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A LITERATURE REVIEW OF BCIs FOR ASSISTING SCIs WITH DISABILITIES FROM A DEVELOPMENTAL POINT OF VIEW AND POTENTIAL FUTURE TRENDS

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ABSTRACT

Brain-computer interfaces (BCIs) are a growing field of science that allows direct connection between the brain and outside machinery, bypassing conventional motor pathways like muscles and nerves. Motor function may be lost completely or partially as a result of spinal cord injuries (SCIs), leading to difficulties with walking, balance, and coordination. This literature review delves into the extensive research conducted over the past decades on BCIs and their application in assisting individuals with SCIs. The study encompasses a comprehensive analysis of the advancements made in BCI research; it explores the evolution of BCI technology, highlighting key milestones and breakthroughs that have shaped its development. Additionally, the paper sheds light on the various methodologies employed in BCI systems, such as invasive, non-invasive, hybrid, motor control, and sensory feedback approaches, specifically focusing on their applicability to SCIs. This review emphasises the challenges encountered during the implementation of BCIs for SCI individuals. These challenges encompass technical limitations, signal processing complexities, and the need for robust and reliable interfaces. Moreover, the study explores the adoption of BCIs; it provides insights into potential solutions to address these limitations and presents a forward-looking perspective by discussing the future trends in BCI research. It identifies emerging technologies, neural networks, and neuroprosthetics, which hold great promise in enhancing the performance and usability of BCIs. Moreover, the paper examines the potential of neurorehabilitation and neuroplasticity to augment the effectiveness of BCIs for spinal cord-injured individuals. In conclusion, this paper provides a synthesis of the past 53 years of BCI research, specifically focusing on its application for SCIs. By highlighting the challenges faced and future trends in BCI technology, this paper contributes to the exploration of innovative solutions that can unlock new possibilities and offer renewed hope for SCIs.

KEYWORDS: Brain-Computer Interfaces (BCIs), Spinal cord injuries (SCIs), artificial actuators, prostheses, neurophysiology, Brain Machine Interface (BMI), Electroencephalography (EEG), and Amyotrophic Lateral Sclerosis (ALS).

مراجعة الأدبيات الخاصة بواجهات الدماغ الحاسوبية لمساعدة مصابى النخاع الشوكى ذوي الإعاقة من وجهة نظر تطورية والاتجاهات المستقبلية

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الملخص

تعد واجهات الدماغ والحاسوب (BCIs) مجالًا علميًا متناميًا يسمح بالاتصال المباشر بين الدماغ والأجهزة الخارجية، متجاوزة المسارات الحركية التقليدية مثل العضلات والأعصاب. يمكن أن تؤدي إصابات النخاع الشوكي (SCIs) إلى فقدان جزئي أو كامل للوظيفة الحركية، مما يؤدي إلى صعوبات في المشي والتوازن والتنسيق. تتعمق مراجعة الأدبيات هذه في البحث المكثف الذي تم إجراؤه على مدار العقود الماضية حول BCIs وتطبيقها في مساعدة الأفراد الذين يعانون من اصابات النخاع الشوكي. تتضمن الدراسة تحليلاً شاملاً للتقدم المحرز في أبحاثBCI ؛ فهو يستكشف تطور تكنولوجياBCI ، ويسلط الضوء على المعالم الرئيسية والإنجازات التي شكلت تطورها. بالإضافة إلى ذلك، تلقي الورقة الضوء على المنهجيات المختلفة المستخدمة في أنظمةBCI ، مثل الأساليب الجراحية وغير الجراحية والهجينة والتحكم الحركي والتغذية الراجعة الحسية، مع التركيز بشكل خاص على إمكانية تطبيقها على اصابات النخاع الشوكي. تؤكد هذه المراجعة على التحديات التي تمت مواجهتها أثناء تنفيذ BCIs لمصابى النخاع الشوكي. تشمل هذه التحديات القيود التقنية وتعقيدات معالجة الإشارات والحاجة إلى واجهات قوية وموثوقة. علاوة على ذلك، تستكشف الدراسة اعتماد واجهات التواصل بين الأشخاص(BCIs) ؛ فهو يوفر نظرة ثاقبة للحلول المحتملة لمعالجة هذه القيود ويقدم منظورًا تطلعيًا من خلال مناقشة الاتجاهات المستقبلية في أبحاث .BCI وهو يحدد التقنيات الناشئة، مثل التعلم الآلي، والشبكات العصبية، والأطراف الاصطناعية العصبية، والتي تبشر بالخير الكبير في تعزيز أداء وسهولة استخدام واجهات التواصل بين الدماغ .(BCIs) علاوة على ذلك، تبحث الورقة في إمكانية إعادة التأهيل العصبي والمرونة العصبية في زيادة فعالية BCIs للأفراد المصابين في النخاع الشوكي. في الختام، تقدم هذه الورقة ملخصًا للـ 53 عامًا الماضية من أبحاثBCI ، مع التركيز بشكل خاص على تطبيقها في اصابات النخاع الشوكي. من خلال تسليط الضوء على التحديات التي تواجهها والاتجاهات المستقبلية في تكنولوجياBCI ، تساهم هذه الورقة في استكشاف الحلول المبتكرة التي يمكن أن تفتح إمكانيات جديدة وتوفر أملًا متجددًا لـ.SCI

1. Introduction

The main focus of this review is to provide insight into how BCIs have evolved in assisting SCIs, examine the conditions of the field, and address potential future trends in BCI development. From an evolutionary standpoint, BCIs have undergone significant advancements since their inception. Initially, early BCI systems focused on basic motor control, aiming to restore movement to paralysed limbs. These systems employed invasive techniques, such as intracortical implants, to decode neural activity and convert it to commands for prosthetic devices. While these invasive approaches demonstrated promising results, they presented challenges related to surgical procedures, long-term stability, and scalability.

The increasing number of surgical procedures and an ageing human population lead to an annual increase in the number of biomedical devices implanted. There are risks when the body contains foreign substances that might result in issues that are difficult to identify until irreversible harm has been done, despite the tremendous advantages of implants. Enhancements of implanted sensors might make it possible to identify even minute alterations in the surrounding tissues or implants immediately, enabling the provision of early cues for action in order to solve this obstacle [1].

The integration of implants with embedded sensors will allow for real-time monitoring and enhance implant performance. As implanted electrodes can deteriorate over time and need frequent maintenance or replacement, it is also critical to address the issues linked to their resilience and longevity. This includes enhancing the ratio of signal to noise in recording neural signals and improving the decoding algorithms for better interpretation of intentions and commands. Additionally, it is vital to overcome these obstacles related to the durability and longevity of implanted electrodes, as they can degrade over time and require regular maintenance or replacement [2].

By using electronic stimulation of the paralysed or artificial limbs, neuroprosthetic devices which are still in development today help survivors restore their capacity to walk independently. Since nervous system illnesses also impact the economy and wider social contexts, neuroprosthetics might ultimately be advantageous to society [3].

SCI had a prevalence of 1 injury per 1000 persons worldwide in 2014 and an incidence of four to nine new injuries per one hundred thousand people each year [4]. The most frequent causes of traumatic SCI include falls, traffic incidents, and violent acts. Researchers found that there were approximately 1 million new cases of SCI per year and over 27 million prevalent cases of SCI worldwide as of 2016 [5]. Over the past 20 years, both the fraction of non-traumatic injuries and the average age of SCI onset have considerably grown.

The brain sends motor signals to contract muscles at certain joints to plan and coordinate movement. These messages originate in the brain and pass along descending spinal cord pathways to effective motor neurons, which then send the orders to the destination muscles. Damaging of these pathways in SCI may result in paralysis below the lesion site. Nonetheless, peripheral nerves, the muscles they affect, and the brain's planning and coordination centres continue to operate [6]. The spinal cord (SC) is split longitudinally into segments and is situated in the canal around the SC, which the vertebral bones of the spine encircle. Spinal nerve roots emerge dorsally and ventrally from the spinal canal in between segments. The striated muscles in the upper or lower limbs are innervated by more than one ventral nerve root, whereas multiple ventral nerve roots innervate the striated muscles in the upper and lower limbs [7].

Based on the level at which the nerve roots exit the spinal cord, the SC is divided into eight segments: eight cervical from C1 to C8, twelve thoracic from Th1 to Th12, five lumbar from L1 to L5, five sacral from S1 to S5, and one coccygeal segment. More body segments are affected in proportion to the degree of rostral (or greater) SCI [8].

Tetraplegia, a disorder typically associated with SCI, is the deterioration that impacts the arms, trunk, and legs' motor and sensation capacities. It is a condition characterised by paralysis or significant impairment in the function of all four limbs (both arms and both legs). A patient who has a degree of lesion of C5 or higher could require artificial ventilation for breathing support. This is a medical device that helps people breathe when they are unable to do so on their own or require assistance to maintain adequate breathing. As a result of a thoracic or lumbar SCI, sensory or motor deficits, or both of them, in the legs and frequently the trunk culminate in paraplegia. Sexual, digestive, and bladder functions are all impacted by SCI.

After SCI, neuroprosthetics can help recover motor function by directly stimulating the muscular-nervous system with electricity. Unluckily, standard neuroprosthetic approaches are limited by a number of issues, including mechanical coupling, inadequate description of the dynamics of nonlinear input as well as output sets, large device size, high power consumption, and the quick onset of muscle fatigue. By combining sensor-based input from the surroundings and the state of the system's functioning with brain-based command signals, a wireless multi-channel closed-loop neuroprosthesis may be able to improve device performance and, in turn, the quality of life for people with SCIs [9].

2. Problem Formulation

The spinal cord passes from the brainstem to the lumbar of the backbone. It is a long, thin,and tubular bundle of nerve tissue. It is a crucial part of the CNS shielded by the bony vertebrae [10], as illustrated in **Figure 1**. Information about sensation and movement is sent via SC to the body. Sensory information, such as touch, temperature, and pain, is transmitted from the peripheral nervous system to the SC, where it is relayed to the brain for processing [11].

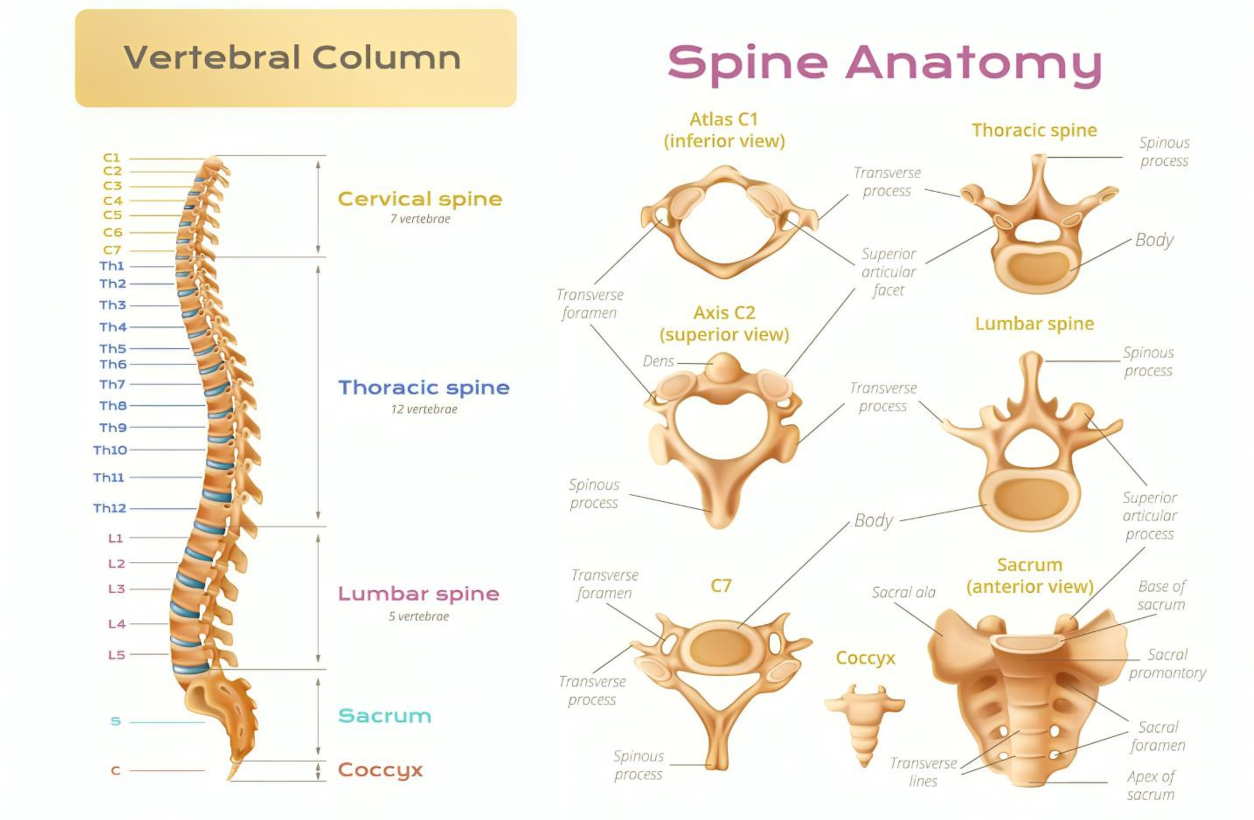

Figure 1: Spinal Cord, and Spine Anatomy

Motor information, such as muscle contractions and movement, is transmitted from the brain to the SC, where it is relayed to the muscles and other effector organs [12], as shown in **Figure 2** in the nervous system. There are two types of matter in the spinal cord: grey matter, which is made up of neuronal cell bodies, and white matter, which is made up of the tract-organised axons of neurons. The information that travels along the pathways between the various spinal cord areas and the brain is sent [13].

