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Artificial Intelligence enabled neuroproteins design for Brain mapping dynamics based on motor imagery classification using HCI (Human computer interface) and (EEG) electroencephalogram

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Abstract
The brain activity can be represented by EEG, which does it by measuring voltage fluctuations in the brain. This paper aims to formulate a system which is capable of classifying and predicting the class of motor movement corresponding to the left or right direction. Such systems can have applications in various fields of human work. There are two datasets used in this study, relating to motor movements - left/right hand movement and eye open/close. The left/right hand movement dataset used in this paper captured brain wave readings recorded with an equipment of 128 Hertz sampling frequency with 16-bit analog converter with 14 electrode channels. The collected data is pre-processed by applying Fast Fourier Transform (FFT) to obtain a frequency domain matrix. The result computed by applying FFT provides a condensed representation of the data. The data was recorded across a 25-minute period by showing participants visuals of left and right movements, and brain waves were recorded corresponding to each movement. The second dataset captured brain impulses corresponding to two states of the eyes - eyes opened and eyes closed, over a period of two minutes. In this work how the split signals were employed, and how they vary from person to person. This Designed system effectively separate and utilize signals, and the adoption of AI techniques in these devices appears to be the most viable option for society 5.0. The integration of neurological data collected from the brain is used to train the prosthesis to conduct activities without encountering any impediments inthis signal. The overall efficiency of this system is 80 to 87%. The proposed AI enabled Neuroprosthetics are cost effective and user friendly. There is no need to have surgical implant to acquire the EMG signals from the individuals to operate Neuroprosthetics.

Keywords: *Artificial intelligence, Neuroprosthetics, Expandable Artificial Intelligence (AI), EEG, Motor Imagery signals, Motor Control, Movement, CNN.*

1. Introduction

According to the World Health Organization (WHO), around 15% of the global population is handicapped, with 40% to 50% of them unable to afford medical care. [1] Around 10 million people worldwide are amputees, with arm/hand/limb/ amputees representing almost 30% of the total. [2] The Smart Prosthetic arm/limbs are one of the best solutions. As we know Prosthetic limbs have been present for many years, but the majority of these solutions have disadvantages, such as being extremely expensive, difficult to install and maintain, and perhaps requiring surgery which is a pain full process and does not insure any guarantee of functionality required [3]. The accidents occurred In India from 2015 to 2021 we can observe the total road accidents along with death and causalities shown below in Figure 1.

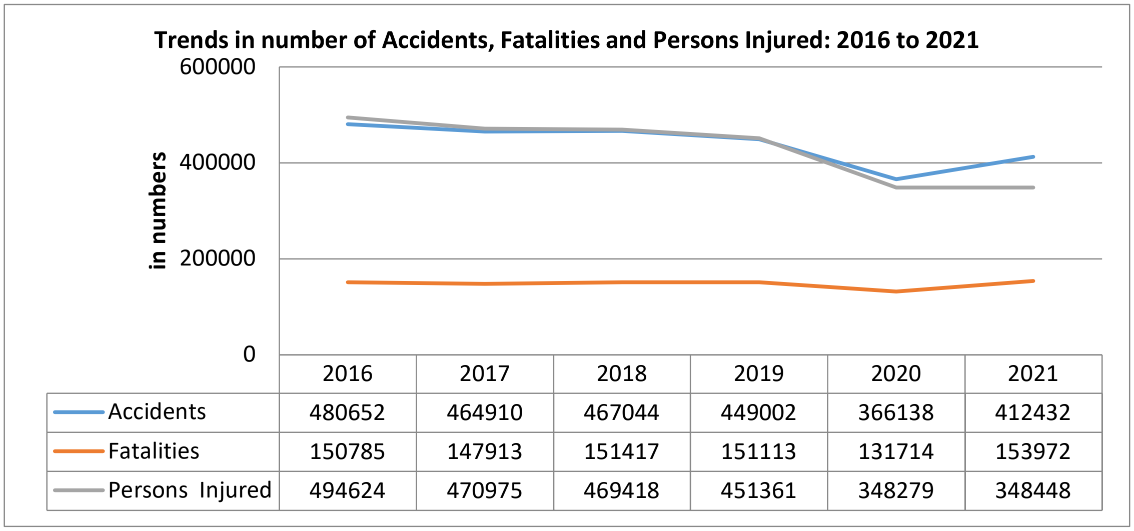

Figure 1 Total Road accidents, Causalities, and lives lost (data from morth.gov.in)

From Figure 1 it is observed that the number of causalities and accidents is more as compared to the lives lost due to road accidents. In several total causalities, about 30- 40% are arm amputees. So, we can interpret the total number of accidents, casualties, and lives lost throughout the world from the above data. As per the study, arm amputees due to accidents are about more than 35% [4]. Even though prosthetic limbs have been available for decades, they do not function or interact with the environment naturally. They demand invasive surgery. The main goal of such difficult procedures is to reroute nerves, allowing amputees to control their prosthetic devices just by thinking about the action they want to take [5]. Science has constantly been striving to understand the intricate workings of the human brain. The brain has been the focus of research across various domains of science and a plethora of research has been conducted on this topic. Over the past few decades, various non-invasive and safe techniques have been developed for the imaging of the brain during a variety of movements and exercises. Electroencephalography (EEG) is one of those techniques which has been an invaluable and useful technique for neuroimaging. It has helped in examining the activity of motor imagery for various motor actions without actually performing the execution. Using the correlation between the EEG readings and motor imagery has been the core driving force in various niche fields like neurotherapy, robotics and sports training. This paper aims to explore these intricate connections and further use the potential for developing advanced motor control systems.

The main objective and target of this study is to explore the utilization capability of EEG readings to predict motor actions based on the mental imagery of motor movements such as hand movement and eye movement. This study heavily relies on machine learning algorithms, particularly Convolutional Neural Networks, to find the intricate patterns and relations between various reading fields. The aim is to decode the deep correlation of the readings made through EEG and attempt to classify actions, using the aforesaid machine learning models. This will contribute immensely in increasing the understanding of the inner brain mechanisms corresponding to the motor movements, and it will provide insights for further research in this field.For the purpose of this study, the data was used which was recorded and refined painstakingly using techniques like the Fast Fourier Transform. The data has images corresponding to motor movements. Across the two datasets, the participants were made to view visuals relating to the left/right hand movements to make readings of such movements with the reading of various electrodes. EEG signals were recorded simultaneously to find the corresponding readings from the various electrodes.

