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An Exploration of Human Brain Activity using BCI with EEG Techniques.

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ABSTRACT

Abstract. Brain-computer interface (BCI) acts as an important domain to determine human brain activities. Human Brain activities can be determined through various interfaces or electronic gadgets. BCI acts as an interface between the human brain and the computer. This paper describes various terminologies of wavelength used to determine human activities. It also describes the mode of detection of BCI such as MEG, fMRI, NIRS, and EEG with their classification, methodologies, and components. This Paper provides an exploration of various approaches and adaptations of the human brain's activities with various EEG techniques.

Keywords: **BCI, Human Brain Activity, EEG, Machine Learning.**

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I. INTRODUCTION

In Recent Years, Electronic Gadgets used widely in education, medicine, and finance. Artificial intelligence (AI) offers a collection of generic methods that, with little assistance from humans, simulate intelligent behavior. These methods include feature extraction and classification of neural signals coming from the brain. Machine Learning (ML) tools, a subfield of AI, are frequently used to automate, expand, and enhance EEG data processing to partially or entirely resolve the challenges.

The overall process of communication between the human and machine interaction (see Fig. 1.) Nervous System facilitates the transmission of brain information to certain parts of the body and stimulates movements of the machine termed to be Man–Machine Communications **(MMC).** A Traditional approach involves a device like a keyboard, touchpad or mouse, microphone, or camera for facial expression to access the brain's information leads to Human–Computer Interaction **(HCI).** A "Brain-Computer Interface (BCI)", acts as an interface between the nervous system of the human brain and the device of the computer.

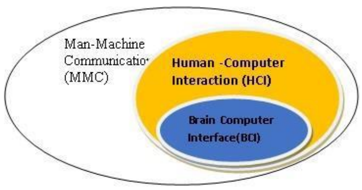

Fig.1 Interface between Man, Machine, and Human Brain

The BCI [16] system comprises various sequential processes organized as signal acquisition, feature extraction from the task, subset selection from the feature set that is more relevant, mental state classification, and output of feedback signals. "Electroencephalography (EEG)", "functional magnetic resonance imaging (fMRI)", and "functional near-infrared spectroscopy (fNIRS)" are some of the non-invasive monitoring methods used, these brain signals are retrieved, processed, and examined.

Temporal EEE Signals[19] have an extreme resolution, However, they also have some drawbacks due to non-stationarity, which renders algorithms for learning models on a temporally constrained amount of data subject to the inadequate expansion of information captured at various times on the identical person as well as substantial inter-subject variability due to unique physiological in nature artifact distinctions.

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II. LITERATURE SURVEY

Zhi-Ping Zhao et.al (2023) described **t**he brain and machines [20] can exchange information in real-time using a brain-computer interface (BCI). Much attention has been given to the fast advancement of invasive BCI, which has been fuelled by existing advancements in materials of electrodes, small and efficient power circuits, and technologies focused on decoding neural signals. The ideas of neural signals used to convert the given data into encoded and decoded format, which provides the information transmission in BCI, are initially introduced in this paper. Then, we go over the background and most recent developments in BCI focused on Invasive, particularly in experiments utilizing signals of neurons for both maintaining the devices and modifying the activity of the brain. This paper concentrates on two methods for electrically stimulating cortical and deep brain tissues to modulate brain activity.

Marios Hadjlaros et al (2023) explained that the current article examines the most common methods and the best techniques for creating and implementing cognitive gaming therapies that integrate "Virtual Reality (VR)' and "Brain-Computer Interface (BCI)" systems (VR). In interventions, cognitive abilities are related to awareness, visual information consideration, and visual memories.. For this reason, this work examines the methods and algorithms typically applied to feature extraction, classification, and data pre-processing in such interventions. Included in this study are the paradigm of BCI, tasks performed, environment, characteristics of the user, algorithms, performance efficiency, and major BCI-VR Cognitive Gaming discoveries. A review of the present difficulties, constraints, potential future research directions, and economic prospects of gaming based on BCI-VR with cognitive skills.