Regeneration of the white and grey matter in the SC is complex and often faces significant challenges. Unlike certain other tissues in the body, the CNS has limited regenerative capacity [14]. The three primary components of a neuron are the axon, dendrites, and cell body (soma). The nucleus and other vital organelles are located in the cell body, while the dendrites are the branch-like extensions that receive incoming signals from neighbouring neurons. The axon, on the other hand, transports the electrical impulses outside of the cell, facilitating communication with other neurons or target cells. The axon may be surrounded by a myelin sheath, as shown in **Figure 4**, a protective layer that enhances signal conduction speed.

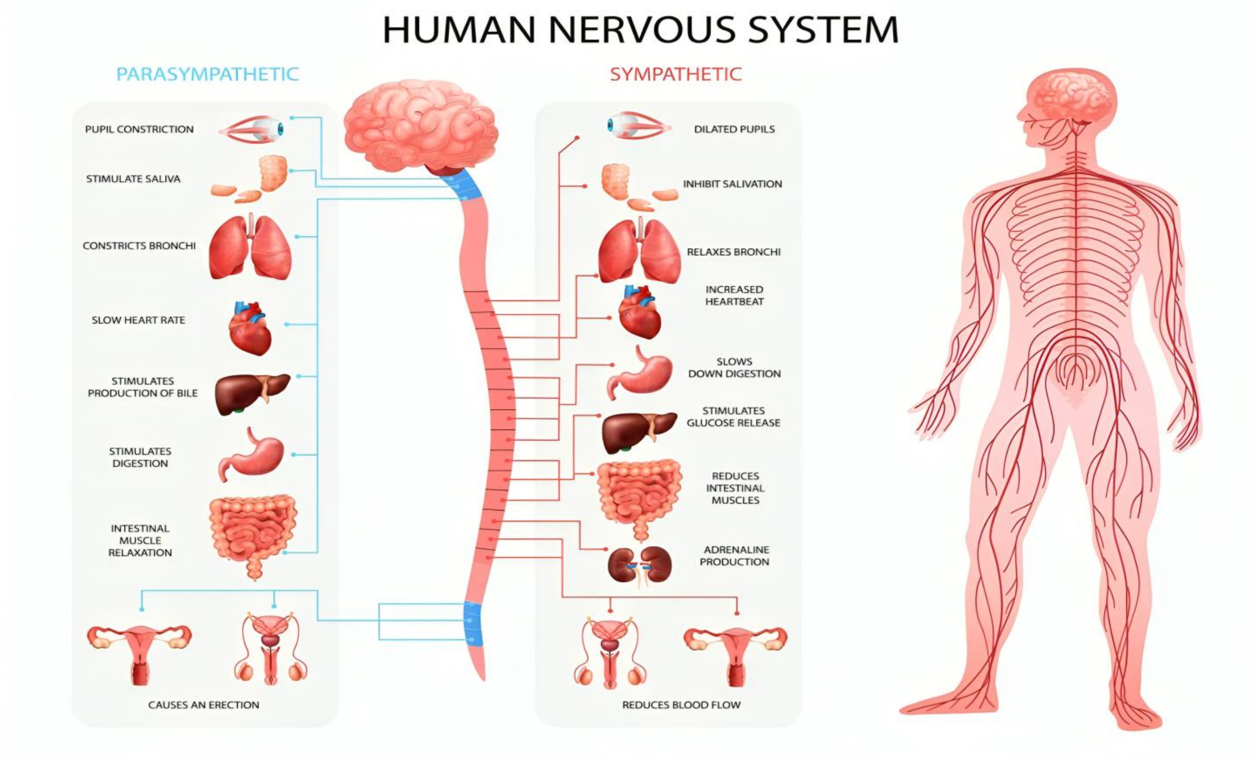

Figure 2: Human Nervous System.

Depending on the position and depth of the injury, SCIs can cause a variety of motor and sensory deficits. Trauma like a car crash or a fall, as well as illnesses like multiple sclerosis or amyotrophic lateral sclerosis (ALS), a progressive neurodegenerative disease that affects the nerve cells in charge of regulating voluntary muscle movement, can result in SCIs [15], as illustrated in **Figure 3**. There are two main categories of SCI: traumatic injuries and non-traumatic injuries. Traumatic injuries are those that result from incidents in which an individual was injured by a factor external to their bodies, such as a car accident, a fall, or an activity-related injury, while non-traumatic injuries are those caused by pathological abnormal lesions of the spinal cord (such as a tumour, infection, or inflammatory condition) [16].

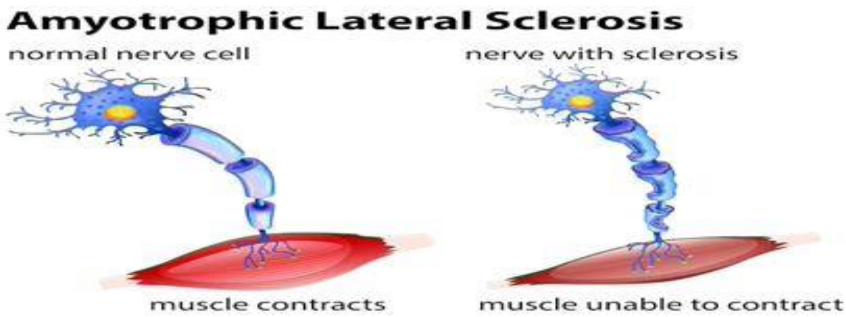

Figure 3: Amyotrophic Lateral Sclerosis.

Understanding spinal cord injuries and mobility challenges Individuals often face significant challenges when it results in difficulties with walking, balance, and coordination [17].

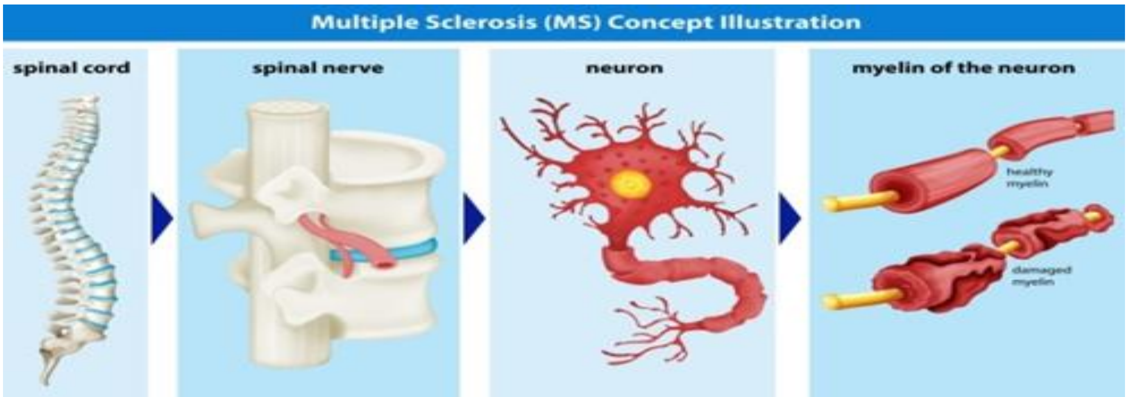

Figure 4: Myelin of the neuron.

Individuals with SCIs can experience a range of mobility challenges, depending on the degree and severity of their injury. Studies have shown that BCIs have the potential to assist individuals with SCIs in regaining mobility and improving their quality of life [18]. BCIs allow for direct brain-to-machine communication, obviating the need for traditional motor channels like muscles and nerves. BCIs provide new opportunities by converting patterns of brain activity into orders that run external devices [19]. Real-time, two-way connections are established between artificial actuators and human brains using BCIs. by combining techniques, ideas, and concepts from engineering, computer science, and neurophysiology [20].

Its work may alter either temporarily or continuously as a result of SCI. Any segment of the SC may sustain a full or partial injury, which means that some nerve signals may still get through the damaged area of the cord and reach the sacral S4-5 spinal cord segments [21]. Lower sacral segment sensory and motor functions are completely lost in full SCIs. Individuals suffering from recurrent quadriplegia due to high cervical SCI may find that functional electrical stimulation (FES), sometimes referred to as coordinated electrical stimulation of peripheral nerve systems and muscles, helps them regain movement in their limbs [22].

Patients who have suffered SCI are frequently told that no medical treatments or cell transplants have been authorised to repair the harm caused and regain voluntary movement [23]. In particular, the arm and hand are of utmost importance. There was little investigation of fresh neurophysiological techniques for gathering extensive brain activity. The traditional aims are the following: In order to regain feelings and movements for people who suffer from severe impairments, it is first necessary to uncover and use the working principles and neuroplasticity of distributed and dynamic brain networks [24]. BCIs have been shown to activate neuroprosthetic devices that can restore neurological functions in individuals with post-traumatic SCI. By recording and interpreting electrical signals from the brain, BCIs can enable individuals to generate mental images of movements and utilise these signals to control external devices, allowing individuals with SCIs to regain control over their mobility or improve some degree of independence using this assistive technology [25].

3. Brain Activities Frequencies':

Capability and Subjective actions or changes in blood flow have the ability to cause a variety of brain functions. Monitoring electrophysiological signals might be used to immediately record such actions:

[1] One of the most used techniques is electroencephalography (EEG).

[2] Electrocorticography (ECOG).
[3] Recordings from a single neuron.
[4] Magnetic resonance imaging (MRI).
[5] Positron emission tomography.
[6] Functional magnetic resonance imaging (FMRI).
[7] Optical imaging (also known as fNIR or functional near-infrared) [26].

The brain exhibits different frequencies of electrical activity, which can be measured using EEG. The brain activity frequencies are typically categorised into several bands, as illustrated in **Figure 5**. Here are the commonly recognised frequency ranges:

Delta waves (0 to 4 Hz): It’s the lowest brain wave;, it’s related to deep sleep, unconsciousness, and some abnormal brain states.

Theta waves (4 to 7 Hz): Theta waves are present during light sleep, deep relaxation, meditation, and dreaming. They are also associated with creative thinking and memory processes.

Alpha waves (8 to 12 Hz): Alpha waves are prominent when someone is calmly awake and has their eyes closed. They are related to mental states of serenity and relaxation.

Beta waves (12 to 30 Hz): Beta waves are typically observed when a person is awake and engaged in mental activity, such as focused thinking, problem-solving, and active concentration.

Gamma waves (30 to 100 Hz and more): The fastest brain waves, or gamma waves, are connected to highly advanced mental processing, perception, and information binding. They have been linked to attention, memory, and consciousness [27].