In the other dataset, relating to the eye state, participants were made to open and close their eyes on cues and, like before, EEG signals were recorded simultaneously. This provides us with 2 types of motor movement data, which will provide variety to the study, and make us understand the relation between EEG signals and motor movements even better.

The data from the dataset was subjected to various preprocessing methods to extract relevant and important features and remove the irrelevant and unimportant data. Data was further cleaned to enhance the quality of the

EEG readings. Afterwards, the models were trained on this processed data to find the patterns and relationships between various fields of each image of the EEG data of each dataset - left/right hand movement and eye open/close state movement. After model building and training, they were further assessed and evaluated against relevant metrics - like precision, recall, and f1-score - to find the usefulness and predicting capabilities. The results of this can have comprehensive applications across various fields, particularly in neurotherapy and neurorehabilitation, where EEG signals can be used to facilitate the creation and development of efficient and accurate therapeutic and strategies. It has immense potential in the field of Brain-Computer interfaces which can be used with people with disabilities to allow them to have normal movements just by the use of their imagination by reading their brain wave through EEG. This study presents an investigation into the complex relationship between brain imagery and EEG signals for various motor movements. By finding the mechanisms involved in these actions, we can contribute to the growing field of study of neuroscience and its practical applications.

1.1 Neuroscience for Brain computer Interface (BCI)

Neuroscientists are steadily creating ways and tools for combining brains and computers, allowing for a wide range of real-time applications. The most important are brain-computer interfaces (BCIs), which can allow even persons with severe impairments to use other ways of communication and operate external devices [6]. Platforms for external instrument control applications that leverage real-time BCIs are now being investigated in depth. Because of its long-term applicability, high temporal precision, simplicity of installation, and low cost, EEG [7] is now the most recognized brain signal for the practical application of BCIs. The human brain interface has progressed to the point where it can do previously inconceivable tasks and achieve useful goals. The breadth of EEG-based BCI [8] controls, the level of technological complexity required, and its application for both disabled patients and the general population are all areas where research is ongoing.

The upper arm is severely impaired after amputation [9]. Dinesh Mohan's research found that 4,24,000 Indians had their arms amputated at or above the wrist. Trauma, such as a job or traffic accident, is the leading cause of arm amputations. Arm immobility occurs when the brain and muscles lose contact due to a spinal cord injury, upper body paralysis, or a stroke. People who suffer from upper-body difficulties today might benefit greatly from the BCI system. Several researchers have developed an EEG-based BCI system with active hand-crafted feature extraction of EEG data to address the problem, but the clinical and financial outcomes remain unsatisfactory [10]. In recent years, several scholars have investigated a range of approaches to increase accuracy. Signal analysis and processing are required because EEG recordings provide a large amount of data. In the processing of this data and decision-making, mathematical modeling of EEG signals, as well as substantial use of machine learning techniques, is crucial. The researchers combined core knowledge with a cutting-edge methodology to create a new algorithm for categorizing upper limb/arm motions [11].

A smart prosthetic arm controlled by EEG would be the optimal solution. The arm is controlled by brain impulses recorded with an EEG headset, and it is equipped with a network of smart sensors and actuators that provide cognitive input to the patient about the surrounding environment and the item in contact [12]. The discovery of EEG impulses by Berger in 1929 prompted the concept of using brain signals rather than peripheral nerves and muscles to drive a robot or prosthetic device [13]. In 1971, brain signals were utilized to operate prosthetic limbs for the first time. Since then, scientists have been attempting to better understand brain waves to produce more effective and reliable external device control. This field of research was eventually dubbed brain-computer interface (BCI), and its applications grew significantly. Analytical tools will greatly facilitate the creation of robust, functional, and active BCIs that humans can operate using thought waves recorded via EEG and comparable sensors. This might be turned into a thrust zone for more demanding applications like Prosthetic Control. The main goal of such sophisticated techniques is to reassign nerves and allow amputees to operate their prosthetic devices just by thinking about what they wish to accomplish. Artificial intelligence-based bionic/robotic arms can easily do this. The main objective of this work is

- To understand the working of Neuroprosthetics
- To explore the existing research on the Neuroprosthetics
- To propose a suitable methodology for designing Neuroprosthetics with AI

2. Literature review

Neuroprosthetics is generally used nowadays and the development in this field has made many researchers contribute a lot of research for many years. The recent development in the field of neuroprosthesis is reviewed below. Junyou Yang, et al. 2016[15] developed a brain-computer interface (BCI) system that combines electrooculography (EOG) and electroencephalography (EEG) to control prostheses using multi-control instructions and the common spatial pattern (CSP) method, and then enables vector machine learning (SVM). The EEG frequency range was chosen using a common spatial pattern (CSP) approach, and the data's attributes were identified using a support vector machine (SVM). To improve the performance of the hybrid BCI system, the EOG signals caused by visual attention and the EEG signals of ERS/ERD were delivered as inputs at the same time. The recommended technique was proven in the lab on a multi-functional robotic prosthesis. The advantage of EOG and EEG, the recognition accuracy of the entire system reaches only 91.1%.

Roy, et al. [16] 2016 devised a genetic technique for route optimization of an EEG-driven robotic arm. An Svm Machine classifier (SVM) with Power feature co-efficient and wavelet co-efficient as features was used to identify left-right hand movement in five healthy volunteers' EEG data for muscle activation. The EEG processing and GA approaches were developed at Mat lab. The trajectory route for an EEG-controlled robotic arm is shown in this paper. For the left-right arm movement, only 75.77 percent of classification accuracy was attained.

The purposed research is based on Two software frameworks to operate a 5-degree-of-freedom robotic and prosthetic hand by Elstob et al. [17] 2016, The Emotive Cognitive Suite (the initial framework) uses an embedded software system (an open-source Arduino board) to control the hand via character input linked to the suite's taught behaviors. The second framework looks like this: This last one enables motor imagery task EEG signal training and categorization. When analyzing the system, a confusion matrix, accuracy measurement, and a signal intensity feedback bar provide clear visual representations of performance and accuracy. The proposed framework's practicality was determined by the fact that brain impulses may be used to operate the chosen prosthesis.