Kumari Annu et al(2023) proposed the "brain-computer interface (BCI)" is a technology that records neural impulses and interprets them as commands for operating output devices including robotic systems, prosthetic devices, computers, and so on. It is a cutting-edge, multidisciplinary study field built on sensors, neurology, signal processing, and other technologies. Researchers in a variety of domains, including cognitive neuroscience, artificial intelligence, medicine,marketing, education, and games, have recently been interested in it. To monitor brain activity, many invasive and non-invasive approaches are used. This paper [7] provides a detailed explanation of the human brain, its various components, and their respective roles. Together with classifiers, pre-processing, and feature extraction techniques are also covered. This study of information will provide knowledge in understanding the technology of BCI and also benefit the researchers to contribute work in their domain.

Lauren R. Krol et. al(2020) provided information [12] about the brain-computer interface focused on Passive brain activities. This work provides details about the history, current, and future research involved in the passive brain-computer interface. Passive Brain-Computer Interface referred by BCI. This Perspective leads to the key aspects of pBCI based system. This pBCI Perspective will be further classified into four categories of various levels of interactivity of the brain such as Adaptation based on open, closed, automated, and mental assessment statements. It also provides significant information on aspects of human-computer interaction that are important to the design of a system based on pBCI.

Damodar Reddy Edla et al. (2018) explained "the Brain Computer Interface" which plays a major role in the significant technologies used in the field of medical industries. BCI acts as a pipeline of interactions between computers and brain of the human. This research work mainly focused on ensemble learning [13] with classifier algorithms such as random forest to construct a model based on a computer interface which is used to determine the mental state of the human brain concentration. This research work is further implemented in the domain of IoT with home automation.

Hend A Hashem et. al(2023) proposed an innovative and effective machine learning-based BCI system determined to predict the Signals of EEG from motor imagery. This research work proposed a framework to predict EEG Signal processing based on meta-heuristic optimizing techniques and machine learning models. Optimizing techniques [5] such as "the Whale Optimization Algorithm (WAO)" are used to determine the neural activity pattern of the Limb Motor tasks. Machine Learning models such as the K-NN algorithm, Decision Tree, and Random Forest are used to enhance and analyze the precision of the EEG signals. This Proposed BCI is a combination of WAO and K-NN algorithms used to predict the overall accuracy of 98.6% of the machine learning model when compared with other learning models.

Zhihan Lv et al. (2020) outlined the Brain-Computer Interface, which uses information transmission to link the human brain to external technologies. The Classification Electroencephalogram (EEG) signal is crucial to the functionality of the devices. The data categorization model was predicted using a transfer

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of machine learning algorithm and a common spatial pattern (CSP) technique. This model will increase the BCI system's reliance on EEG signals for accuracy. The major purpose of this study [10] is to anticipate the precision of left- and right-hand movements at various speeds. This proposed approach combined with "Adaptive Composite Common Spatial Pattern (ACCSP)" and Self Adaptive Common Spatial Pattern algorithm used to predict classification with 5 subjects and the accuracy of classification leads to 83.58%.

Aggarwal et al. (2022) Analysis of the methodology for classifying EEG signals for specific operations using an EEG-EEG-based BCI system [2]. The development of artificial intelligence technology has encouraged researchers to use machine learning (ML) techniques to classify BCIs based on EEG signals. The brain-computer interface can adapt to the categorization rules of the generated studies and use machine learning techniques to learn from the subject's brain in each subsequent session. This improves the performance of the system. The authors present a detailed analysis of the application of various ML/DL techniques to EEG-EEG-predicted BCI. Motor imagery, p300, and steady-state inspired contingency are three EEG paradigms that are used to some extent. Based on ideal signal processing techniques, BCI performance and the difficulties of modern EEG-EEG-based BCI systems

III. BCI Terminologies

Brain-computer interface to detect the activities of the human brain using EEG. The Human Brain Wavelength is determined by the electrodes. Two Electrodes are used to fix the scalp of the forehead and near the ear of the human. These two electrodes will be incorporated with the chip that pre-processed the raw data obtained. This chip with two electrodes generates 8 waves with appropriate Hz values to determine the behavior of the human brain activity (see Fig 2.)