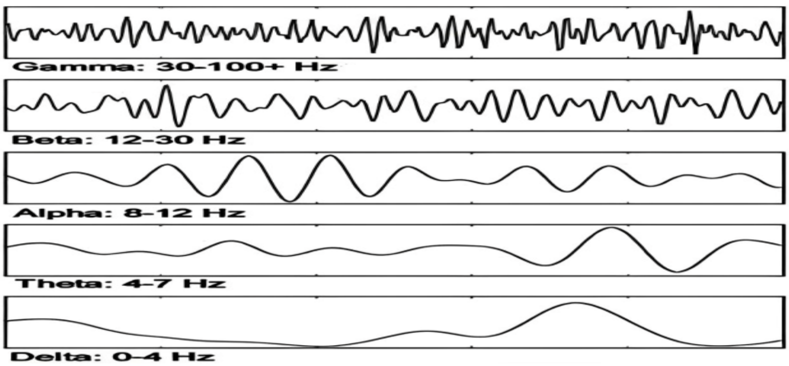

Figure 5: EEG bands

The technology behind BCIs is still in its infancy and has to be improved upon to ensure dependable and precise functioning. To better read intentions and orders, this also entails decreasing the impact of the artifact ratio by filtering the noise while capturing brain impulses and upgrading the decoding algorithms [28].

4. General Classification of BCIs

BCIs come into a variety of categories based on various factors. Here's a general classification such as surgical or invasive, non-invasive, hybrid, motor control, and sensory feedback in the past decades and upgraded BCIs as follows:

The concept of BCIs originated in the 1970s, primarily through the work of Dr. Jacques Vidal. He conducted experiments that demonstrated the potential for brain-computer contact to occur directly. These early prototypes focused on basic tasks like controlling cursor movements on a screen through brainwave patterns. His research explored the potential of using brain signals, such as event-related potentials (ERPs), and the detection of specific brainwave patterns, to control external devices [29, 38].

Sensorimotor Rhythm (SMR) BCIs: In the 1980s, researchers discovered that individuals could learn to control their brainwave patterns, specifically the sensorimotor rhythm, which consists of specific frequency bands recorded over the sensorimotor cortex. This discovery led to the development of SMR-based BCIs [9]. In this era, researchers explored the use of steady-state visual-evoked potentials (SSVEPs) for BCI applications. SSVEPs are the brain responses evoked by visual stimuli flickering at specific frequencies. By selectively attending to different flickering stimuli, users could generate distinct SSVEP patterns that could be detected and used as control signals for BCIs [30].

In In the 1990s, researchers began exploring invasive BCIs, which involved implanting electrodes directly into the brain. This allowed for more precise neural recordings and control. The first successful application of invasive BCIs for spinal cord injury assistance occurred in the early 2000s, when a paralysed individual controlled a computer cursor using neural signals [31].

In 2004, BCI technology allowed paralysed individuals to control a computer cursor using neural signals. One notable development during this period was using invasive BCIs, specifically microelectrode arrays implanted in the brain, to record neural activity for cursor control. One significant milestone in direct neural control of a computer cursor was shown by Matthew Nagle, a paralysed individual. Nagle participated in a clinical trial conducted by Brown University and Cyberkinetics Neurotechnology Systems researchers. Nagle was implanted with a sensor array consisting of one hundred microelectrodes in his brain's motor cortex. Using his neural signals, Nagle was able to control a computer cursor and perform various tasks. By imagining moving his hand, he had control of the screen's cursor. and could use it to manipulate virtual objects. This breakthrough exemplified the potential of invasive BCIs in providing individuals with paralysis with the ability to interact with their environment using their thoughts [32].

As the field progressed, non-invasive BCIs gained traction. These systems utilise electroencephalography (EEG) to detect electrical activity in the brain without the need for surgical implants. Non-invasive BCIs provided increased accessibility and user-friendliness despite being less accurate. Researchers developed techniques to decode brain signals associated with specific commands, like manoeuvring a wheelchair or a prosthetic limb [33].

In the following years, significant progress was made in enhancing motor control and providing sensory feedback through BCIs [34]. Research teams successfully developed systems that enabled paralysed individuals to control robotic arms, allowing for more dexterous movements and interactions with the environment. Additionally, some experiments incorporated sensory feedback, permitting users to experience touch and proprioceptive sensations [35].

More recently, hybrid interfaces have emerged, combining invasive and non-invasive techniques. These interfaces utilise invasive implants for high-resolution neural recordings and non-invasive methods for long-term use. Such approaches have shown promise in fine motor control, allowing users to perform complex tasks with greater precision. Moreover, efforts have been made to restore functionality directly to the spinal cord by using BCIs to stimulate neural circuits and bypass damaged areas [47].

As of 2023, BCIs continue to advance rapidly. Researchers are refining the technology, improving decoding algorithms, and enhancing the reliability and longevity of implants. The focus is shifting towards developing more practical and user-friendly BCI systems that can be seamlessly integrated into daily life, providing individuals with SCIs greater independence and functionality [36].

We previously mentioned the change in BCIs in past eras regarding the basic technology of the BCIs. Now, we will mention in more detail some of the influential research from these eras. Theoretical concepts and a few prototype experiments about directly Brain-machine interfaces have existed since the 1960s., but brain-machine interface research didn't really take off until the end of the 1990s, when this strategy was closely associated with novel neurophysiological methods for gathering extensive brain activity samples [37]. Portable functional-electrical-stimulation (FES) sets are utilised to replace functions lost as a result of SCI. This section attempts to give a brief summary of the most widely used motor neuroprostheses, such as those that generate motions for the upper and lower extremities and respiration pace in patients with extremely high SCI.

Three different phases may be identified in the technological advances in BCI: the first involves the use of a BCI to provide impaired people with a direct line of communication. In the second level, more complex closed-loop BCIs are enhanced. In closed-loop BCIs, the interaction facilitates not only efficient device control but also the restoration of human functions [38]. Functional electrical stimulation (FES) devices that are portable are used to restore lost functionalities due to SC damage.

This section aims to provide a concise overview of the most popular motor neuroprostheses, including those that allow patients with extremely severe SCI to create movements for their upper and lower extremities and diaphragm pacing. The evolution of BCIs includes three stages: In the first stage, a BCI is used to deliver impaired information. In the third stage, more generic platforms for fusing AI and biological intelligence are suggested and built, made possible by the quickly advancing AI technology [39].

5. Development of BCIs Through Half-century

Here, we evaluate several BCI system paradigms in accordance with the evolution stages of BCI models. The history of BCI's evolution spans the last 53 years, from 1970 to 2023..

5.1. Thinking up and Development of First BCIs

Since Vidal thought up and designed the first BCI using visual-evoked potential (VEP), Jacques Vidal designed a system in the 1970s called the scalp-recorded VEP throughout the visual cortex for determining the direction of the human being's eye gaze, also known as the direction in which someone desires to move a computer pointer in relation to the visual fixation point [40].

In 1988, the researcher discussed developing and evaluating a system that allows individuals to communicate using the event-related brain potential's (ERP) P300 component. The term P300 ERP refers to a beneficial offset in the EEG signal that happens about 300 milliseconds following a stimulus. The individual concentrates attention on the characters they want to convey, while the system shows a matrix of letters in addition to commands. The selected character is identified by the matrix's rows and columns flashing, eliciting the P300 component of the brain potential. The study explores the optimal number of trials, inter-stimulus interval, and detection algorithms for accurate and efficient communication [41].

A number of prototype BCI systems have been produced one after another using various EEG signal types and the slow cortical potentials (SCPs)-based BCI; for instance, a study aimed to develop a BCI using EEG to move the cursor on a computer screen. The main objective of the study discussed in The purpose of the paper was to ascertain whether people could learn to reliably and quickly increase or decrease the mu rhythm, which is a particular pattern of brainwave activity in the 8–13 Hz frequency range that is observed over the sensorimotor cortex, and then utilise this rhythm to control a cursor on the screen of a computer. The goal was to demonstrate that the mu rhythm could serve as a code for directing a device. The mu rhythm may have potential applications for people with significant motor disabilities. The paper also mentions potential improvements in control and the possibility of achieving 2-dimensional control [42].

A direct brain interface that utilises steady-state-visual-evoked-response (SSVER) is used to direct a signal. Scalp electrodes and sophisticated signal processing techniques are used to measure the SSVER. People can learn to control the SSVER through biofeedback, and that control can be converted into instructions to control a physical device or computer programs. BCIs have the ability to enhance the lives of people with severe disabilities by controlling various systems, such as computers, prosthetic limbs, wheelchairs, or home systems, using P300 event-related-potential-based BCIs [43].

5.2. BCIs depend on the response to repetitive visual stimulation

It has been presented as a BCI system that permits users to enter their phones' numbers. SSVEP refers to the types of brain activities that occur in response to frequent visual stimulation. They are measured using electroencephalography (EEG) and are characterised by rhythmic oscillations in electrical activity in the brain occurring at similar frequencies as the visual stimulus. The system has a high transfer rate and is noninvasive, requiring little training for use. The study discussed the use of BCIs to enter phone numbers by looking at buttons that flicker on and off at various frequencies that are seen on a computer screen. The buttons stand in for the numbers 0 through 9, BACKSPACE, and ENTER on a virtual phone keypad. Gazing at the chosen button allows users to choose it, and each selection is followed by a beep from the computer's speakers. Users can determine whether their pick was right by looking at the outcome that is shown on the monitor.

By looking at the BACKSPACE button, users can remove a selection if it is erroneous. When the ENTER button is selected, the input number is sent out through a modem connected to the telephone network using frequency-coded SSVEPs. The results showed that eight out of thirteen subjects were successful, and the system's rate of data transfer was 27.15 bits/min on average. This study suggested that increasing the number of visual cues and utilising more advanced signal processing algorithms can further improve the transfer rate [44], and the SSVEP-based BCIs are some of the best-known early systems.

BCI has been described depending on motion-onset visually evoked potentials (mVEPs). Although extensively explored in fundamental research, mVEP has never been employed in BCI studies. In the BCI application, time-locked mVEP was evoked by the fleeting movement of objects included in on-screen virtual buttons. This model's spatiotemporal pattern of mVEP was examined using EEG data collected from fifteen individuals. The N2 and P2 elements, with their separate parietal or temporo-occipital topographies, are chosen as the important elements of the brain response when the subject selects the existing item by looking at it at that target. The button that produced the most noticeable N2/P2 components is what the computer uses to identify the attended target [45].

Brain signals have been explored to control a robotic humanoid that utilises motion-onset visual evoked potentials (mVEPs) and N200 potentials to code human brain functions and perform online operation tasks. The study evaluated factors that affect control success rates and completion time for tasks. It also discussed the importance of repetition numbers and proposed a N200 model for controlling the robot. Where mVEP is a type of event-related potential (ERP) that is induced by the onset of motion in visual stimuli.

When the brain is exposed to visual inputs, electrical potentials take place that involve motion. In the context of controlling a humanoid robot, mVEPs can be used to decode a person's mental activities and translate them into commands for the robot. The mVEPs are generated by presenting visual stimuli that represent different robot behaviours, and the person focuses their attention on the desired behaviour. The mVEPs are then recorded using electroencephalography (EEG) and analysed to extract features that correspond to the person's intention. These features are used to control the robot's behaviour, such as navigating in an environment or picking up an object [46].

5.3. From Classic to Hybrid BCIs

The hybrid BCI front of these paradigms, also known as classical BCIs or conventional BCIs, shows that there is a chance for direct brain-machine connection. Many other paradigms have arisen in the years that have followed in an effort to enhance the overall performance of traditional BCIs. To develop the user’s experience of VEP-based BCIs, the motion-onset VEP (mVEP)-based BCI was created to eliminate the pain feeling brought on by the flickering stimulation [47].

In order to enhance overall BCI implementation, this reference suggested a collaborative paradigm that incorporated data from several users in order to compare the precision of the categorization of single-user and collaborative BCIs using EEG data from twenty participants in the development of motions for physical activity in order to evaluate the viability of a collaborative BCI. Additionally, three alternative techniques were investigated in this work for combining and evaluating EEG data from various issues: (1) Event-related Potentials (ERP) Averag, (2) Feature Concatenation, and (3) Voting. As the number of individuals rose from 1 to 5, 10, 15, and 20, respectively, the precision with which movement directions may be classified (reaching left and reaching right) significantly improved between 66% and 80%, 88%, and 93%. By decoding the ERP activity, which mostly originates from the posterior-parietal cortex (PPC) and is associated with the processing of visuomotor transmission, the choice of around 100–250 ms before the participant's real movement response can be ascertained [48].