Bright et al. [19] 2016, to perform the two main actions of the arm's fingers: flexion and extension, an EEG-based brain-controlled prosthetic limb was built utilizing BCI and a NeuroskyMindwave headset. An EEG sensor is used to gather the brain signal, which is then analyzed in MATLAB using the Think Gear module. The acquired brain signals are used as command signals that are sent via radio frequency to the Microcontroller. To carry out the instructions, the prosthetic arm module is fitted with an Arduino board and servo motors. The low-cost wireless BCI device might allow disabled people to manage their prosthetic limbs and live a self-sufficient life by using their brain impulses.

Anderson et al. [20] 2017, The research presented centered on the development of an EEG-controlled hybrid arm prosthesis. Inputs from a headset that monitors brain electrical activity were processed by a microcontroller in the prosthesis. They produced low-cost devices concerning the cost of existing prostheses.

Ghaemi et al, [21] 2017, An automated method for choosing optimal channels has been devised for Brain-Computer Interfaces (BCIs). The necessity of discovering effective channels in BCI systems to reduce their complexity was emphasized. To automatically locate the effective electroencephalography (EEG) channels in left and right-hand categorization, the Improved Binary Gravitation Search Algorithm (IBGSA) is used. To accomplish so, the data were first filtered with a bandpass filter to limit the amount of merging noise. Blind Source Separation (BSS) was used to rectify the electrooculography (EOG) and electromyography (EMG) artifacts. For Event-Related Synchronization (ERS) analysis, the data was epoched according to left or right-hand motor imageries, and the center beta frequency band was recovered. The feature extraction approach uses time and wavelet analysis of Eeg recordings domains. Automatically selecting suitable channels can help simplify and improve BCI-based system installation.

Ruhunage, et al.[22] 2017, EMG and EEG signals are used to operate a transhumeral prosthetic arm. It is based on Steady-State Visual Evoked Potentials (SSVEP), which allows the user to open and close the hand prosthesis using brain signals. The UOMPro transhumeral prosthetic arm has one DOF elbow joint and six DOF prosthetic hands. The flexion/extension motions of the elbow joint are achieved in this system using EMG signals from the biceps and triceps muscles. EMG signals are used to operate the elbow joint of the prosthetic arm utilizing a real-time fuzzy-neuro network-based technique. The users can successfully manage the elbow and hand open/close

motions to control the hand prosthetic's open/close motions.
Gayathri, et al. [23] 2018, This paper introduces a novel technique for extracting eyeblink signals from EEG to operate a prosthetic arm. The extracted coded eyeblinks are employed as a key task command for prosthetic arm movement control. 3D printing was used to create the prosthetic arm. The microcontroller converted the principal work into micromechanical chores. Machine learning algorithms were used to extract characteristics from the temporal and spectral domains of the EEG data to identify the directives. Linear Discriminant Analysis (LDA) and K-Nearest Neighbour (K-NN) are the two classification approaches employed (KNN). In comparison to KNN, LDA approaches demonstrated high accuracy, precision, and recall.
Idowu, et al. [25] 2018, The EMG data collected by pattern recognition were inadequate. It is necessary to have intelligent robotic (or prosthetic) control. They used a stacked autoencoder to produce features, and then a softmax layer to categorize five different motor imagery Tasks. To design an intelligent robotic (or prosthetics) system that moves items smoothly with several degrees of freedom, a sophisticated learning algorithm that can govern the prosthetic arm while interacting with the environment is required (DoF). However, like with standard machine learning, using handcrafted traits to design a robot controller that can do several tasks is not a practical approach. As a consequence, they provide a reliable learning control system based on the unsupervised learning method of a deep autoencoder. This method was a feasible option for robotic (or prosthetics) systems to control/operate.
Bhavesh P, et al. [26] 2019, A Brain-PC interface was established using a Brainwave external device as part of research on how to operate the arm prosthesis. The brain wave signal was separated into two frequencies. These signals were used to control the prosthesis, and a static analysis was carried out to better understand the behavior of the arm joint. They were unable to maintain the level of control required to perform all the moving jobs.
Ruhunage, et al. [27] 2019, Electroencephalography (EEG) and electromyography (EMG) signals were used to control hand motions of a transhumeral prosthesis in a hybrid approach. The prosthesis employed in this study comprises a UOMPro prosthetic hand with 6 degrees of freedom (DOF) and a 1 DOF elbow joint. To choose the hand-ripping pattern, EEG motor imagery/motor mobility data generated by users are classified using a neural network (NN). After classifications of EMG data, the opening and closing of the hand are accomplished.
the muscles of the biceps and triceps the movement control of transhumeral prosthesis were presented well with a set of experiments.
Hong, et al. [32] 2020, are attempting to construct an EEG brain wave-driven system in which amputees may control the movement of their prosthetic limb by picturing it using DWT and SVM. The intelligent 3D-printed prosthetic arm with EEG-based brain wave control is structured to use the amputee's brain wave to handle the prosthetic arm's movement. The amputee's EEG signal must be obtained by visualizing four movements of the left forearm: up, down, left, and right. To obtain the alpha wave, the EEG data was pre-processed, and the Discrete Wavelet Transform (DWT) was used. The alpha wave was then converted to a frequency domain by performing FFT on it. To regulate arm movement, the two-stage binary classifier employed a machine learning approach called Support Vector Machine (SVM). The amputee needs to be trained to control every arm movement correctly.
Kokate, et al. [33] 2021, A unique algorithm for classifying left/right-hand movements by utilizing Multi-layer Perceptron Neural Network was proposed. For categorizing left and right motions from EEG data, a novel method was given. Contaminated and undesired impulses are common in EEG signals. Contamination is successfully removed using ICA and a unique method. When both sectors' feature vectors were added, the method outperformed. Validation was done on several participants using the intra-subject validation technique. Finally, the suggested model's execution approximated that of the deep learning model. This technique is used to control the upper arm effectively.
Buerkle, et al. [34] 2021, showed there are walls and limits in place to safeguard human operators, preventing close collaboration. Because safety systems are largely reactive rather than predicting motions or intents, this is the case. Although clustering techniques are being developed to address these constraints, forecasting human behavior remains a difficult task. The goal of this project is to safeguard the human from the prosthesis's protective harm. An electroencephalogram (EEG) can be used to determine upper-limb movement intentions (EEG). Up to 0.5 seconds before a motor activity is carried out, the human brain analyses and assesses it. As a result, a safety system might be improved to provide early notice of impending movement. A new data processing technology was created to categorize the EEG signals as quickly as feasible while minimizing fine-tuning attempts. This comprises labeling movement intentions using Time Series K Means, which is subsequently used to train a Recurrent Neural Network with a Long Short-Term Memory (LSTM-RNN). This was tested only on a human-

