, the FC of the brain is stronger than when listening to familiar music.
Paszkiel *et al.* (2020) [28]	ASMR, Calm and Rap Music	9	Emotiv EPOC+ EEG equipment	Mean, SD	-	Kruskal–Wallis test (ANOVA on ranks)	As a result, rap music has a negative effect on stress reduction. Relaxing music and ASMR music are more peaceful than silence.
Wang *et al.* (2021) [29]	Music	-	-	ICA, VMD, power spectral features.	-	Statistical linear regression model	When a driver listens to music, his brain waves are active for an additional 30 minutes compared to when he is not listening to music.
Wang *et al.* (2018) [30]	Slow and Fast Rhythm Music	47	-	Variance and synchronism features.	-	-	Fast-rhythm music causes psychological stress and disorder.
Balasubramanian *et al.* (2018) [31]	Liked and Disliked Music	12	RMS EEG-32 Super Spec	Wavelet packet decomposition	-	Friedman test	In the frontal portion of the brain, theta band increases when listening to liked music, while beta band increases

							when listening to disliked music.
Naser *et al.* (2021) [32]	DEAP	-	-	Wavelet decomposition, Graph-theoretic method.	k-fold scale classification	Cross-validation	Dominance, arousal, and valence of brain waves are 19.44 %, 22.50 %, and 14.87 %, respectively.
Geethanjali *et al.* (2018) [33]	Dharmavathi Raga and Bhairav Raga	16	International 10-20 EEG sensor placement system	Wavelet packet decomposition.	-	PANAS, SAM	Listening to the Dharmavathi raga elevated the frontal theta band more than quiet.
Cai *et al.* (2020) [34]	Positive, Negative, and Neutral Auditory Input	92 healthy people and 86 depressed people	Pervasive three-electrode EEG acquisition sensor	Feature-level fusion technique	KNN	-	Accuracy = 86.98%
Ahirwal and Kose. (2020) [35]	DEAP	-	-	Frequency domain, time domain, and entropy-based features.	ANN	-	Accuracy = 97.74 %
Asif *et al.* (2019) [36]	Music	27	MUSE headband.	Relative power, absolute power, phase lag, coherence, and amplitude asymmetry features.	LR classifier	-	Accuracy = 98.76%.
Wallroth *et al.* (2018) [37]	Salty, Sour, Bitter, and Sweet Tastes	16	64 channel EEG equipment	-	-	-	Within 130 milliseconds of tasting, the changes in the delta frequency activity are detected in the brain.
Chandran and Perumalsamy. (2019) [38]	Sour, Sweet, Bitter, and Salty Tastes	12	Mindwave Mobile wireless electrode	SWT, RMS, mean, SD, PSD, median, kurtosis, SD.	SVM	-	Accuracy = 95%

Songsamoe *et al.* (2019) [39]	Taste	-	-	EEG power spectrum analysis.	-	-	A larger EEG power spectrum in the left and right lobe indicates food acceptance and food rejection, respectively.
Kirkland *et al.* (2022) [40]	Taste	18	g.tec device	PSD using FFT	-	SPSS	In the ADHD group, AFC led to a rise in gamma and a decrease in alpha mean power, as well as an increase in inattentive symptoms.
Chandran and Perumalsamy. (2018) [41]	Sour, Sweet and Bitter Tastes	12	MindWave Mobile	SWT, PSD	-	-	Preprocessing and feature extraction are done using Spartan—6 FPGA kit that increases the computational speed.
Ko *et al.* (2021) [42]	Essential Oils Aroma	9	CURRY Scan NuAmps Express system	PSD using STFT	-	Wilcoxon signed-rank test	Participants' alpha activity reduced, and delta activity increased.
Hou *et al.* (2020) [43]	5 Odors	11	Cerebus system	PSD using AFBD	SVM	Cohen's kappa, precision, recall, and F1-measure.	Average accuracy = 88.5%.
Sadik *et al.* (2022) [44]	Rosemary Scent	30	Nihon Kohden gadget	Welch approach	Regression tree	-	Accuracy = 96.88%.
Kim *et al.* (2019) [45]	Aromatic Chemicals	20	QEEG-8 system	EEG power spectrum analysis	-	-	C10 odour primarily affected the left parietal site (P3) rather than other brain areas.
Zhang *et al.* (2021) [46]	OPPD Dataset and a Self-Collected Dataset	-	-	WSDF	SVM	-	Average accuracy of 100 % and 99.50 % for OPPD and self-collected dataset.
Amin *et al.* (2019) [47]	MI Dataset BCI	-	-	Spatio-temporal	MCNN	-	Accuracy = 75.7% (for 2a)