Hybrid BCIs were developed to increase communication capacity by combining several BCI paradigms or merging additional physiological signals into conventional BCIs, such as the electromyogram EMG. The idea of machine learning-based co-adaptive calibration was proposed by C. Vidaurre, and it significantly enhanced performance for a range of users. He took the same approach and looked at the extent to which co-adaptive learning permitted considerable BCI control for both wholly inexperienced users and those who were unable to gain control using a traditional sensorimotor rhythm SMR-based BCI [49].

It has been shown that collaborative BCI may be utilised to combine ERPs from various individuals to make decisions as a group. There were many challenges faced by BCI developers, so Singh, A., depended on There are two main causes of this: (a) user variability, which refers to large differences in performance within and among users; and (b) signal variability, which refers to high signal changes within or across BCI sessions. Modern signal processing and classification techniques can adjust to the variations to some extent. This allows robots to adjust to their users; nevertheless, these methods ignore the reasons behind these users' variability and their signals. Co-adaptive BCI systems are recently proposed ideas that determine the reason for variability and include suitable measures to address it. This makes it possible for the person and the device to adjust to one another [50].

5.4. ECOG and MEG neurofeedback BCIs

After that, Astrand, E., explored the feasibility of using attention-related signals to control BMIs and provided an overview of studies that have attempted to decode attention-related information using various recording methods. He focused on the challenges and limitations of attention-driven cognitive BMIs and discussed potential applications in cognitive rehabilitation and communication. Astrand, E. illustrated the different recording methods used in studies on attention-driven cognitive BMIs, including invasive methods such as SEEG electrodes inserted via the cranium and into the brain and ECoG electrodes applied to the dura, as illustrated in **Figure 5**. The electrodes were inserted intracortical into the brain. EEG electrodes applied to the scalp and MEG squids put all over the head are examples of non-invasive techniques. Among these methods, non-human primates using invasive attention-based methods have demonstrated the best decoding skills when compared to human subjects using both invasive and non-invasive recording methods. This is most likely because it is possible to conduct the recordings in the closest vicinity of the attention-related signal source. Furthermore, activations in certain regions of interest (ROIs) that have been recognised based on their relevance to mechanisms involved in spatial concentration drive the fMRI decoding of spatial attention, and it has also shown a high decoding performance [51].

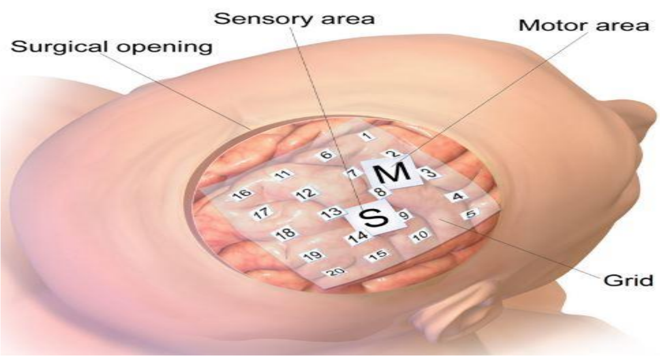

Figure 5: ECoG electrodes.

Bagherzadeh, Y., illustrated in his study that he trained subjects to regulate the brain's parietal alpha on the left versus the right synchronisation using MEG neurofeedback. The findings demonstrated that a spatial bias in attention and visual processing was brought about by modulating alpha synchrony. According to the study, alpha synchrony influences attention and visual processing causally. The study's primary conclusions were: During the neurofeedback trials, participants were able to reliably regulate parietal alpha lateralization. Neural and behavioural effects in line with the training direction showed that neurofeedback training produced a persistent regulation of spatial attention.

There is a bias in free-viewing behaviour when the behavioural effects after training are observed on trials without a strong, top-down spatial signal. In a single short training session, the study's naive participants were able to exert control over their own parietal alpha power, indicating that neurofeedback is a potentially useful and accessible technique for a variety of populations without requiring specialised training or advanced skills. Overall, the research showed that neurofeedback training may produce persistent regulation of spatial attention and allow online control of alpha power over the parietal cortex.

The participants in the study successfully modulated alpha power in the desired direction by using neurofeedback training. They received real-time feedback on their alpha power levels in the parietal cortex and were instructed to increase or decrease their alpha power based on the feedback they received. Through trial and error, participants learned to self-regulate their alpha power and achieve the desired modulation [52].

Sitaram, R., discussed the concept of neurofeedback, its applications in altering neural function, and its potential in various clinical settings. He explored the use of different neuroimaging modalities in neurofeedback, the neural plasticity and specificity that can occur as a result of training, and the potential targets for neurofeedback in neuropsychiatric disorders. The researcher also discussed the theories and psychological factors that influence neurofeedback learning, as well as the difficulties and possibilities of research in this field. Neurofeedback training works by providing online feedback on neural activation to the participant, allowing them to learn control over specific neural substrates and ultimately self-regulate their behaviours or pathologies.

The participant gets information regarding how the brain’s activities work in real-time, typically through visual or auditory cues, and is encouraged to modify their brain activity in a desired direction. This feedback is often based on specific biomarkers or the neuronal activity patterns that have been associated with the target behaviour or pathology. Through repeated practice and reinforcement, the participant learned to modulate their brain activities in a sense that is associated with the desired outcome. This process is thought to involve neuroplasticity, which refers to the brain's power to alter its structure, organisation, and operation in reaction to experiences, learning, stimuli, the environment, and neurological adaptations.

It is the brain's capacity to modify its neural connections, synaptic strength, and even the formation of new neurons as the brain learns to reorganise and adapt its neural connections and activity patterns in response to feedback [53]. This paradigm stresses mutual learning from both controllers. Such closed-loop devices are frequently employed in research into the neurological underpinnings of mental processes, which refers to anything related to the neurological system, comprising peripheral nerves, the brain, and the spinal cord, such as perception, attention, and memory.

5.5. Augmented BCIs

Liao, L.D., showed that dry electrode solutions are more suitable and straightforward than standard EEG sets with wet electrodes. Wet electrodes have been used to provide exceptional sensitivity, so the ability to create enhanced BCIs (ABCIs) was made possible by the advancement of biosensing. An ABCI uses biosensors to monitor brain activity in its natural surroundings, much like a BCI. After that, the signals are instantly analysed to track an individual's movements and use an ABCI as a portable brain-imaging device. This page provides an overview of the various biosensor techniques currently employed for ABCIs. He demonstrated how wet electrodes have independent and reliable reading circuitry. It is crucial to build an appropriate reading device for daily usage using dry or noncontact electrodes. Insights into the development of flexible electronics and display technologies, the expansion of power-efficient data processing algorithms, and the reduction of sensors, electronics, and power sources might potentially considerably augment the capabilities of ABCI in the future [54].

Recently, a platform that combines artificial intelligence (AI) and brain-computer intelligence was introduced. To research people's cognitive states and perhaps reach computational intelligence to improve human capabilities, new paradigms like cognitive BCIs and enhanced BCIs have been created [55]. Speech signals captured on audio, images, and psychophysiological data originating from the central and peripheral nervous systems may all be used to study emotions, which are referred to as bioregulatory remarks of facial expressions [56, 57].

By comprehending how emotions impact brain activity, other paradigms, including affective BCIs, The primary complaints levelled at this model by those who oppose it are that the variety and abundance of emotions, as well as contradictions, are not fully understood, in the physiological patterns of those emotions, and that the definition of fundamental emotions is too ambiguous and does not adequately capture the complex emotions. However, when it comes to fundamental emotion models, dimensional models are more concerned with the structure of emotional responses than they are with the underlying mechanisms that connect an event to a particular emotion organism [58].

Complex systems of evaluation involving a variety of consecutive emotional reactions are determined by event checks on several analytical levels, including relevance, consequences for current aims, coping capabilities, and normative importance. Numerous cognitive and motivational processes, such as self-concept, inspiration, retention of information, focus, and reasoning, are used to guide these tests. The results of this review procedure are defined as constructs [59], emotional BCIs [60], and mood BCIs [61, 62], which identify and manage emotion. Here, we have witnessed the development of BCIs from an interface to an interaction with intelligence. In the subject matter that follows, we go into further detail on the development of two key BCI applications.

In the interface stage, issues with brain signal generation and translation are the main focus of BCIs for communication and control. Primary visual, auditory, and sensorimotor BCI paradigms encode and decode brain signals so users may control output devices directly. Co-adaptation has been employed at the interaction stage to enhance communication rates in addition to facilitating system calibration. The accuracy and resilience of decoding are considerably increased by the adaptive classifiers. Additionally, the modulation and demodulation techniques used in telecommunications considerably improve the link between the brain and computer in visual and auditory BCIs [63, 64].

5.6. Neural Coding and Decoding in Sensorimotor BCIs

Artificial intelligence (AI) methods have been included to accomplish neural coding and decoding in BCIs at the intelligence stage. Speech BCIs, which interpret and translate speech-related brain processes into genuine language, have therefore achieved unheard-of advancements [65, 66]. BCI uses ECoG signals and an encoder-decoder architecture based on neural networks to achieve high decoding accuracy at typical speech speeds [67, 68]. Neuro-rehabilitation has had success with the application of sensorimotor BCIs, particularly for the treatment of stroke. The main technological advancement at the interface level is the production of strong brain signals for efficient operation of the rehabilitation equipment. The method of active training that works the brain directly has received increased attention throughout the interaction stage. According to co-adaptive learning of the brain and algorithms, the performance of sensorimotor BCIs enhances the BCI system, bringing about a wider control dimension, more accuracy, and quicker speed [69].

BCI-based rehabilitation may be made even more effective by combining BCI-enabled intelligent rehabilitation systems at the intelligence level. For example, the use of intelligent exoskeletons in conjunction with BCIs has great potential for assisting patients in regaining their motor skills [70]. Strict neurointervention was used to implant a novel vascular Stentrode BCI near the primary motor cortex in the upper sagittal sinus.Using wirelessly communicated electrocorticography data associated with attempted motions, the participants underwent ML-assisted training to manage a range of mouse-click actions, including zoom and left-click. Participants were able to perform instrumental activities of daily living using Windows 10 when paired with an eye-tracker for a computer's pointer movement [71].

Applications of BCI include monitoring and regulating normal and abnormal cognitive activity, detecting and preventing brain diseases, controlling and analysing psychophysiological states, and directing the movement of robots and exoskeletons [72].

5.7. ML/DL techniques in EEG-based BCI

As As artificial intelligence technology advances, researchers are able to classify EEG-based BCI through the use of ML and DL techniques. With every session, BCI is able to learn more about the subject's brain. The efficacy of the system is improved by modifying the guidelines that were set forth for concept labelling [73].

The authors provide a concise overview of the usage of several ML/DL techniques in EEG-based BCI. He uses the steady-state evoked potential paradigm, p300, and motor imagery to categorise the EEG. Recently developed EEG-based BCI systems have challenges with regard to best practices for signal processing, BCI functionality, performance assessment, and commercialization. These issues are also covered. They believed that the information formed would help in the deployment of appropriate ML algorithms and offer a base for BCI scientists to enhance future BCIs [74].

In the interface stage of neuro-rehabilitation, sensorimotor BCIs have proven to be successful applications. The essential technology here is the generation of a strong brain's signals to efficiently control the rehabilitation equipment. An active training approach that works on brains directly has received increased attention in the interaction stage. The sensorimotor BCI system performs better when the brain and algorithms learn together, which increases management speed, precision, and dimension [75].

Furthermore, in order to facilitate healing, neuromodulation techniques have been used to alter cortical excitability and plasticity. Intelligent rehabilitation systems can greatly boost the efficacy of BCI-based rehabilitation when paired with BCIs. For instance, the combination of intelligent exoskeletons with BCIs has the potential to greatly improve patients' ability to regain their motor abilities [76].

An innovative endo-vascular Stentrode BCI was inserted into the higher sagittal sinus, which is next to the primary motor cortex, using a minimally-invasive neurosurgical technique. The participants received ML-assisted training to manage several pointer-click operations, such as zoom, using wirelessly transmitted electrocorticography signals associated with attempted motions. Using an eye tracker to guide the mouse, participants were able to operate the Windows 10 operating system and perform IADL tasks [77].