robot collaborative environment, but it will be best if it has experimented on human and prosthesis interfaces
The literature review is carried out to understand the new technological developments in prosthetic arm design. In this study we considered the research work carried out by the researchers in previous years. The following are key findings in this review are as follows.
The prostheses developed by many researchers are manually working and the response time is too large and as well as operation will be complicated for the end-user. That means an intelligent Prosthetic Arm System was not proposed by most of the researchers. The BCI was widely used by the researchers but most of the cases interface with the BCI was not explored by the researchers. The BCI used to design prostheses required brain mapping. Brain mapping was one of the major issues that were not discoed by the researchers since the brain acts sometimes vigorously and signals generated were varies accordingly. Proper AI methodology must be adopted for analyzing the signals generated by the brain to control prostheses, but a few researchers had explored this, and still, the systematic control of a system to control Bio robotic Prosthetic Arms is not in place.

3. Overview on the existing Design of Neuroprosthetics

Neuroprosthetics (also known as neural prosthetics) is an area of neurology and biomedical engineering concerned with the creation of neural prosthetics. A brain-computer interface, on the other hand, is a device that links the brain to a computer rather than replacing biological functions [28]. It was 1957 when the first cochlear implant was created. He also developed the first motor prosthesis for hemiplegia foot drop in 1961, the first auditory central nervous system implant in 1977, and a peripheral nerve bridge implanted into the spinal cord of an adult rat in 1981. Functional electrical stimulation (FES) and the lumbar anterior root implant were employed to assist paraplegics with standing and walking in 1988 [29]. Neuroprostheses are devices that help people who have lost nerve function. The technology either detects natural voluntary control biosignals or uses electronic components to translate motion or other patient efforts into electrical signals [30].An early problem in the development of electrodes implanted in the brain was precisely finding the electrodes, which was first accomplished by introducing needles into the electrodes and snapping the needles off at the required depth. Sophisticated probes, such as those used in deep brain stimulation to treat Parkinson's disease symptoms, are used in more modern systems. The problem with both methods is that the brain floats freely in the skull while the probe does not, and even minor impacts can cause the brain to float. The problem with either strategy is that the brain floats freely in the skull while the probe does not, causing the brain to float even in minor accidents. Some experts, such as the University of Michigan's Kensall Wise, have urged for "electrodes to be placed on the exterior surface of the brain" linked to the inside surface of the skull. The design of neuroprosthetics consists of the designing of different components and is explained under the following heads [31].

4. EEG sensors detect different forms of brainwaves:

The EEG is the electric potential generated by the distribution or redistribution of opposite charges cations and anions in each neuron in the brain cell. The amplitude of the EEG, the electroencephalogram, ranges from 2 to 200 microvolts and the frequency ranges from 0.5 to 50 freq[35]. This EEG frequency range is usually divided into five bands, with EEG wave analysis based on the frequency generated in the neurons. Delta, theta, alpha, beta, and gamma are the five bands that make up the EEG frequency. The delta frequency has a frequency range of 0.5 to 4 hertz. The alpha frequency range is between 8 and 13 hertz, whereas the theta frequency range is between 4 and 8 hertz. Gamma frequencies vary from 22 to 50 hertz, whereas beta frequencies range from 13 to 22 hertz.[36] Out of these five bands, The most significant is the alpha frequency range. Because it shows the brain's level of awareness, this is the most significant frequency band on the EEG. The other bands are significant as well, but this one is crucial since it signals the brain's degree of awareness and is used to deliver anesthetic to patients undergoing surgical procedures. The EEG waveform is analyzed to determine the level of awareness or brain activity [37]. The electroencephalogram is a cross-sectional view of a neuron cell in the resting state. This neuron cell has a negative charge along the inner surface and a positive charge along the outer surface. This positioning of the opposite type of charges, cations, and anions, produces an electric potential between them, which is called the EEG. In ECG, a similar principle was used [38].

4.1 Electroencephalogram (EEG) signals processing:

The fundamentals of electroencephalography (EEG), which records electrical activity related to heart function, and electroencephalography (EEG), which records electrical activity linked to brain function. A recording of electrical activity in the brain and the neurons that make up the brain is called an electroencephalogram [39]. The electroencephalogram is a cyclic electric potential generated by hundreds of neurons in the brain as a result of charge migration, charge redistribution, and charge distribution in various ways.

4.2 Connection between Computer and brain:

There are two possible ways to connect the computer with the brain They are classified into two types: brain-computer interfaces (BCIs), which transform neural signals from one brain into computer commands, and computer-brain interfaces (CBIs), which transfer computer commands to another brain.

4.3 CBI (Computer Brain Interface)

Natural human interaction is two-way communication possible between computers and the brain so we can have two different settings here the first is brain-computer interface versus computer-brain interface so in brain compute interface what we have is we have human brain connected to an external device and the communication goes in one direction from the brain to outside device so brain puts information into a computer or some other device in CBI(Computer Brain Interface) we have external device this can be a computer that is putting information into brain there are some brain disease disorders such as Parkinson's disease they, for instance, use some so-called neurostimulation to stimulate certain parts of the brain and we can think of this kind of stimulation as putting some information to the brain also there are some other brain disease conditions such as epilepsy in practice. systems being used in clinically clinical areas, so the aim is to stimulate certain parts of the brain to disrupt or to change the way neural connections and perform a solution for the problem Figure 2 shows the CBI interface [40].