	Competition IV Dataset 2a and High Gamma Dataset			characteristics			95.4% (High Gamma).
Dai *et al.* (2020) [48]	BCI Competition IV 2a and 2b Datasets	-	-	Use single convolution scale in the CNN layer to extract the EEG features	HSCNN	-	Average classification accuracy of 91.57% and 87.6%.
Masood *et al.* (2019) [49]	Self-Induced Visuals and Videos	15	Emotiv EPOC EEG Headset	Common spatial pattern approach	LDA classifier	-	Subject-independent EEG. at significant frequency bands and brain areas.
Agarwal *et al.* (2022) [50]	26 Alphabets Imagery	13	32 channel MOBITA wireless physiological data acquisition device	DWT	SVM, RF	-	Mostly the alpha, theta, and beta bands are generated more than the other bands during alphabet classification.
Ullah *et al.* (2021) [51]	EEGMMIDB, BCI2a and Locally Collected Datasets	10	Emotiv Epoc+headset	Morlet wavelet transformation	DCNN	-	Accuracy = 99.45% Average recognition rate = 95.2%.
Willet *et al.* (2021) [52]	Hand Imagery	1	Invasive micro electrode array	-	RNN	-	90 characters per minute may be typed online with 94.1% and 99% accuracy offline with auto-correct.
Wang (2018) [53]	Hand Imagery	34	Emotiv EPOC headset	-	RNN containing LSTM and GRU	Pearson correlation	RNN with LSTM and GRU improved the model's performance.
Kim *et al.* (2019) [54]	Video Clips	60	EEG cap 10–20 system	ERP, PCA	SVM	t-test	BCI users were able to manage TV channels, digital door lock and light with an accuracy of 83.0% ± 17.9%, 78.7% ± 16.2%, and 80.0% ±

						15.6%, respectively.
Korovesis *et al.* (2019) [55]	Eye Blink	12	OpenBCI Ganglion device	DFT	MLPNN		Accuracy = 92.1%.
Wu *et al.* (2019) [56]	BCI Competition IV Datasets 2a, 2b and High Gamma Dataset	-	-	Temporal and spatial features	MSFBCNN	-	The suggested method has outstanding quality, resilience, and transfer learning ability when compared with conventional methods.
Lu *et al.* (2020) [57]	Motor Imagery	15	Emotiv-EPOC+ System	Spectral characteristics	RNN	-	Accuracy = 94.5% Time = 0.61 milliseconds.
Shao *et al.* (2020) [58]	Motor Imagery	7	-	SSVEP	-	CCA	Accuracy = 89.92 %.
Gandhi *et al.* (2014) [59]	Motor Imagery	5	egUSBamp dry electrode system from g.Tec	Hjorth and Band power features	five-fold cross-validation	-	Most participants hit the goals on their first or second try, and as the sessions went on, they became familiar with the adaptive interface with ease.
Gupta *et al.* (2019) [60]	Emotion	SEED and DEAP Dataset	-	Flexible analytic wavelet transform	random forest and SVM	-	Accuracy on SEED database = 83.33 % Accuracy on DEAP database = 59.06 %.
Gupta *et al.* (2018) [61]	Emotion	25	Emotiv EPOC device	wavelet transform	Random Forest Classifier, LSTM	-	Accuracy = 74.95 %
Murugappan *et al.* (2020) [62]	Emotion	40	Emotiv EPOC neurohea dset	tunable Q wavelet transform	probabilistic neural network	-	For Normal Control: Accuracy = 96.16 %, Sensitivity = 97.59 %, Specificity = 88.51 % For Parkinson's disease:

							Accuracy = 93.88 %, Sensitivity = 96.33 % Specificity = 81.67 %.
Liu *et al.* (2020) [63]	Emotion	SEED and DEAP Dataset	-	CNN, SAE	DNN	-	The average recognition accuracy of the proposed network can reach 89.49% on valence, 92.86% on arousal for DEAP and 96.77% for SEED.
Ahmed *et al.* (2022) [64]	Emotion	SJTU and DEAP dataset	-	AsMap	CNN	-	Accuracy = 97.10%.