Alexander E. highlighted the most often used methods for categorising and analysing electroencephalogram (EEG) and magnetoencephalogram (MEG) data. Particular attention is placed on contemporary technologies centred on reservoir computing and machine learning. We go over the key findings from the development and use of BCIs derived from both non-invasive and invasive EEG recordings. Initially, he thought of using neural interfaces to manipulate the motion of exoskeletons and robots. Second, he discussed the use of BCIs in the diagnosis and management of abnormal brain activity, including epilepsy. He also talked about how invasive BCIs have been developed to forecast and mitigate the lack of epileptic episodes [78].

Three Three EEG paradigms are employed for the classification in ML/DL approaches to EEG-based BCI: motor imagery, p300, and steady-state evoked potential. Furthermore, optimal signal processing techniques, BCI functionality, and performance evaluation are all used to overcome the difficulties that modern EEG-based BCI systems encounter [79]. BCI may recognise certain EEG patterns and translate them into orders for external devices, providing an additional or different channel of communication for those with significant difficulties with movement [80].

Incorrect use of the loss function and less sensible hyperparameter configurations. A novel deep-learning model called NeuroKinect is introduced to overcome these drawbacks and provide precise hand kinematics reconstruction using electroencephalography (EEG) data. To increase computational efficiency, NeuroKinect is trained using grasp and lift task data with the fewest pre-processing pipelines. One major enhancement that NeuroKinect brings to the table is the use of a new loss function called L Stat to correct for the mismatch in hand kinematics prediction involving correlations and mean square error. The study highlights how choosing the parameters to improve accuracy is guided by scientific intuition. Event-related potential and brain source localization data are used to examine the spatial and temporal dynamics of the motor movement task. There are significant connections between the model's predicted and observed hand motions [81].

Ferrero, L., examined the use of a BCI based on motor imaging (MI) to lower limb exoskeleton control as a means of promoting motor recovery following brain damage. Ten volunteers in good health and two patients suffering from SCIs underwent BCI evaluations. To expedite training with the BCI, five participants in good physical condition participated in a training virtual reality session. When the outcomes of this group were contrasted with those of a control group consisting of five participants who were able-bodied, it was shown that using virtual reality for shorter training did not lessen the BCI's effectiveness in fact, in certain situations, it substantially enhanced it.

Patients were satisfied with the approach and were able to manage trial sessions without becoming overly physically or mentally exhausted. Future studies should look into the promise of the MI-based BCI system, since these findings support the application of BCI in rehabilitation initiatives. Robotic exoskeletons and orthoses have become commonplace wearable with the promise to improve mobility and physical performance. It has been demonstrated that including them in rehabilitation programmes aids in the restoration of motor function, especially for patients who have had a stroke or spinal cord injury. Lower-limb MI is more challenging due to the deep location of the motor cortex's leg area, making it difficult to accurately record. However, these approaches have poor performance metrics. Interest has been piqued in closed-loop control of external devices, especially for lower-limb MI. Motion intention, a cortical potential generated by the motor cortex immediately before a movement, has been the basis for closed-loop control advocated by certain authors [82].

Khan S. proposed that 61-channel EEG equipment be used to capture the EEG signals of fifteen people, and the recordings are available to the public. He focused on a technique that used spectrograms of the EEG data and deep learning (DL) models that had already been trained to categorise four groups for various subjects. The suggested approach has produced noteworthy results; the greatest average classification accuracy was 87.36%, while the maximum classification accuracy was 97.03% for one topic. This research has therapeutic importance; it uses an EEG spectrogram and a pre-trained deep-learning model that is optimised for the downstream goal of classifying upper limb movement execution with notable accuracy [83].

5.8. Assistive BCIs Depend on Rehabilitation Therapy

Iahn Iahn Cajigas and Kevin C. Davis reported that, in a case study, an electroencephalogram (ECoG) sensing device, as shown in **Figure 6**, was placed over the sensorimotor hand area of the brain in a 24-year-old male individual with cervical SCI. The participant trained decoders to categorise sensorimotor rhythms using motor imagery (MI). During the next fifteen sessions of closed-loop trials, the participant walked for an hour on a weight-supported treadmill once or three times a week. The top-performing decoder achieved an average accuracy of 84.15% over a period of nine weeks.

The outcomes show that it is possible to employ UL MI as a control signal for lower-limb motor control by decoding it. Intrusive BCI systems designed for upper-extremity motor control can be extended to control systems that do not need upper-extremity control. Crucially, over a few weeks with the invasive signal, the decoders in use were able to separate MI from the invasive signal. Further research is needed to determine the long-term consequences of UL MI and the ensuing lower-limb control [84]. The study participants demonstrated that by using wrist joint muscular contractions, people with SCI were able to successfully operate a virtual cursor. The sonomyography-based interface's ability to control the cursor at different grade levels revealed its capacity to acquire very accurate and stable endpoint control.

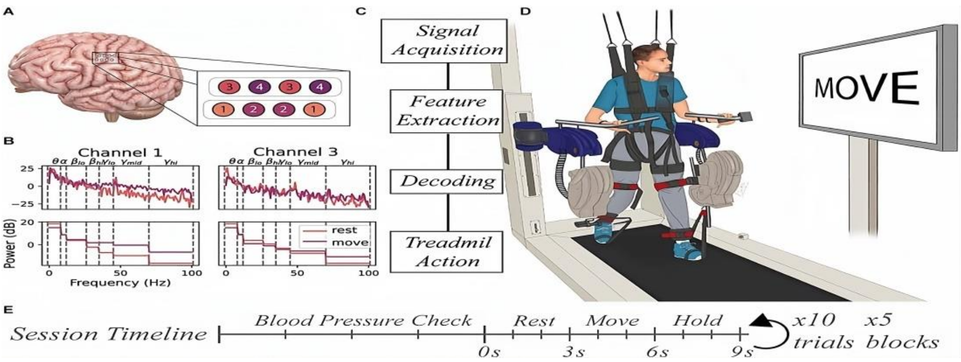

Figure 6: Assistive BCIs depend on rehabilitation.

Rehabilitation therapy effectiveness is closely related to the techniques used to operate the robotic end-effector. There have been several reports on two strategies: the cooperative or active control method and the passive control technique. With the use of passive methods, patients may be repeatedly trained to reach and grip objects along predefined trajectories without having to move voluntarily. Active strategies, on the other hand, maximise the use of residual motor function by preventing disuse-induced muscle atrophy. Electromyography is no longer the only method available to monitor muscle activity; ultrasound-based detection of mechanical muscle contractions has been used to operate prosthetic devices. Detecting individual finger positions and joint forces is possible with ultrasound imaging, a non-invasive sensing modality that can also resolve deep-seated muscle compartments. It has also been used to achieve proportionate control of multiple degrees of freedom, which is necessary to control multi-articulated prosthetic arms and legs [85].

6. Potential Risks and Challenges of BCI Implementing Technology for SCI:

Invasive Procedures: Some BCI technologies require invasive procedures, such as implanting electrodes or neural interfaces into the brain. These invasive procedures carry risks such as infection, tissue damage, or adverse reactions to the implant. Minimising these risks and ensuring the safety of the individual undergoing the procedure is of paramount importance [86, 117].

Long-Term Reliability: BCIs intended for long-term use need to be reliable and robust. The longevity of implanted devices, their stability over time, and the potential for degradation or malfunction are critical concerns. Ensuring the long-term reliability of BCI technology is crucial for its practical application and user acceptance [87].

Calibration and Individual Variability: BCI systems often require calibration to establish accurate and consistent communication between the brain signals of the user and the intended control commands. However, individual variability and changes in brain signals over time can pose challenges. Variations in signal quality, signal-to-noise ratio, and the need for frequent recalibration can affect the performance and usability of the BCI system [88].

Limited Control Accuracy and Speed: Achieving high levels of control accuracy and speed can be challenging. Factors such as signal decoding algorithms, signal processing delays, and the complexity of mapping brain signals to intended actions can limit the precision and speed of control [89]. These limitations may affect the practicality and effectiveness of BCI systems in real-world scenarios.

Training and Learning Curve: Effective use of BCIs often requires training and practice to optimise the user's ability to generate reliable and distinct brain signals for control commands. The learning curve associated with BCI technology can vary among individuals, and some users may face difficulties mastering the control strategies or maintaining consistent performance [90, 116, 120].

Adaptation and Plasticity: The brain's ability to adapt and reorganise itself, known as neuroplasticity, poses challenges for BCI implementation. Changes in neural activity and connectivity over time, as well as the potential for adaptation to the BCI system itself, can impact the stability and accuracy of control signals [91].

User Acceptance and Usability: User acceptance and usability are crucial for successful BCI implementation. Factors such as comfort, convenience, ease of use, and the overall user experience play a significant role [92].

Ethical and Privacy Considerations: BCI technology raises ethical considerations, including privacy, informed consent, and potential risks to personal autonomy. The collection and storage of neural data, especially if it relates to sensitive information or brain activity, require appropriate safeguards to protect user privacy and ensure ethical use of the technology [93].

Biocompatible Materials: The use of biocompatible materials in the design of implantable BCI devices is crucial for long-term reliability. Researchers are investigating materials that are less likely to cause adverse reactions, inflammation, or tissue damage. Biocompatible coatings and encapsulation techniques are also being explored to protect implanted electrodes or neural interfaces from degradation or rejection by the body [94, 117].

7. Elimination of BCIs Challenges:

The successful elimination of challenges associated with BCIs marks a ground-breaking achievement in the realm of neurotechnology. Overcoming technical hurdles such as signal noise, limited bandwidth, and the need for invasive procedures has paved the way for more seamless and effective BCIs.

Minimally Invasive Implantation Techniques: Minimally invasive procedures for implanting BCIs can reduce the risks associated with invasive surgeries. Techniques such as stereotactic implantation, which uses precise imaging and targeting, can minimize tissue damage and improve the accuracy of electrode placementas shown in **Figure 7**. Minimally invasive approaches can also facilitate easier removal or replacement of devices if necessary [95].

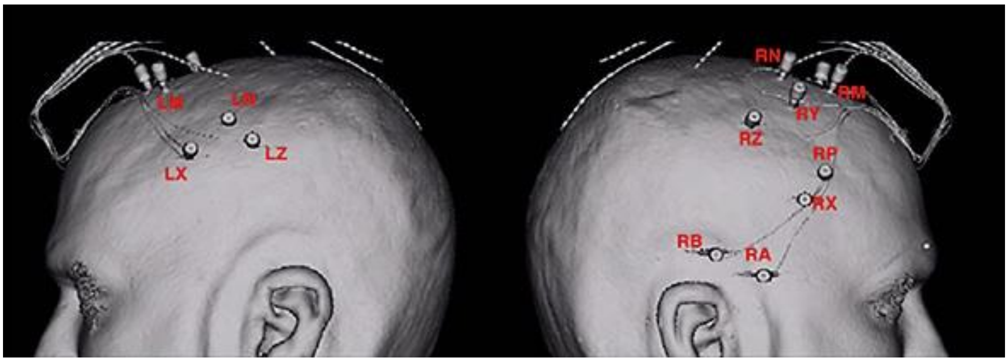

Figure 7: Stereo EEG

Advanced signal processing algorithms and machine learning techniques have significantly improved the accuracy and reliability of extracting meaningful information from the brain's electrical signals. Non-invasive BCI technologies, utilising methods like electroencephalography (EEG), have gained prominence, offering a user-friendly approach for widespread adoption.

Additionally, the ethical and privacy concerns surrounding BCIs have been addressed through stringent regulations and the development of transparent and secure frameworks. This collective progress has not only enhanced the usability of BCIs in medical applications, such as prosthetics control and neurological rehabilitation, but also opened up new frontiers in human-computer interaction and cognitive augmentation.

Wireless and Implantable Telemetry: Wireless communication and implantable telemetry systems eliminate the need for physical connections between external devices and implanted BCI components. This reduces the risk of infection, mechanical strain, or damage to the implanted electrodes or interfaces [96,118]. Wireless technology also allows for more freedom of movement and reduces the burden of external wiring.

Long-Term Stability and Bio stability: Ensuring the long-term stability and bio stability of implanted BCI devices is crucial. Bio stability refers to the ability of the device to maintain its functionality and performance over an extended period within the biological environment [97]. Researchers are exploring materials and device architectures that can withstand the physiological conditions and minimize degradation or loss of signal quality over time.