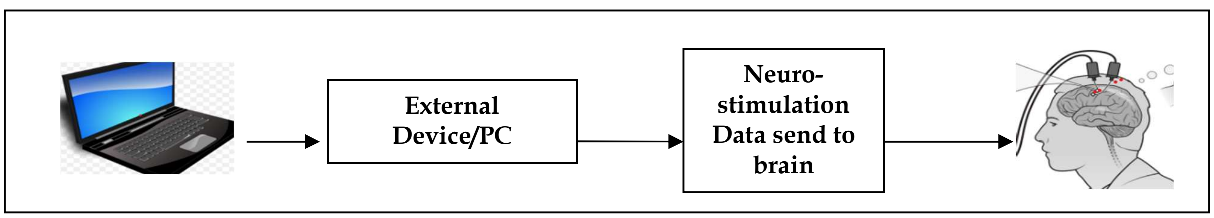

Figure 2 Computer Brain Interface

4.4 BCI- Brain Computer Interface

A brain-computer interface (BCI) is a gadget that allows someone to control a computer only via their mind [41]. The person is taught a specific concept, such as controlling one's knee by flexing it. Cognition generates both electrical activities in nerve cells and brainwaves. To pick up electrical impulses, electrodes can be placed on the scalp or a chip can be implanted in the brain. In patients with paralysis or amputation, BCI can be utilized to regulate muscle, limb, and prosthetic movement. A chip inserted in the user's brain or electrodes put on the scalp are used in a brain-machine interface. The prosthetic device will thereafter be able to understand brain impulses. The BCI is a brain-computer interface that connects prosthetic devices to the brain. To do this, the same impulses that regulate the firing of a biological limb would be utilized. The impulses might be sent by electrodes on the scalp, the brain's surface, peripheral nerves, or even the brain itself. Depending on the type of electrodes used and the BCI interface [43], it might be a reasonably simple procedure or more invasive implantation.

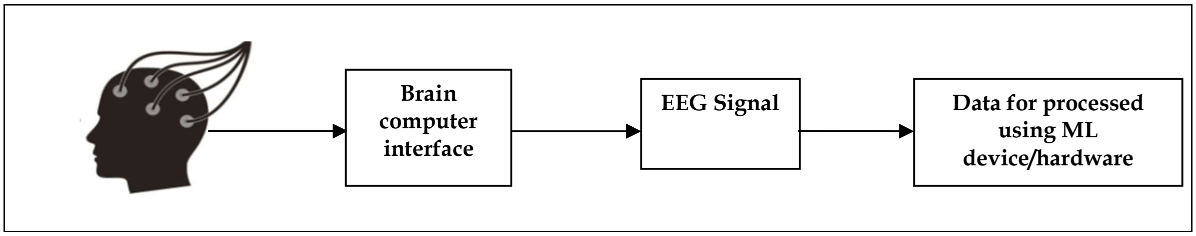

Figure 3 Brain-computer interface

The simplicity of use and control go together in hand. Electrodes on the scalp work well for fundamental control tasks like bending and straightening a knee. Intraparenchymal electrodes, or electrodes implanted in the brain, on the other hand, allow significantly more fine motor control, such as the ability to manipulate arms and drink from cups. Neuroprosthetics is different from ordinary prosthetics in that they are more closely linked to how the human body functions. The brain delivers electrical impulses to a limb when you move it, prompting it to perform the action you desire [44]. BCI with Prosthesis Control and Other Applications is depicted in Figure 3.

5. Importance of Explainable Artificial Intelligence (AI) enabled devices:

The AI enabled devices to have more efficient in comparison with traditional devices. These devices are used in many applications in which neuroprosthesis is the most important. This will overcome all the drawbacks of traditional methods. These devices are consisting of data collection, data filtration, feature extraction, and utilization of the final output to operate the devices [45].

- **There is a need for signal analysis and to enhance the signal efficiently to make the devices smart.**
- **The feature extraction of the data is enhanced to select the required type of signals to operate the devices smartly.**
- **The devices must be made user friendly**
- **The devices must be cost-effective and meet all the requirements of the end user.**

The use of AI devices will help society more effectively. For this, we proposed a model based on the AI and it is called Model for Society 5.0.

6. Proposed model for Society 5.0

The proposed model is a combination of different steps, and these steps are successfully used to make this model work efficiently. In this model, traditional methods are used along with the AI to make the proposed model more flexible and user-friendly. It is explained under the following heads.

6.1 Architecture for AI enables Neuroprosthetics system for brain mapping

The proposed model architecture is shown in Figure 4. It is known that machine learning works with data, thus the first step in implementing a machine learning model is to gather enough data. EEG sensor: The billions of cells in your brain produce very tiny electrical signals, which combine to form non-linear patterns known as electrical impulses. An EEG machine analyses the electrical activity in the cerebral cortex, the brain's outer layer, during an EEG exam. EEG sensors are attached to the user's head, and the electrodes measure brainwave activity. EEG sensors can capture thousands of electrical activities occurring in the brain in a single second. The electrical impulses are collected and sent through amplifiers, which then transfer the data to the microcontroller to be processed. The improved signals, which appear as wavy lines, can be stored in a computer, a mobile device, or a cloud database [46-47]. By acquiring data from the brain using BCI while the individual is considering a certain action.

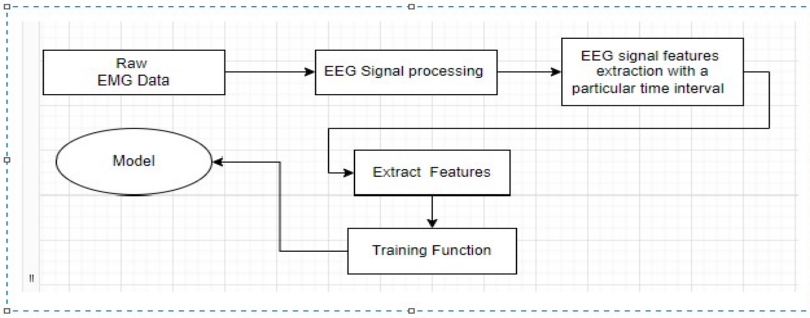

Figure.4 Proposed AI-enabled Neuroprosthetics

7. Working

It works on EEG and BCI devices and trained neural networks which makes its control smooth and perfect. EEG data mapped with BCI using machine learning. After the Train and test model is implemented in the system. In this purpose model, we will first utilize hardware to record our brain waves, then apply machine learning to extract features from those recorded waves, and then use those anticipated characteristics to produce our desired output. In the future, we will employ this model with a variety of additional applications. The AI is extensively used from data aquation to device control to make this proposed model for society 5.0 more effective and efficient. The work is shown in Figure 5.