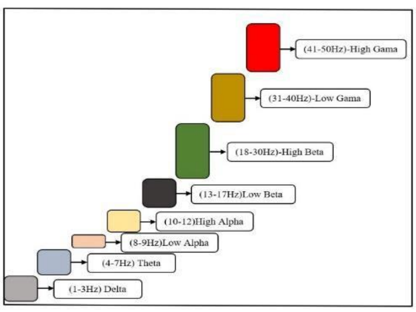

Fig.2. Terminologies of BCI

Fig.2 shows the level of human brain activity designed by the chip incorporated with raw data classified as Alpha Waves and Beta Waves. Alpha Waves were classified into two categories High Alpha and Low Alpha. High Alpha ranges from 10-12Hz and Low Alpha range from 8-9 Hz. These Alpha waves mainly focused on the absence of visualizations. Beta Waves were differentiated into two categories High Beta and Low Beta waves. High Beta waves range 18 to 30 Hz and low Beta waves range 13 to 17 Hz. These Beta Waves are used to determine the particular regions of the brain waves.

IV. BCI - MODE OF DETECTION

An activity based on neurons leads to determining the activities of the brain. The physical motion of electric charges boils down to generating two types of fields such as an electric and magnetic field. This Brain Computer Interface which used to determine the level of brain activities that lead to the consequence of task-based mental and certain stimuli. A sensor is plotted to the scalp of the human brain to determine the electric and magnetic waves of the human brain this wave will categorize the activity of the human brain. "The brain-computer interface" will detect activities of the human brain mode. (see Fig.3.)

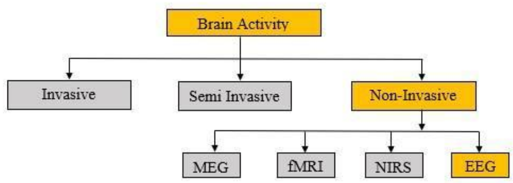

Fig.3. Mode of Detection

The mode of detection was classified into three types Invasive, Semi Invasive, and Non-Invasive

- **Invasive method:** Initially, the experiment of BCI with the invasive method was conducted on animals like mice, monkeys, and cats. These invasive methods require a surgical intervention which is used to cut the skin of the head or open the skull to place the electrode on the surface of the cortex [14] resulting in electrocorticography(ECoG)
  ECoG does not damage the neurons where the electrodes are not entered inside the brain. The main features of this invasive method are a good signal, Amplitude level with low noise, and spatial revolution will be good, each activity of the brain's neurons will be registered through the internal electrodes placed on the surface of the cortex This invasive method has a flaw which leads to a

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complex surgical intervention into the brain which affects the ethical controversy.

- **Semi Invasive:** This Semi Invasive method mainly focuses on the physical components placed inside the brain to determine human brain activity. This invasive method is effective in recording the details of the human brain activities, sometimes it may lead to problems for humans, based on the body fluids reacting to the electrodes.
- **Non-Invasive**: The activity of the human brain can be determined through the sensors placed on the head part of the human termed non-invasive methods. This Non-Invasive method uses four different types of approaches to determine Human Brain Activities.

Mangentoencephalography(MEG)

Magnetoencephalography(MEG) refers to a Non-Invasive Sensor which is placed on the surface of the head. This MEG technique measures the magnetic and electrical field of the human brain with high resolutions. A Cortex refers [8] to a particular portion of the scalp used to measure these magnetic and electrical fields of the human brain using MEG. These measured data are represented in the graphical format, and classified into three functionalities: Spatial Distribution, Orientation, and Inverse Problem, (see Fig 4.)

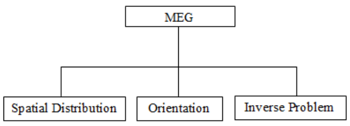

Fig.4. Classification of MEG

- Spatial Distribution: The arrangement of measured data with the phenomenon of graphical format leads to Spatial distributions.
- Orientation and Inverse Problem: The process of calculation from the set of observed data leads to the problem of the inverse. Therefore the inverse problem is solved by the existing feasible solution to determine the optimal solution that matches the constraints.

a) Functional Magnetic Resonance Imaging(fMRI)

fMRI is a neuroimaging method that records cerebral blood flow measurements to depict brain activity. fMRI is frequently used in AD research to visualize the activation of different brain regions and the interactions between them over time. In the latter case, connectivity is functional. Data collection, pre-processing, and analysis are the three processes that traditional fMRI procedures typically follow.