2.7 Infinity Walk as a Stimuli

Though many people acclaim technological advancements, it has made people very lethargic. Every work done by a human is replaced by machines, from small to large work. People work hard to make a living by throwing their health on the line but spending the same hard-earned cash on getting their health back. This "8-shaped" walking will assist us in improving our health by just performing what we do every day differently.

Walking is an integrative brain exercise because our arms are wavering with the opposite leg movements. Walking is indeed a very significant activity suggested by all doctors and therapists to maintain our physical and mental health. However, people who cannot perform difficult workouts choose to walk. There are several different walking styles, such as slow walking, quick walking, and so on. The "8-shaped" walking is the most popular among them. The Infinity Walk or Figure-of-Eight walk has several functional benefits, including preparing the brain for learning, improving coordination for sports that involve a ball or other moving item, and improving concentration and reasoning ability [65]. It aids in the development of multi-sensory integration in people, particularly those with learning difficulties. Overall, it aids in the improvement of brain function. Figure 2 illustrates the proposed block diagram. Initially, data is gathered from subjects who have not yet begun infinite walking. Once they began this task, the same volunteers underwent infinite walking for months or years, during which data were once again obtained from them every 15 days using non-invasive techniques. Processed data are extracted and graded. Based on these findings, the brain region that responds to this stimulus most frequently is identified, along with the physiological and cognitive alterations that took place in the subjects.

This research aims to determine the brain's functional connectivity during normal and Figure-of-Eight walks in children, adults, and elders. Also, to identify the part of the brain that is active during the Figure-of-Eight walk. This study contributes to empirically confirming the above-mentioned advantages of cognitive behavior.

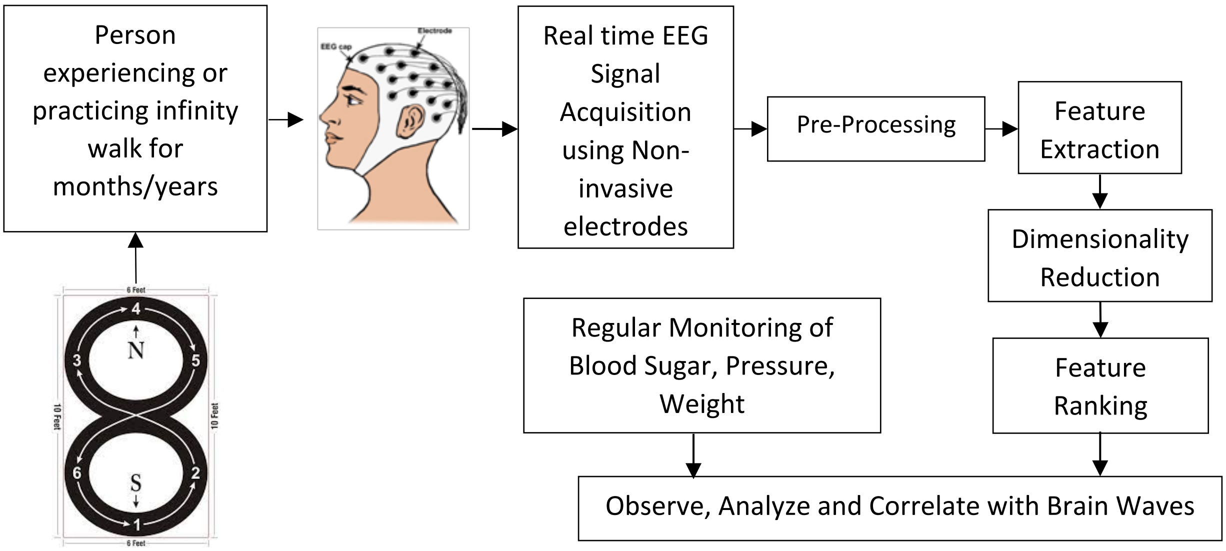

Figure 2. Proposed Block Diagram

3. Experimental Discussion

3.1 Data Collection

The steps to be followed in collecting and analyzing the EEG data from infinity walk practiced subjects are exemplified in Figure 3. This experiment will involve many male and female contestants of ages ranging from 12 to 60. The benefits and changes that will result from the infinity walk will be demonstrated in both the short and long term, especially for students.