This research paper included two datasets relating to motor movements based on EEG recordings from participants. The first dataset consisted of preprocessed EEG brain impulse data corresponding to motor movements correlated to left or right hand movement. The second dataset used in this study had data of two states of eyes - open and closed - and EEG readings corresponding to those states.

The first dataset used in this research consists of EEG recordings obtained from participants engaging in motor imagery tasks. A total of 4 participants were recruited for the study.

To record the left/right hand movement data, a special way was devised in which, in a series of cycles of recordings, participants were presented with visuals representing specific motor actions, relating to the left/right or no movement. These visuals consisted of arrow images to prompt directional movements and a circle image was shown to indicate no motor movements. Simultaneously, EEG signals were recorded for each visual.

The EEG data acquisition was performed using a state-of-the-art 128-Hz, 14-channel EEG system. For each reading, the EEG equipment provided a 16-bit 128x14 matrix, capturing electrical activity from specific electrode placements on the scalp.

The readings from the electrodes were initially in the range of 0 to 30 hertz, which were not right for our usage, hence they were further processed through the Fast Fourier Transform algorithm to obtain them in the desired range of frequency.after the transformation, the data was further processed to condense it for compact usage. The weighted and arithmetic mean of each wave classification were computed, resulting in a final matrix with dimensions of 14x4x2. Each instant of the collected data was thus represented by the weighted and arithmetic mean values for each of the 14 device channels and the 4 wave classifications.

To ensure that the data was reliable and usable, various measures and techniques were implemented like manually inspecting the recordings for noise and interference. Data which can cause data integrity and bias problems and further make the models unreliable and incorrect was promptly removed.
The second dataset consisted of EEG recordings obtained from a single continuous measurement using the Emotiv EEG Neuroheadset. The measurement duration spanned 117 seconds, capturing a substantial amount of neural activity related to eye states.

Additional data for the field of eye state was added manually using the recorded video. Each image has an additional field representing the open or close position of the eye, with a value of 1 representing that the eye was closed and a value of 0 representing that the eye was open. These two states were the independent variables on which the model was going to be further trained.

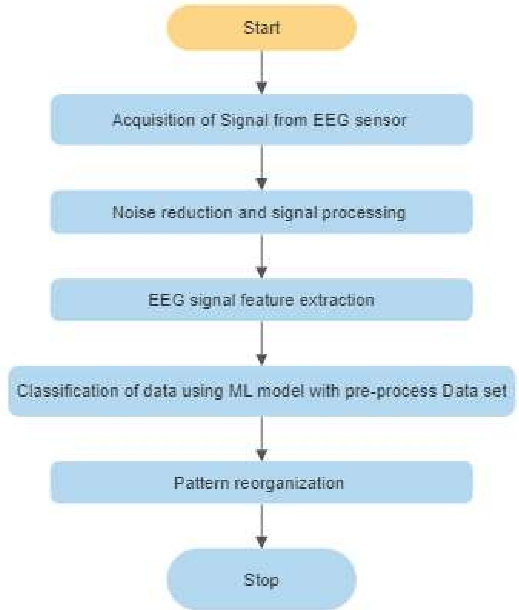

Figure.5 Working

This dataset provided a comprehensive collection of synchronized EEG data and corresponding eye state labels, enabling the investigation of the relationship between neural signals and the eye-closed and eye-open states.
It can be said that the datasets used in this study provided a comprehensive collection of EEG recordings showing a variety of motor imagery. The presence of various participants in the data allowed the data to have variability and encompass the range of different readings of each human, and not limit itself to only one person and their unique reading. The preprocessing of the data made is suitable for further steps to be applied to it and it also made it apt for model building and further prediction of the motor actions based on the EEG readings.

7.1 Experimental Results

The proposed model is a combination of different steps, and these steps are successfully used to make this model work efficiently. In this model, traditional methods are used along with AI(Artificial Intelligence) to make the proposed model more flexible and user-friendly.

1. Data Preprocessing: The data from the datasets of the EEG recordings were made to go through various steps of preprocessing to make sure that the quality and relevance of the data remains useful and utilizable. This was done by carefully examining the data and manually removing the data which may have been compromised because of sudden muscle movements, eye blinks, or environmental factors.
   Afterwards, a filter was applied on the data to remove any frequency which was unwanted and outside the range of interest, which in our case was 0 to 30 Hz. This allowed us to only focus on the data which was relevant to the motor imagery and our primary aim of further predictions. Feature extraction was then performed to extract meaningful information from the preprocessed EEG signals. The Fast Fourier Transform (FFT) algorithm was applied to convert the time-domain signals into the frequency domain. This resulted in a matrix representing the power spectral density across different frequency bins for each channel. Following the transformation to the frequency domain, the data were further condensed by calculating the weighted and arithmetic mean of each wave classification. This resulted in a reduced-dimensional representation of the EEG data, capturing the essential information for subsequent analysis and modeling.
2. Model Development: The Convolutional Neural Network (CNN) approach was chosen for our modeling purposes

as there were a lot of target variables in play, and CNN generally is quite accurate when it comes to finding hidden patterns in data sets which are large and complex.For our purpose, we constructed a CNN model with two hidden layers, each consisting of 256 nodes. It should be noted that layers with 128, 512, and 1024 nodes were also tried in the course of this study. The input layer of this CNN model consisted of the preprocessed EEG data which had its dimensions determined by the number of channels and the reduced-dimensional structure obtained after feature extraction. The model was trained using a supervised learning approach where the input EEG data were paired with the various corresponding motor action labels, which were represented by a field named “class”. The model was optimized using the Adam optimizer and the output was optimized using the softmax optimizer. These optimizers helped in improving the speed of convergence and the overall performance. The loss function which was employed was sparse categorical cross-entropy which is best suitable for datasets which require multi-class classification tasks, which in the case of our first dataset consisted of 3 classes and 114 target variables.