Because they need a lot of money, computing power, and technical know-how as compared to other approaches, fMRI [18] methods are not widely used (e.g., cognitive tests). Hence, it is not surprising that fMRI has historically been understudied and underutilized.

b) Near Infrared Spectroscopy(NIRS)

The basics of fNIR [9] optical brain monitoring is the propagation of photons from after passing through the epidermis, scalp, and spinal fluid, a near-infrared light source (such as a laser or light-emitting diode) penetrates the brain tissue. The near-infrared region[17] (600–1,000 nm) has an optical window where water and lipid absorption are reduced, allowing photons to penetrate through the skin and scalp. Given that light absorption in this range is largely correlated with both oxygenated hemoglobin (HbO) [3] and deoxygenated hemoglobin (Hb) (HbT), it is simple to discern between changes in cerebral blood oxygenation (i.e., HbO and Hb) and total blood volume. Most commercial fNIRS systems employ continuous waves, which illuminate the area of interest continuously and monitor intensity changes to spot changes in hemodynamic concentrations relative to baseline values.

c) Electroencephalography(EEG)

The majority of existing methods centered on improving the precision of EEG-based BCIs. A direct transformation of information between the brain and the outside objects can be created with the help of BCI
like a computer or robot. Active tactile exploration, neurally controlled robotic arms, emotion regularisation, etc., have all been accomplished with the use of BCIs. The most widely used method to gather brain signals is the electroencephalogram (EEG), which is typically measured from the scalp and is convenient and inexpensive.

d) "A non-invasive technique"[11] determining activities of the bioelectric of the human brain is electroencephalography (EEG). Electrodes positioned on the scalp's surface collect signals by monitoring potential changes brought on by the activation of cerebral cortex neurons. Epilepsy and sleep disorders can be monitored and diagnosed with EEG.

V. CLASSIFICATION OF EEG

The Classification of Traditional EEG (see Fig. 5.)

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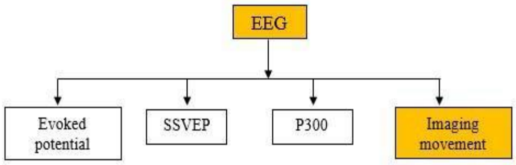

Fig.5. Classification of EEG

a) Evoked Potential

Evoked potentials (EP), [15] in addition to the conventional examination of EEG data, are utilized to help medical diagnosis. Evoked potentials are electrical impulses that are detected using a few electrodes on the surface of the skull after stimulation from a suitable external stimulus. We distinguish between visual, auditory, and somatosensory evoked potentials because the majority of stimuli are visual (such as a flash of light), auditory, or sensory. Also frequently used is the phrase Event-Related Potential (ERP). It refers to both EP and other brain reactions that are brought about by cognitive processes that accompany and follow external inputs or by pre-motor mechanisms. On the scalp, potentials have relatively small amplitudes. There is also the brain's spontaneous electrical activity. To employ evoked potentials, a certain stimulus is repeated, and the findings are then averaged. A doctor can determine the status of the neurological system by examining their latency. Moreover, a BCI can use these signals.

b) SSVEP

"The so-called steady state visually evoked potentials (SSVEP)" [4] applicable in BCI systems. SSVEP is gathered in the back of the skull and originates in the visual cortex. Let's say a user sees a light source (stimulus) that pulses at a given frequency, say 6 to 45 Hz. The visual cortex of the brain experiences waves with the same frequency in response to such a stimulus. We can see from the EEG data analysis that this frequency is by far the most prominent. By detecting the dominant frequency of the EEG potential, it is feasible to identify which light source the user is looking at at any one time when they are exposed to many light sources that pulse at various frequencies.
Each command sent to operate the machine is often connected to a light source that pulses at a specific frequency. SSVEP-based interfaces are rather common they function external to the field of user perception, any special training is not required, and work well for the majority of individuals. Unluckily, some individuals who are exposed to a pulsating light source may experience an epileptic seizure.