8. Optimizing BCIs Performances and Requirements Keys:

Neural Interface Design: Improving the design of neural interfaces is a key strategy to enhance long-term reliability. This includes optimising the shape, size, and mechanical properties of the electrodes or interfaces to minimise tissue damage, inflammation, or degradation. Flexible and biocompatible electrode designs are being investigated to improve the interface with neural tissue and reduce the risk of chronic inflammation or scar tissue formation [98, 119].

Signal Processing and Adaptation: These approaches aim to adapt the BCI system to variations in signal quality, neural activity, or connectivity that may occur as a result of long-term implantation. Adaptive algorithms can enhance the system's ability to decode and interpret brain signals accurately, even as they evolve [99].

Long-Term User Training and Adaptation: Training protocols that facilitate long-term user adaptation and learning are being explored. Continuous training and feedback mechanisms can help users maintain consistent and reliable control of the BCI system over time [100]. Adaptive training paradigms that adjust to individual users' changing needs and abilities can improve long-term performance and usability.

Biocompatibility Testing and Preclinical Studies: Rigorous biocompatibility testing and preclinical research studies are essential to evaluating the extended effects of BCI devices and identifying potential risks or limitations. These studies involve evaluating the device's performance, stability, and safety over extended periods in relevant animal models or simulated human models. Such research provides valuable insights into the durability of brain-computer interface technology [101].

By combining these strategies and continuing research efforts, the goal is to enhance the long-term reliability of BCI technologies, improving their practicality and effectiveness for SCIs and other conditions..

9. A Promising and Adaptive Training Paradigms in BCIs:

Adaptive Task Difficulty: One approach is to dynamically adjust the difficulty of the BCI task based on the user's performance. The task difficulty can be modified by altering parameters such as the speed, complexity, or required accuracy of the control task. If the user consistently achieves high performance, the task difficulty can be increased to provide a challenging experience and promote skill improvement. Conversely, if the user struggles, the difficulty can be adjusted to a more manageable level to avoid frustration and maintain engagement [102].

Error Augmentation: Error augmentation is a technique where artificial errors are introduced into the BCI's feedback to enhance the user's learning and adaptation. The system intentionally amplifies or distorts the feedback based on the user's performance, providing exaggerated errors. By making errors more noticeable, users can better understand the consequences of their actions and adjust their strategies accordingly [103]. This approach encourages users to explore different control strategies and refine their performance over time.

Co-adaptive Training: Co-adaptive training involves simultaneous adaptation of both the BCI system and the user. The system continuously adapts its decoding.

Feedback-Driven Adaptation: Feedback-driven adaptation involves providing real-time feedback to the user during training and BCI operation. The feedback may come in the form of audio, or visual, or tactile cues that indicate the quality or accuracy of the user's brain signals. By utilising this feedback, it is possible for users to control their brain activity more effectively, leading to increased control accuracy and improved performance over time [104].

Context-Aware Adaptation: Context-aware adaptation takes into account the changing context or conditions in which the BCI system operates. It adapts the system's parameters or strategies based on factors such as user state, environmental conditions, or task difficulty [105]. By dynamically adjusting the BCI system to a specific context, users can achieve better performance and maintain consistent control accuracy over time.

Transfer Learning: Transfer learning leverages knowledge or models acquired from previous BCI users to accelerate training and adaptation for new users. By using pre-existing models or data, the system can initialise training with a foundation of knowledge, reducing the training time and improving the learning curve for new users. Transfer learning has the potential to enhance long-term performance by leveraging collective knowledge and experience [106].

It's important to note that adaptive training paradigms are still an active area of research, and their effectiveness may vary depending on factors such as the specific BCI modality, user characteristics, and task requirements. The success of an adaptive training paradigm also depends on individual user variability and the ability to generalise adaptations to different contexts.

10. Our Proposed Approach

According to further review of the previous research in that domain, the research group selected an approach for processing data acquisition and designing BCIs involving the following:

Sensor Placement: Depending on the type of BCI system, sensors or electrodes are placed on or near the user's scalp or brain to detect neural activity. The specific sensor placement depends on the chosen BCI modality, such as EEG, fNIRS, or invasive methods [107].

Signal Acquisition: The sensors or electrodes capture the electrical or optical signals generated by the brain. This can be done using either invasive techniques like implanted electrodes or non-invasive techniques like EEG. The signals are then amplified and converted into a digital format for further processing [108].

Pre-processing: The acquired signals often undergo pre-processing steps to enhance the quality and extract relevant information, as shown in **Figure 8**. This may involve filtering to remove noise, artifact, or unwanted frequencies, as well as signal normalisation or baseline correction [109].

Feature Extraction: In this step, meaningful features are extracted from the pre-processed data. Feature extraction aims to identify specific patterns or characteristics in the signals that are relevant for the BCI application. These features can include frequency patterns, event-related potentials, or other neural signatures that represent specific mental states or intentions. In another sense, the features can include spectral power, event-related potentials, or other domain-specific measures [110].

Calibration or Training: The BCIs typically require a training or calibration phase to establish a mapping between the extracted features and the user's intended commands or actions [111]. During this phase, the user performs specific tasks or engages in mental activities while the BCI system records their brain signals. The recorded signals are utilised to train a regression or classification model that maps the features to the desired outputs [112]. The system is exposed to a dataset containing EEG recordings associated with various hand movements. These movements could include actions like grasping, pointing, or other specific gestures. The model learns to recognise patterns and correlations within the EEG signals that correspond to different hand movements. Through a process called supervised learning, the BCI model adjusts its parameters to accurately map EEG patterns to specific hand movements, forming a robust understanding during the training stage.

Testing, Prediction, and Evaluation: Once the calibration or training is complete, the BCI system is tested to assess its performance. The user performs tasks or provides commands, and the system predicts the intended actions based on the acquired data [113]. For predicting hand movements through EEG signals, the trained model is deployed to interpret real-time EEG data. As a user thinks about or initiates a hand movement, the BCI system processes the incoming EEG signals and employs the learned patterns from the training stage to predict the corresponding hand movement. This involves mapping the current EEG patterns to the established associations learned during training, ultimately providing real-time predictions of the intended hand movement based on the user's brain activity. The accuracy and reliability of the system are evaluated using a variety of measures, including keeping up with information transfer, reaction time, and the accuracy of categorization [114].

Real-time Operation: In the final step, the BCI system is deployed for real-time operation. The acquired data is continuously processed and interpreted by the BCI algorithms to provide control signals for external devices or applications, such as controlling a robotic arm, typing on a screen, or interacting with a virtual environment [115].

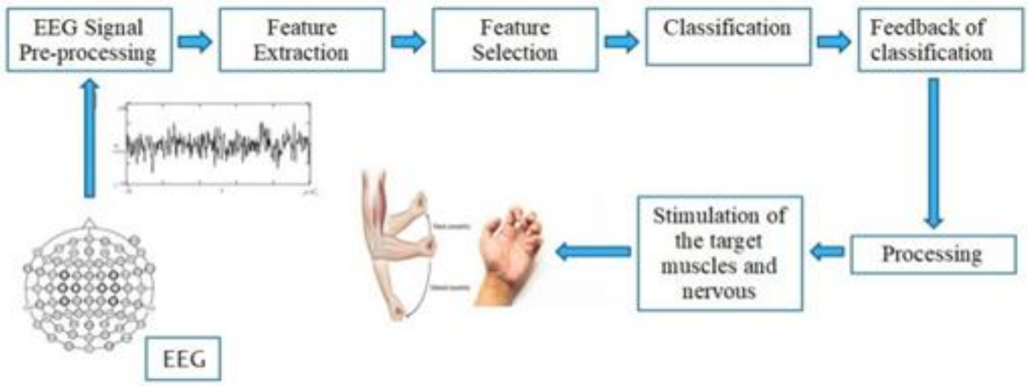

Figure 8: Our proposed approach.

It's It's important to note that the specific steps and details can vary depending on the BCI modality, hardware setup, and intended application. Additionally, we focused on developing more efficient and automated techniques for data acquisition and processing in BCIs. We present a short overview of the publicly accessible BCI software platforms. A platform is a system that enables communication and interaction between the human brain and a computer or other external devices. It serves as an intermediary between the user's brain signals and the intended application or output. A platform is a website devoted to stimulus presentation and response [26]. BCI2000, OpenViBE, TOBI Common Implementation Platform (CIP), BCILAB, BCI++, xBCI, BF++, Pyff, and OpenBCI are the nine platforms.

The BCI software platform typically consists of several components: signal acquisition, signal processing, feature extraction, classification and decoding, and application interface. We suggest this approach to and performance of a low-cost and lightweight neuroprosthetic. A high-density multielectrode will be placed across the sensorimotor cortex region that regulates hand movement in a person with SCI who has lost the ability to move. We'll build AI models for categorization using deep learning methods of the brain's signal patterns in the recorded cortical activity to move the hand directly, bypassing the brain's signals on a device that translates them and electrically stimulates the muscles and nerve axons responsible for hand movement (up, down, grasp, relaxation), and enabling tactile reactions by placing sensors on the hand.

11. Conclusion

The literature review yields several key findings regarding the use of BCIs for individuals with SCIs. Continued research and development efforts are aimed at refining and optimising these adaptive training paradigms to achieve better long-term performance in BCI systems. Implementing transfer learning for adaptive training in BCIs presents several challenges that need to be addressed. BCIs have been used successfully to enable individuals with spinal cord injuries to control prosthetic limbs, wheelchairs, and other assistive devices. Furthermore, the review sheds light on the future trends in BCI development for SCIs, considering both technological advancements and user-centred perspectives. It explores emerging technologies such as optogenetics, nanotechnology, and neuroprosthetics, which hold the potential to revolutionise BCI capabilities in order to enhance the quality of life for spinal cord injured people. Additionally, the review discusses the importance of user feedback, personalised training paradigms, and collaborative interdisciplinary efforts in driving the future development and widespread adoption of BCIs.

In conclusion, this literature review seeks to provide a comprehensive overview of BCIs for assisting SCIs from an evolutionary perspective. By examining the historical progress, current state, and future trends in BCI development, it aims to contribute to the understanding of how BCIs can continue to empower individuals with SCIs, promote neuro-rehabilitation, and enhance their overall lives..

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References

[1] Wolpaw, J. R., Millán, J. D. R., & Ramsey, N. F. (2019). Brain-computer interfaces: Definitions and principles. Handbook of Clinical Neurology, 168, 15-23. https://doi.org/10.1016/B978-0-444-63934-9.00002-0

[2] Radovic, T. (2022). Neuroprosthetics: The Restoration of Brain Damage. UC Merced: School of Social Sciences, Humanities, and Arts. Retrieved from https://escholarship.org/uc/item/7553d0qc

[3] Merante, A., Zhang, Y., Kumar, S., Nam, C.S. (2020). Brain–Computer Interfaces for Spinal Cord Injury Rehabilitation. In: Nam, C. (eds) Neuroergonomics. Cognitive Science and Technology. Springer, Cham. https://doi.org/10.1007/978-3-030-34784-0_16

[4] Grahn Peter J., Mallory Grant W., "Restoration of motor function following spinal cord injury via optimal control of intraspinal microstimulation: toward a next generation closed-loop neural prosthesis" JOURNAL Frontiers in Neuroscience , VOLUME 8, 2014,URL https://www.frontiersin.org/articles/10.3389/fnins.2014.00296,
DOI=10.3389/fnins.2014.00296, ISSN=1662-453X.

[5] Richings, L., Nelson, D., Goosey-Tolfrey, V., Donnellan, C., & Booth, V. (2023). Effectiveness of the 'evidence-based scientific exercise guidelines' in increasing cardiorespiratory fitness, cardiometabolic health and muscle strength in acute spinal cord injury rehabilitation: a systematic review. Archives of Rehabilitation Research and Clinical Translation, 100278

[6] DeVivo MJ, Chen Y (2011) Trends in new injuries, prevalent cases, and aging with spinal cord injury. Arch Phys Med Rehabil 92(3):332–338. https://doi.org/10.1016/j.apmr.2010.08.031

[7] Scivoletto G, Farchi S, Laurenza L, Molinari M (2011) Traumatic and non-traumatic spinal cord lesions: an Italian comparison of neurological and functional outcomes. Spinal Cord 49 (3):391–396. https://doi.org/10.1038/sc.2010.85

[8] Gundelach, L.A., Hüser, M.A., Beutner, D. et al. Towards the clinical translation of optogenetic skeletal muscle stimulation. Pflugers Arch - Eur J Physiol 472, 527–545 (2020). https://doi.org/10.1007/s00424-020-02387-0

[9] Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. Clinical neurophysiology, 113(6), 767-791.