To avoid the problem of overfitting, a train-test strategy was used. The dataset was divided into two parts in the ratio of 3:7, where 30% of the the dataset was used for testing purposes and 70% was used for training purposes. The model was trained on the training subset and afterwards tested on the testing subset, this ensured that model was generalized, and it also helped in evaluating its performance.

3. Model Evaluation: The model was evaluated on its performances using a variety of the widely used evaluation metrics, including accuracy, recall, precision, and f-1 score. Accuracy value provided the ability of the model’s ability to make correct predictions, whereas the precision score represented the ability of the model to output the correct class for a given input, lastly recall represented the ability of the model to identify the instances of a given motor action correctly. F-1 score provided a balanced measure of the above, as an all-encompassing score.To ensure that our model is reliable and not overly generalized to the data it was trained on, a variety of cross-validation techniques were used. This part of the study involved performing multiple iterations of the train-test split and training and testing of the model on different subsets, until no improvement was made. At last, the results were averaged across the various iterations to obtain an evaluation which was robust and accurate, and that would give correct results for our problem.
4. Result: In this section, the results of the study are presented using various graphical tools. The study incorporated various methods to test the accuracy of the trained models such as f1-score, precision, and support for each of the classes of motor movement for the first dataset and for each state of eyes for the second dataset. In case of the first dataset, the trained Convolution Neural Network model achieved an accuracy of 62.65%. Various techniques such as the precision, recall and f1-score were used to determine the accuracy of the model that was generated, It demonstrates the ability of the model to classify the motor actions from the EEG readings.

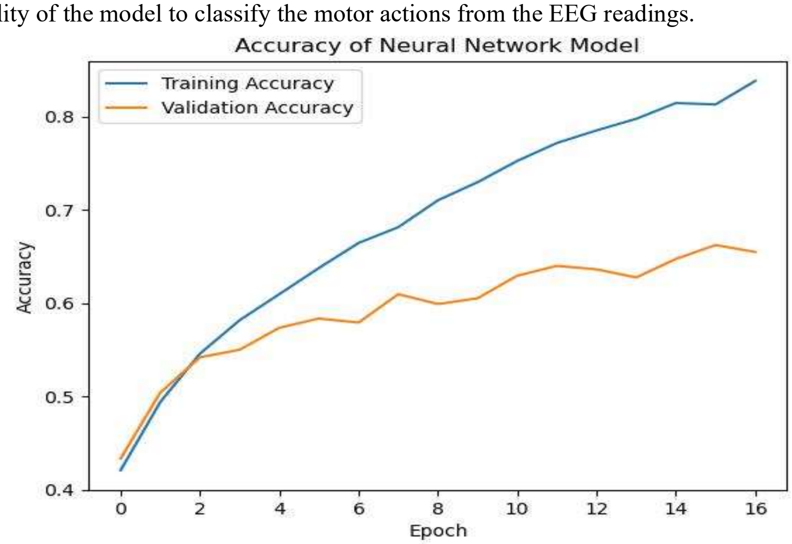

Figure 6. Validation and Accuracy for the first model

The precision values ranged from 0.58 to 0.65, indicating the model's ability to correctly classify specific motor actions. The recall values varied from 0.57 to 0.67, illustrating the model's capability to identify instances of each motor action. The F1 score, which combines precision and recall into a single metric, averaged 0.63, providing an overall measure of the model's performance.

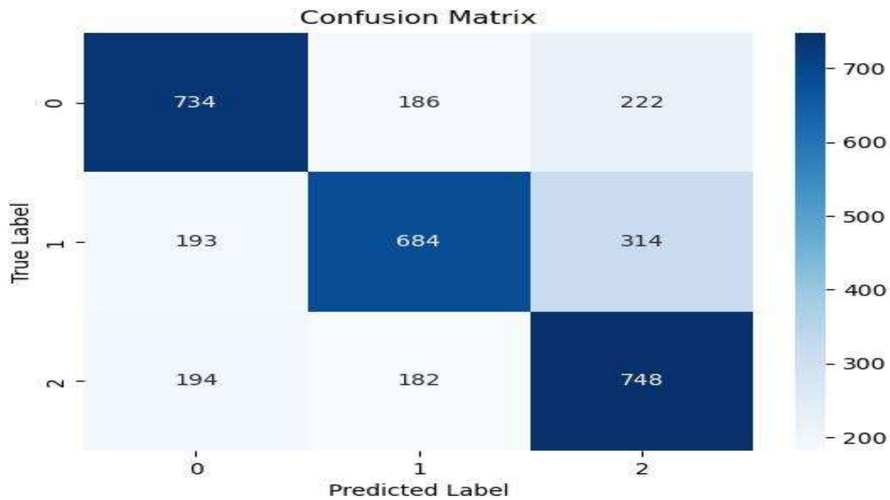

Fig. 7. Confusion matrix for the first model.

It should be noted that 62.65% is a reasonable resulting accuracy, for a model trained on 114 target variables, to predict the motor functions. Considering the inherent and deep complexity and intricacy of the data associated with EEG readings, the model achieved a fair accuracy rate, but there is definitely a scope of improvement in this, by fine tuning the methods or by reducing the target variables to focus on certain areas of the brain. Other studies have shown that by reducing the target variables to only required ones, the accuracy is acutely increased.

Now, in case of the second dataset, the model achieved a significantly higher accuracy of 87.22%. The higher rate of accuracy can be attributed to lesser variability in the independent variables values and lesser target variables present in the dataset. While the first dataset had 3 types class variables and 114 target variables, our second data set only had 2 types of class variables and 14 target variables. However, it is nonetheless a great accuracy rate, which proves the viability of the model and the technique used to create it.