c) P300

The P300 evoked potential [6] is the most frequently used. This manifests a reaction to either sight or audio stimulation that a user has anticipated—often with great emotion. The P300 potential appears about 300 ms after the stimulus first appears, thus its name. The exact parameters of the response to a stimulus, such as its magnitude and latency, depend on numerous unpredictable psychophysical elements. In reality, the viewer views a collection of signs that are randomly illuminated, such as letters or other characters, for visual stimulation.
"An EEG potential" with tiny arises in the head region of the human brain at the precise instant the user's anticipated sign illuminates (on which the user had focused his attention). The same character is viewed by the user with emphasis numerous times, and average responses to the stimuli to assess the P300 potential. The user can type a text by shifting his focus to another sign. The complete rows and columns are frequently highlighted to speed up the selection of the right characters.

VI. METHODOLOGY OF EEG SIGNALS

The Traditional Representation of EEG Signal was classified into 4 categories (see Fig.6.)

Type	Frequency(Hz)	Waves	Behavior
Delta	0-4		Deep rest, dreamless sleep
Theta	4-8		Deeply relaxed
Alpha	8-13		Day dream, calm
Beta	13-30		Alter, active Thinking, anexity, panic attack, focus, concentrate
Gamma	30-100		Combination of two senses

Fig.6. Methodology of Signals

The recorded EEG signal is essentially a unique characteristic that fluctuates depending on a person's psychophysiological condition. The dominating frequencies and the signal's amplitude both fluctuate. A healthy human brain is thought to produce waves with frequencies between 0.5 and 100 Hz and amplitudes between several and several hundred there are certain identifiable rhythms of the EEG signal, usually small variations

- **Alpha rhythms**, which are particularly noticeable when visual stimuli are absent, have frequencies between 8 and 13 Hz.
- **Beta rhythms,** which are present in the frontal lobe of the human brain and can be noticed with concentration, with frequencies ranging from 12 to 30 Hz;
- **Gamma rhythms**, which occur between 30 and 100 Hz and are visible during motor movements,

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- **Delta rhythms,** which can be seen throughout stages 3 and 4 of sleep and range in frequency from 0.5 Hz to 4 Hz,
- **Theta rhythms** between 4 and 8 Hz, which appear while hypnotized and happen during light sleep, the Motor Imagery (MI) BCI paradigm uses a mu motor rhythm between 8 and 12 Hz.

VII. COMPONENTS OF EEG SIGNALS

The Component of the EEG Signal (see Fig .7.)

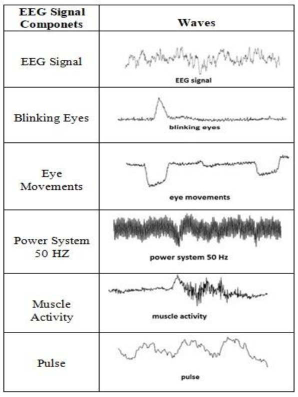

Fig.7. Component of Signals.

EEG Signal measurement is used to discover the properties and rules of diagnosing disease. It is also used to identify specific signals such as mental tasks or muscle activities. This measurement of signals could be used to construct an algorithm with acts as an interface between human–computer interactions. Eye Blink Signal using EEG which is used to determine the activity of the human brain. This signal is used to determine the recognition of epilepsy, detection of spikes, and diagnosis of encephalitis. Corner-retinal dipole alterations, saccadic spike potentials, and eyelid motions are all characteristics of eye movement.

VIII. BCI APPROACH

A Classification of the BCI Approach into two categories a) Traditiona Approach, and b) Recent Approach.

a) **Traditional Approach:** The Traditional Approach of EEG Signal through BCI Evoked Potential. This Evoked Potential is used to determine the electrical signals with the surface of the scalp with a few electrodes with an external stimulus. This Stimulus focused on flashes of light, such as auditory or sensory evoked potentials. Event Related Potential is commonly used to determine the brain's Responses to cognitive processes (see Fig. No.8.)