[10] Park, K. S. (2023). Nervous System. In Humans and Electricity: Understanding Body Electricity and Applications (pp. 27-51). Cham: Springer International Publishing.

[11] Banerjee, D., Das, P. K., & Mukherjee, J. (2023). Nervous System. In Textbook of Veterinary Physiology (pp. 265-293). Singapore: Springer Nature Singapore.

[12] Banerjee, D., & Das, P. K. (2023). Check for updates Muscular System Dipak Banerjee, Pradip Kumar Das, and Joydip Mukherjee. Textbook of Veterinary Physiology, 235.

[13] Sayaca, C. (2023). The Nerve Structure and Function. In Functional Exercise Anatomy and Physiology for Physiotherapists (pp. 93-110). Cham: Springer International Publishing.

[14] Bray, E. A. (2023). Supporting the transition of children and young people with a spinal cord injury from paediatric to adult healthcare services.

[15] Karabacak, M., & Margetis, K. (2023). Precision medicine for traumatic cervical spinal cord injuries: accessible and interpretable machine learning models to predict individualized in-hospital outcomes. The Spine Journal.

[16] Canori, A., Lakshminarayanan, R., Nunn, M., Schmidt-Read, M., Intille, S. S., & Hiremath, S. V. (2023). Potential of social engagement for overcoming barriers to physical activity in individuals with spinal cord injury. Journal of Rehabilitation and Assistive Technologies Engineering, 10, 20556683231185755.

[17] Miskala, M. L. (2023). Case study: Benefits and challenges of automated assistive technology devices for spinal cord-injured citizens in Greece. World Federation of Occupational Therapists Bulletin, 1-5.

[18] Angulo-Sherman, I. N., & Salazar-Varas, R. (2023). Recent Applications of BCIs in Healthcare. In Advances in Smart Healthcare Paradigms and Applications: Outstanding Women in Healthcare—Volume 1 (pp. 173-197). Cham: Springer Nature Switzerland.

[19] Rezvani, S., Hosseini-Zahraei, S. H., Tootchi, A., Guger, C., Chaibakhsh, Y., Saberi, A., & Chaibakhsh, A. (2023). A review on the performance of brain-computer interface systems used for patients with locked-in and completely locked-in syndrome. Cognitive Neurodynamics, 1-25.

[20] Soekadar, S. R., Vermehren, M., Colucci, A., Haslacher, D., Bublitz, C., Ienca, M., ... & Blankertz, B. (2023). Future Developments in Brain/Neural–Computer Interface Technology. In Policy, Identity, and Neurotechnology: The Neuroethics of Brain-Computer Interfaces (pp. 65-85). Cham: Springer International Publishing.

[21] Ajiboye, Abidemi Bolu, et al. "Restoration of reaching and grasping in a person with tetraplegia through brain-controlled muscle stimulation: a proof-of-concept demonstration." Lancet (London, England) 389.10081 (2017): 1821.

[22] Failli, Vieri, et al. "Experimental Treatments for Spinal Cord Injury: What you Should Know." Topics in Spinal Cord Injury Rehabilitation 27.2 (2021): 50-74.

[23] Lebedev, M. A., & Nicolelis, M. A. (2017). Brain-machine interfaces: From basic science to neuroprostheses and neurorehabilitation. Physiological reviews, 97(2), 767-837.

[24] Davis, K. C., Meschede-Krasa, B., Cajigas, I., Prins, N. W., Alver, C., Gallo, S. ... & Prasad, A. (2022). Design-development of an at-home modular brain–computer interface (BCI) platform in a case study of cervical spinal cord injury. Journal of neuroengineering and rehabilitation, 19(1), 53.

[25] Susan Philip, B., Prasad, G., & Hemanth, D. J. (2023). A systematic review on artifact removal and classification techniques for enhanced MEG-based BCI systems. Brain-Computer Interfaces, 1-15.

[26] Ramadan, R. A., & Vasilakos, A. V. (2017). Brain computer interface: control signals review. Neurocomputing, 223, 26-44.

[27] Pal, M., & Panigrahi, P. K. (2022). Coupled Oscillator Dynamics in Brain EEG Signals: Manifestation of synchronization and Across Frequency Energy Exchange by Neutral Turbulence. IEEE Access, 10, 20445-20454.

[28] Veletic, M., Apu, E. H., Simic, M., Bergsland, J., Balasingham, I., Contag, C. H., & Ashammakhi, N. (2022). Implants with sensing capabilities. Chemical Reviews, 122(21), 16329-16363.

[29] Wolpaw, J. R., Birbaumer, N., Heetderks, W. J., McFarland, D. J., Peckham, P. H., Schalk, G., ... & Vaughan, T. M. (2000). Brain-computer interface technology: a review of the first international meeting. IEEE transactions on rehabilitation engineering, 8(2), 164-173.

[30] Regan, D. (1989). Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine. Elsevier.

[31] Barbosa, A. O., Achanccaray, D. R., & Meggiolaro, M. A. (2010, May). Activation of a mobile robot through a brain computer interface. In 2010 IEEE International Conference on Robotics and Automation (pp. 4815-4821). IEEE.

[32] Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., ... & Donoghue, J. P. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature, 442(7099), 164-171.

[33] Remsik, A., Young, B., Vermilyea, R., Kiekhoefer, L., Abrams, J., Evander Elmore, S. ... & Prabhakaran, V. (2016). A review of the progression and future implications of brain-computer interface therapies for restoration of distal upper extremity motor function after stroke. Expert review of medical devices, 13(5), 445-454.

[34] Jabban, L., Dupan, S., Zhang, D., Ainsworth, B., Nazarpour, K., & Metcalfe, B. W. (2022). Sensory feedback for upper-limb prostheses: opportunities and barriers. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30, 738-747.

[35] Wang, X. (2023). Intracortical Brain-machine Interface for Restoring Sensory Motor Function: Progress and Challenges. International Journal of Biology and Life Sciences, 3(2), 31-38.

[36] Masengo, G., Zhang, X., Dong, R., Alhassan, A. B., Hamza, K., & Mudaheranwa, E. (2023). Lower limb exoskeleton robot and its cooperative control: A review, trends, and challenges for future research. Frontiers in Neurorobotics, 16, 913748.

[37] Lebedev, M. A., & Nicolelis, M. A. (2017). Brain-machine interfaces: From basic science to neuroprostheses and neurorehabilitation. Physiological reviews, 97(2), 767-837.

[38] Vidal, J.J. (1973) Towards direct brain-computer communication. Annu. Rev. Biophys. Bioeng. 2, 157–180.

[39] Elbert, T. et al. (1980) Biofeedback of slow cortical potentials. I. Electroencephalogr. Clin. Neurophysiol. 48, 293–301.

[40] Birbaumer, N. et al. (1990) Slow potentials of the cerebral cortex and behavior. Physiol. Rev. 70, 1–41.

[41] Farwell, L.A. and Donchin, E. (1988) Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr. Clin. Neurophysiol. 70, 510–523.

[42] Wolpaw, J. R., McFarland, D. J., Neat, G. W., & Forneris, C. A. (1991). An EEG-based brain-computer interface for cursor control. Electroencephalography and clinical neurophysiology, 78(3), 252-259.

[43] McMillan, G. R., Calhoun, G., Middendorf, M. S., Schnurer, J. H., Ingle, D. F., & Nasman, V. T. (1995, June). Direct brain interface utilizing self-regulation of steady-state visual evoked response (SSVER). In Proc. RESNA '95 Annual Conf.(Vancouver, BC) (pp. 693-5).

[44] Cheng, M., Gao, X., Gao, S., & Xu, D. (2002). Design and implementation of a brain-computer interface with high transfer rates. IEEE transactions on biomedical engineering, 49(10), 1181-1186.

[45] Guo, F., Hong, B., Gao, X., & Gao, S. (2008). A brain–computer interface using motion-onset visual evoked potential. Journal of neural engineering, 5(4), 477.

[46] Li, W., Li, M., & Zhao, J. (2015). Control of humanoid robot via motion-onset visual evoked potentials. Frontiers in Systems Neuroscience, 8, 247.

[47] Pfurtscheller, G., Allison, B. Z., Brunner, C., Bauernfeind, G., Solis-Escalante, T., Scherer, R. ... & Birbaumer, N. (2010). The hybrid BCI Front. Neurosci, 4(3), 10-3389.

[48] Wang, Y., & Jung, T. P. (2011). A collaborative brain-computer interface for improving human performance. PloS one, 6(5), e20422.

[49] Vidaurre, C., Sannelli, C., Müller, K. R., & Blankertz, B. (2011). Co-adaptive calibration to improve BCI efficiency. Journal of neural engineering, 8(2), 025009.

[50] Singh, A., Lal, S., & Guesgen, H. W. (2017, December). Architectural review of co-adaptive brain computer interface. In 2017 4th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE) (pp. 200-207). IEEE.

[51] Astrand, E., Wardak, C., & Ben Hamed, S. (2014). Selective visual attention to drive cognitive brain–machine interfaces: from concepts to neurofeedback and rehabilitation applications. Frontiers in systems neuroscience, 8, 144.

[52] Bagherzadeh, Y., Baldauf, D., Pantazis, D., & Desimone, R. (2020). Alpha synchrony and the neurofeedback control of spatial attention. Neuron, 105(3), 577-587.

[53] Sitaram, R., Ros, T., Stoeckel, L., Haller, S., Scharnowski, F., Lewis-Peacock, J., ... & Sulzer, J. (2017). Closed-loop brain training: the science of neurofeedback. Nature Reviews Neuroscience, 18(2), 86-100.

[54] Liao, L. D., Lin, C. T., McDowell, K., Wickenden, A. E., Gramann, K., Jung, T. P., ... & Chang, J. Y. (2012). Biosensor technologies for augmented brain–computer interfaces in the next decades. Proceedings of the IEEE, 100(Special Centennial Issue), 1553-1566.

[55] Lance, B. J., Kerick, S. E., Ries, A. J., Oie, K. S., & McDowell, K. (2012). Brain–computer interface technologies in the coming decades. Proceedings of the IEEE, 100(Special Centennial Issue), 1585-1599.

[56] Nijboer, F., Morin, F. O., Carmien, S. P., Koene, R. A., Leon, E., & Hoffmann, U. (2009, September). Affective brain-computer interfaces: Psychophysiological markers of emotion in healthy persons and in persons with amyotrophic lateral sclerosis. In 2009 3rd international conference on affective computing and intelligent interaction and workshops (pp. 1-11). IEEE.

[57] Mühl, C., Allison, B., Nijholt, A., & Chanel, G. (2014). A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges. Brain-Computer Interfaces, 1(2), 66-84.

[58] Daly, I. et al. (2020) Personalised, multi-modal, affective state detection for hybrid brain-computer music interfacing. IEEE Trans. Affect. Comput. 11, 111–124.

[59] Garcia-Molina, G., Tsoneva, T., & Nijholt, A. (2013). Emotional brain–computer interfaces. International journal of autonomous and adaptive communications systems, 6(1), 9-25.

[60] Shanechi, M. M. (2019). Brain–machine interfaces from motor to mood. Nature neuroscience, 22(10), 1554-1564.

[61] Sani, O.G. et al. (2018) Mood variations decoded from multisite intracranial human brain activity. Nat. Biotechnol. 36, 954–961.

[62] Gao, S., Wang, Y., Gao, X., & Hong, B. (2014). Visual and auditory brain–computer interfaces. IEEE Transactions on Biomedical Engineering, 61(5), 1436-1447.

[63] Chen, X., Wang, Y., Nakanishi, M., Gao, X., Jung, T. P., & Gao, S. (2015). High-speed spelling with a noninvasive brain–computer interface. Proceedings of the national academy of sciences, 112(44), E6058-E6067.

[64] Guenther, F. H., Brumberg, J. S., Wright, E. J., Nieto-Castanon, A., Tourville, J. A., Panko, M., ... & Kennedy, P. R. (2009). A wireless brain-machine interface for real-time speech synthesis. PloS one, 4(12), e8218.