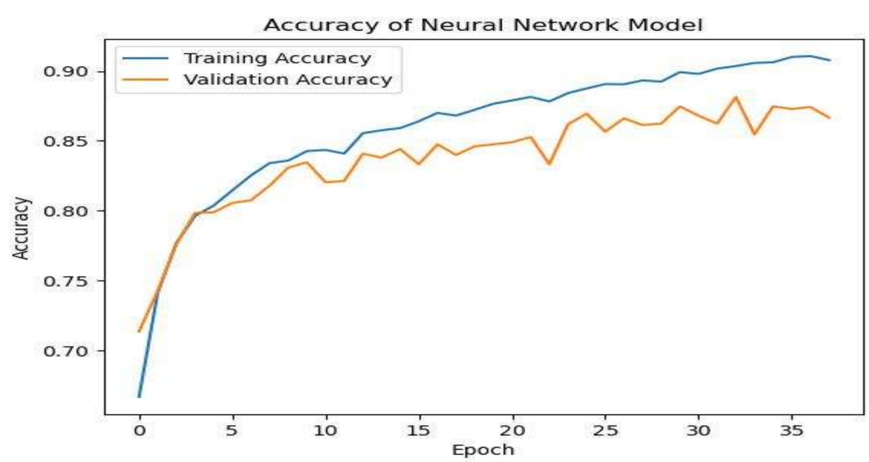

Fig. 8. Validation and Accuracy for the second model

Following the trend, the second model also treaded higher in other assessment metrics with precision ranging from 0.86 to 0.88, recall from 0.85 to 0.89 and f1-score at 0,87. This shows a high ability of the model to correctly predict the state of the eye for an image of EEG readings.

*

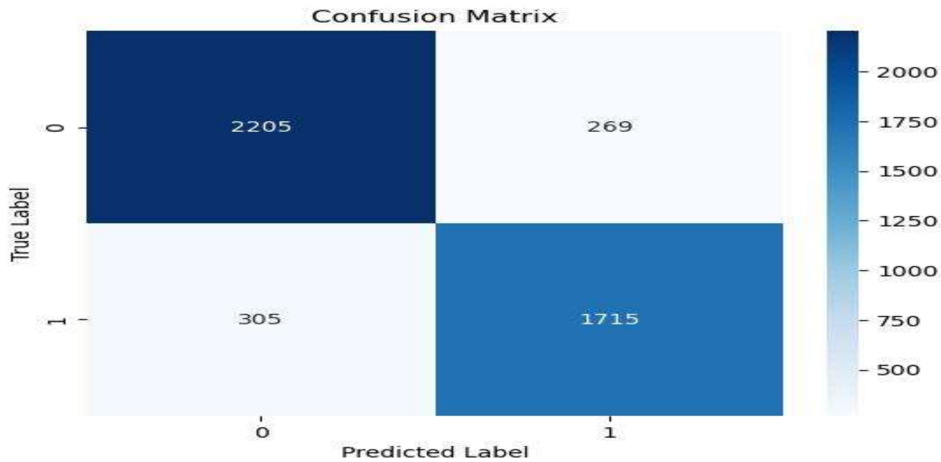

Fig. 9. Confusion matrix for the second model.

The accuracy of 87% is fairly high, but it can be honed even further with necessary changes and tweakings in the methodology and process of model generation. Like before, the target variables can be reduced and made more focused to find particular solutions.

Overall, the results indicate that the developed CNN model effectively leverages EEG data to predict motor actions. The consistently good accuracy rates and performances across various benchmarks goes on to show the ability of the model to make accurate predictions, and also displays the deep potential to be developed further for real-life applications in the field of medicine and rehabilitation.

It should be noted that, although the results are promising and the models show great potential, there are limitations to this domain of research. The performance of the model can further be attributed to other factors such as individual variations in the neural data, electrode placements, device accuracy and data quality. There is definitely scope of further research and improvement to enhance the model to make more accurate and reliable predictions, with regards to various types of motor movements.

Finally, it can be said that the study aptly demonstrates the effectiveness of the CNN model in making correct predictions of the motor movements based on the input of EEG readings. The good performance of the models across various evaluation metrics only goes on to show the immense capabilities of using CNN model for motor movement prediction from neural signals. This can be employed to learn more about the inner workings and complex mechanisms of our brain. It will open more avenues, particularly in the inter-disciplinary domains and greatly benefit mankind.

8. Conclusion and Future recommendation

The existing neuroprosthesis and its technology are explained and along with AI-enabled neuroprosthesis for society 5.0 is proposed. This study focused on giving insight into making neuroprostheses work smartly and accurately. The integration of neurological data collected from the brain is used to train prostheses to conduct activities without encountering any impediments in the signal by adopting AI. A method is proposed for society 5.0 and this method helps to overcome most of the limitations of the present existing methods used in operating neuroprosthesis. The research paper aimed to explore the potential of using EEG data for meaningful applications by applying machine learning algorithms to find useful correlations and models between the readings.The findings of the study assisted in understanding the usefulness of CNN to create reliable and accurate models for predicting and understanding motor movements in association with EEG datasets. The models were found to be highly capable of finding patterns and relations even in such complicated and vast data, hence proving its capability of predictions.

The results of this paper can be used in a variety of fields like driver fatigue detection, sleep research, and human-computer interaction, where monitoring eye states can offer valuable insights and improve safety and performance. The hand movement based models can have possible applications in the field of robotics to stimulate human-like movements. The investigations and outcomes of the study were promising and have potential to be used in a litany of areas of human endeavor. This research project has demonstrated the potential of utilizing EEG data to predict human computer interface (HCI) like motor movements and eye states. The developed models have shown promising results, indicating the feasibility of using neural signals for motor action classification and eye state detection. These findings contribute to the growing body of knowledge in the field of EEG-based analysis and pave the way for advancements in neurorehabilitation, brain-computer interfaces, and related domains.

The future scope of this work is to explore the benefits of smart neuroprosthesis and its ease of use made many researchers develop the smarter prosthesis. So, this work can be carried out further by

- Designing the hardware to collect the neuro/brain signal effectively this way the cost of the neuroprosthesis will reduce considerably making this device available for all levels of people.
- The accuracy of the required signal will be enhanced with the help of hybrid AI.
- The mind control training of the patients can be avoided by collecting more training and testing data set to train the neuroprosthesis.

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