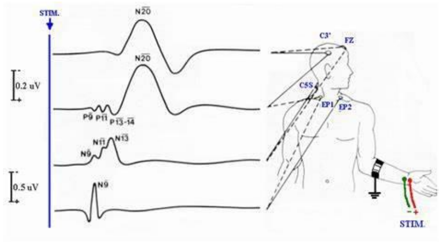

Fig No.8 Tradition Way of Implementing BCI

The next level of implementation is Steady State Visually Evoked Potential (SSVEP) which is mainly focused on the visual cortex which is collected from the backside of the skull. The most popular application for P300 is visual stimulation, where the user views a collection of signs that are randomly lighted, such as letters or characters. This P300 is mainly used for the text or character-based process. Advantages over Evoked potential don't require much training to build an application with an interface. Similarly, P300 and SSVEP are used to build an application with an interface to move the cursor, activate the robot, or write text. The main drawback of P300 and SSVEP is that the user must move his or her eyes, which can be challenging for someone who is immobilized.

b) Latest Approach

An EEG Device is used to capture the electrical activity of the human being from the sensor placed on the head termed a **Neurosky Mindwave**. This Neurosky Mindwave device consists of dual electrodes The human's forehead receives the first electrode, while the second electrode is put close to the ear. Both electrodes generate the raw data and process it into 8 values which are delta, theta, low alpha, high alpha, low beta, high beta, low gamma, and high gamma. The device of the Neurosky Mindwave is available in the market for researchers to predict the activity of the human brain using mobile applications for future research. These Neurosky Mindwave devices are connected to any device such as a computer or mobile via Bluetooth (see Fig. 9.)

Fig.9. Neurosky Mindwave

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IX. BCI ADAPTATIONS

BCI Adaptation is classified into a) Open – Loop adaptation b) Closed Loop Adaptation and c) Automated adaptation (see Fig.10.)

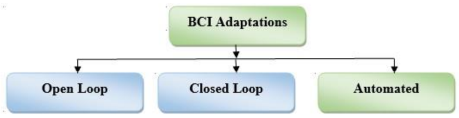

Fig.10. BCI Adaptations

Classification of BCI Adaptations [1] is given in the below table

Table 1. Classification of BCI Adaptation.

Adaptation	Definition	Process	Description
Open Loop Adaptation	A Machine will perform the same action for particular instructions of input given from the brain termed an Open Loop	**Input→ Process→Responses** viewed in isolations for one-time stimulus–response logic.	To measure the mental state of the human online and process the specific instruction as programmed.
Closed Loop Adaptation	The Output of Response that causes the changes in the next input.	The output of one response acts as an input of another cycle.	To measure the mental state of the human online and process the specific states or changes in the state or action that influence the same state.
Automated	A Model built to represent human cognitive processes or affective responses.	Autonomous Behaviour – Multiple stimuli –response logic	A Model with autonomous behavior and adaptions based on the activity of the human brain.

X. PROPOSED METHODOLOGY

Different approaches and different adaptations are used to determine the mental state of human brain activities. In this Proposed work, the researchers proposed a neuro sky mind wave that is used to determine the mental state of the human brain in the proposed methodology using imaging movements. The User can think about the movement of the body virtually rather than the physical approach leads to imaging movements. In the proposed methodology, automated adoption with movements of imaging techniques leads to an effective model.

XI. CONCLUSION

This Paper explores the fundamental knowledge in the field of EEG Terminologies, Mode of detection, and components of signals. Also, analysis of various approaches and adaptations of the Brain-Computer Interface were explored. This paper concluded that a recent approach with neuro sky mind wave would be effective in implementing a proposed model using imaging movement. Determining the electrical activity of the human brain activity using BCI with Automated adoption would be effective and efficient in the proposed model.

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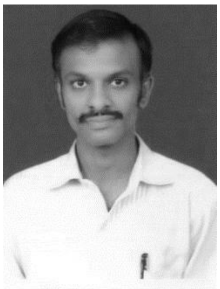

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