3.2 Data Analysis

The recorded EEG data have noise and artefacts due to the hand or leg movement and eye blinking even during the relaxed position. This noise must be removed using a Gaussian filter, band-pass filter, etc. The significant features from the obtained signals were extracted using feature extraction methods like wavelet, fast fourier transform, etc. The redundant data has to be removed using dimensionality reduction techniques like principal component analysis, independent component analysis, etc. Using statistical tests like ANOVA and t-test, the changes in the waves present in the brain lobes are identified and evaluated.

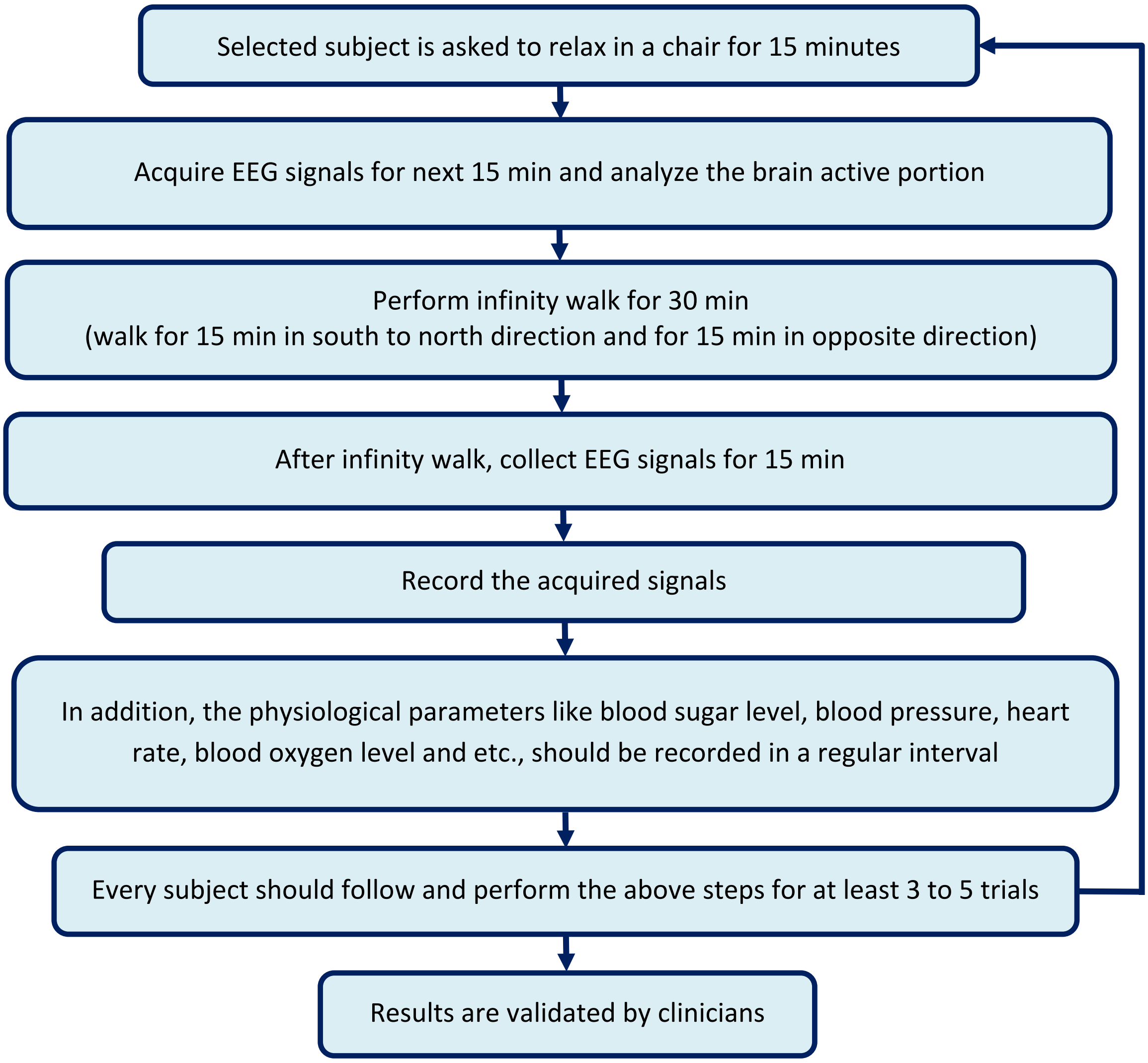

Figure 3. Steps in collecting and analyzing the EEG data

4. Methodological interventions

4.1 Pre-processing

Because of noise and distortions, raw EEG data is often unreliable. There are four main sources of noise and artifacts, which are:

i) EEG equipment

ii) Electrical interference from outside the subject and recording system

iii) The leads and electrodes

iv) The subject: electrical activity from the heart, eye blinking, eyeball motions, and general muscle movements

After a series of pre-processing stages, when the signal is free of most artifacts and noise, the recording is sliced into epochs of a few seconds, allowing us to extract a large number of features from a single EEG recording and utilize them in statistics or classifiers.

4.2 Feature Extraction

The next phase is feature extraction, which involves analyzing the signal and extracting data. This step computes the objects' features or properties and transmits them to be classified further. Because the EEG signal is so complicated, it's impossible to extract useful information from it simply by looking at it. Then processing algorithms must be used to find information that would otherwise be invisible to the naked eye.

4.3 Dimensionality reduction

Dimensionality refers to how many input features, parameters, or columns are found in a particular dataset, while dimensionality reduction refers to the process of reducing these features, ensuring that it provides multicollinearity and avoids removing significant details. In many circumstances, a dataset has significant input data, complicating the predictive modelling process. For training datasets with many features, it is extremely challenging to visualize or predict the future; hence, dimensionality reduction techniques must be used.

4.4 Feature ranking

By ranking features according to their significance in the model, feature ranking is the process of choosing "n" significant characteristics for a problem. In contrast to feature selection, which has the single goal of reducing the dataset size, feature ranking has the additional goal of creating a hierarchical order of the value of features given a particular learning assignment.

4.5 Validating the results

After experimenting/practising the infinity walk, the changes in physical parameters, such as Body Mass Index (BMI), physiological parameters like blood pressure, blood glucose level, blood oxygen level and cognitive behaviors like thinking, memory, reasoning etc., are observed, evaluated, and correlated with the information obtained from brain waves and validated with clinicians.

5. Discussion

This review focuses on identifying the brain's responses to functional connectivity based on various stimuli. Important elements, including the stimuli, dataset, EEG hardware, feature extraction, classification and validation methods, have been described in this context. Certain sorts of stimuli used up to this point in this field have been categorized and contextually highlighted. So far, 65 papers have been thoroughly collected, and the results are compiled. Walking is rarely used as a research stimulus; currently, only very few studies are recorded. The 8-shape walk or infinity walk workout approach is one of the best walking exercises. Following the advice of the Yogis and Siddhars, this is one of the best techniques that offer remarkable advantages to human health. For this suggested work, the infinite walk serves as the stimulus. For this stimulus, the changes in brain functional connectivity, physical, physiological and cognitive changes should be evaluated, and then a machine learning technique could be utilized to identify the region of the brain that is predominantly active. Ultimately, changes in the active brain region are corroborated by correlating the findings with the actual functions of the active brain lobes.

6. Conclusion and Future Work

The objective of this paper is to see how different stimuli affect the FC in the human brain. EEG data was used to examine the impact of different types of stimulation. A stimulus is anything or a condition that causes the brain to direct a particular operational response in the organs. Different stimuli cause different reactions inside an organism, which helps in sensing environmental changes. The authors have systematically analysed research articles that used diverse stimuli and examined their research techniques and outcomes for this study.

Yoga, meditation, music, audio, motor imagery, visual imagery, taste, emotion and scent are some of the stimuli investigated in this work. The dominating bands in particular lobes of the brain are recognized based on the stimuli, and whether the stimuli caused relaxation, reduced depression, increased memory and reasoning ability, or properly controlled the devices and other activities are all identified and examined. The changes in the brain lobes FC are noted/recorded after the prolonged 8-walk practice in the proposed work. This work helps to identify and justify the advantages of this 8-walk practice on psychological and physical health parameters.

As a part of future work, this study will be carried out with numerous male and female participants from various age groups. The benefits and changes that will result from the infinity walk will be verified both in the short and long term, especially for students. According to clinicians, both long-term and short-term infinity walk users have several advantages, such as better coordination in sports activities, enhanced focus and reasoning, assistance in regulating bodily physical parameters, and the ability to reverse all diseases. With the help of the suggested methodology, the effectiveness of the infinity walk practise can be validated. Using various machine learning techniques, the researchers can examine how the infinite walk impacts change in physical, physiological and cognitive behaviour.

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