[65] Cooney, C., Folli, R., & Coyle, D. (2018). Neurolinguistics research advancing development of a direct-speech brain-computer interface. IScience, 8, 103-125.

[66] Rabbani, Q., Milsap, G., & Crone, N. E. (2019). The potential for a speech brain–computer interface using chronic electrocorticography. Neurotherapeutics, 16, 144-165.

[67] Anumanchipalli, G.K. et al. (2019) Speech synthesis from neural decoding of spoken sentences. Nature 568, 493–498.

[68] Makin, J. G., Moses, D. A., & Chang, E. F. (2020). Machine translation of cortical activity to text with an encoder–decoder framework. Nature neuroscience, 23(4), 575-582.

[69] Edelman, B. J., Meng, J., Suma, D., Zurn, C., Nagarajan, E., Baxter, B. S. ... & He, B. J. S. R. (2019). Noninvasive neuroimaging enhances continuous neural tracking for robotic device control. Science robotics, 4(31), eaaw6844.

[70] Benabid, A. L., Costecalde, T., Eliseyev, A., Charvet, G., Verney, A., Karakas, S., ... & Chabardes, S. (2019). An exoskeleton controlled by an epidural wireless brain–machine interface in a tetraplegic patient: a proof-of-concept demonstration. The Lancet Neurology, 18(12), 1112-1122.

[71] Oxley, T. J., Yoo, P. E., Rind, G. S., Ronayne, S. M., Lee, C. S., Bird, C., ... & Opie, N. L. (2021). Motor neuroprosthesis implanted with neurointerventional surgery improves capacity for activities of daily living tasks in severe paralysis: first in-human experience. Journal of neurointerventional surgery, 13(2), 102-108.

[72] Alexander E. Hramov, Vladimir A. Maksimenko, Alexander N. Pisarchik, Physical principles of brain–computer interfaces and their applications for rehabilitation, robotics and control of human brain states, Physics Reports, Volume 918, 2021, Pages 1-133, ISSN 0370-1573, https://doi.org/10.1016/j.physrep.2021.03.002.

[73] Aggarwal, S., Chugh, N. Review of Machine Learning Techniques for EEG Based Brain Computer Interface. Arch Computat Methods Eng 29, 3001–3020 (2022). https://doi.org/10.1007/s11831-021-09684-6

[74] Edelman, B.J. et al. (2019) Non-invasive neuroimaging enhances continuous neural tracking for robotic device control. Sci. Robot. 4, eaaw6844.

[75] Benabid, A.L. et al. (2019) An exoskeleton controlled by an epidural wireless brain-machine interface in a tetraplegic patient: a proof-of-concept demonstration. Lancet Neurol. 18, 1112–1122.

[76] Ferrin-Bolaños, C., Loaiza-Correa, H., Pierre-Díaz, J., & Vélez-Ángel, P. (2019). Assessing the Contribution of Covariance Information to the Electroencephalographic Signals of Brain-Computer Interfaces for Spinal Cord Injury Patients. TecnoLógicas, 22(46), 158-176.

[77] Oxley TJ, Yoo PE, Rind GS, et al, Motor neuroprosthesis implanted with neurointerventional surgery improves capacity for activities of daily living tasks in severe paralysis: first in-human experience Journal of NeuroInterventional Surgery 2021;13:102-108.

[78] Alexander E. Hramov, Vladimir A. Maksimenko, Alexander N. Pisarchik, Physical principles of brain–computer interfaces and their applications for rehabilitation, robotics and control of human brain states, Physics Reports, Volume 918, 2021, Pages 1-133, ISSN 0370-1573, https://doi.org/10.1016/j.physrep.2021.03.002.

[79] Aggarwal, S., Chugh, N. Review of Machine Learning Techniques for EEG Based Brain Computer Interface. Arch Computat Methods Eng 29, 3001–3020 (2022). https://doi.org/10.1007/s11831-021-09684-6.

[80] Palumbo, Arrigo, Nicola Ielpo, and Barbara Calabrese. "An FPGA-Embedded Brain-Computer Interface System to Support Individual Autonomy in Locked-In Individuals." Sensors 22.1 (2022): 318.

[81] Pancholi, S., & Giri, A. (2023). Advancing Brain-Computer Interface System Performance in Hand Trajectory Estimation with NeuroKinect. arXiv preprint arXiv:2308.08654.

[82] Ferrero, L., Quiles, V., Ortiz, M., Iáñez, E., Gil-Agudo, Á., & Azorín, J. M. (2023). Brain-computer interface enhanced by virtual reality training for controlling a lower limb exoskeleton. Iscience, 26(5).

[83] Khan, S. U., Majid, M., & Anwar, S. M. (2023). Upper Limb Movement Execution Classification using Electroencephalography for Brain Computer Interface. arXiv preprint arXiv:2304.06036.

[84] Cajigas, I., Davis, K. C., Prins, N. W., Gallo, S., Naeem, J. A., Fisher, L., ... & Jagid, J. R. (2023). Brain-Computer interface control of stepping from invasive electrocorticography upper-limb motor imagery in a patient with quadriplegia. Frontiers in human neuroscience, 16, 1077416.

[85] Shenbagam, M., Kamatham, A. T., Vijay, P., Salimath, S., Patwardhan, S., Sikdar, S., ... & Mukherjee, B. (2023). A Sonomyography-based Muscle Computer Interface for Individuals with Spinal Cord Injury. arXiv preprint arXiv:2308.06278.

[86] Abouseif, N., Ibrahim, N., Jaber, M., Hassan, M., & El-Ameen, A. M. (2023). Reasons for Removal of Miniplates Used in Fixation of Maxillofacial Bone Fractures: Systematic Review and Meta-Analysis.

[87] Teng, Q., Hu, Y., Cheng, R., Wu, Y., Zhou, G., & Gao, D. (2023). Reliability challenges in CMOS technology: A manufacturing process perspective. Microelectronic Engineering, 112086.

[88] Sibilano, E., Suglia, V., Brunetti, A., Buongiorno, D., Caporusso, N., Guger, C., & Bevilacqua, V. (2023). Brain–Computer Interfaces. In Psychophysiology Methods (pp. 203-240). New York, NY: Springer US.

[89] LIU, N., LI, W., & TAO, R. (2023). Typical Application of Graph Signal Processing in Hyperspectral Image Processing. 电子与信息学报, 45(5), 1529-1540.

[90] Kolimár, O., Kušnirák, K., Kučera, E., & Haffner, O. Current State of Brain-Computer Interface Device Usage in Personal and Professional Applications.

[91] Yoshimura, H. (2023). Neuroplasticity and Nutrition: The Role of Diet in Brain Resilience and Repair. Nutrition.

[92] Kies, A., & Paluch, S. (2023). Examining User Perceptions of Brain-Computer Interfaces for Practical Applications: An Exploratory Study.

[93] Lahtinen, T., & Costin, A. (2023, July). Linking Computers to the Brain: Overview of Cybersecurity Threats and Possible Solutions. In International Symposium on Business Modeling and Software Design (pp. 383-392). Cham: Springer Nature Switzerland.

[94] Huynh, M. A., Nguyen, T. H., Nguyen, T. K., & Nguyen, N. T. (2023). Convergence of Implantable Bioelectronics and Brain–Computer Interfaces. ACS Applied Electronic Materials.

[95] Rihana Begum, P., Mohammad, B. D., Saravana Kumar, A., & Muhasina, K. M. (2023). Making Hospital Environment Friendly for People: A Concept of HMI. Human-Machine Interface: Making Healthcare Digital, 247-278.

[96] Sarkar, S. (2023). Advanced spike sorting approaches in implantable VLSI wireless brain computer interfaces: a survey. arXiv preprint arXiv:2309.00913.

[97] Zhu, Y., Yang, Y., Ni, G., Li, S., Liu, W., Gao, Z., ... & Zhou, J. (2023). On-demand electrically controlled melatonin release from PEDOT/SNP composite improves quality of chronic neural recording. Frontiers in Bioengineering and Biotechnology, 11, 1284927.

[98] Abyzova, E., Dogadina, E., Rodriguez, R. D., Petrov, I., Kolesnikova, Y., Zhou, M., ... & Sheremet, E. (2023). Beyond Tissue replacement: The Emerging role of smart implants in healthcare. Materials Today Bio, 100784.

[99] Li, J., Qi, Y., & Pan, G. (2023). Phase-amplitude coupling-based adaptive filters for neural signal decoding. Frontiers in Neuroscience, 17, 1153568.

[100] Rimbert, S., & Fleck, S. (2023). Long-term kinesthetic motor imagery practice with a BCI: Impacts on user experience, motor cortex oscillations and BCI performances. Computers in Human Behavior, 146, 107789.

[101] ALMofleh, A., Alseddiqi, M., Najam, O., Albalooshi, L., Alheddi, A., & Alshaimi, A. (2023). Brain Computer Interfaces: The Future of Communication Between the Brain and the External World. Science, Engineering and Technology, 3(2).

[102] Mai, X., Ai, J., Ji, M., Zhu, X., & Meng, J. (2024). A hybrid BCI combining SSVEP and EOG and its application for continuous wheelchair control. Biomedical Signal Processing and Control, 88, 105530. https://doi.org/10.1016/j.bspc.2023.105530

[103] Kalaganis, F. P., Chatzilari, E., Laskaris, N. A., Nikolopoulos, S., & Kompatsiaris, I. (2020). Error-aware BCIs. Signal Processing to Drive Human–Computer Interaction, 231.

[104] DARVISHI, Sam. Stroke Rehabilitation Method and System Using a Brain-Computer Interface (BCI). U.S. Patent Application No 17/265,235, 2021.

[105] Pham, T. (2023). Context-Aware Gaze-Based Interface for Smart Wheelchair (Doctoral dissertation, The University of Texas at Arlington).

[106] Xie, Y., Wang, K., Meng, J., Yue, J., Meng, L., Yi, W., ... & Ming, D. (2023). Cross-dataset transfer learning for motor imagery signal classification via multi-task learning and pre-training. Journal of Neural Engineering, 20(5), 056037.

[107] Jeyakumar, V., Krishnan, P. T., Sundaram, P., & Raj, A. N. J. (2022). Brain-computer interface in Internet of Things environment. In 5G IoT and Edge Computing for Smart Healthcare (pp. 231-255). Academic Press.

[108] Prasad, A. S., Jayaram, M. N., Mounashree, B., & Supreetha, M. (2022, December). GNR Electrode acquried EEG Signals analysis. In 2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT) (pp. 1-7). IEEE.

[109] Manimegalai, P., Pamela, D., Michael, P. A., Nigel, K., Stanley, P. K., & Jenny, J. R. (2023, September). Comparison on denoising of electro cardiogram signal using deep learning techniques. In AIP Conference Proceedings (Vol. 2764, No. 1). AIP Publishing.

[110] Kulkarni, V. V. (2023). Brain Computer Interface Using EEG signal.

[111] Lee, S., Zhang, R., Hwang, M., Hiranaka, A., Wang, C., Ai, W., ... & Wu, J. (2023, August). NOIR: Neural Signal Operated Intelligent Robot for Everyday Activities. In 7th Annual Conference on Robot Learning.

[112] DALIN, Y. (2018). A Real-time hybrid BCI System for Simultaneous Detection and Classification of the Fusion MI & SSVEP Signals (Doctoral dissertation, Pukyong National University).

[113] Sibilano, E., Suglia, V., Brunetti, A., Buongiorno, D., Caporusso, N., Guger, C., & Bevilacqua, V. (2023). Brain–Computer Interfaces. In Psychophysiology Methods (pp. 203-240). New York, NY: Springer US.

[114] Alkhawaldeh, R. S., & Al-Dabet, S. (2023). Unified framework model for detecting and organizing medical cancerous images in IoMT systems. Multimedia Tools and Applications, 1-28.

[115] Guanopatin, A. V., & Ortiz, J. S. (2023, October). Meaningful Learning Processes of Service Robots Through Virtual Environments. In Proceedings of the Future Technologies Conference (pp. 59-73). Cham: Springer Nature Switzerland.

[116] Mohamed, S. M., & Rohaim, M. A. (2023). Multi-Class Intrusion Detection System using Deep Learning. Journal of Al-Azhar University Engineering Sector, 18(69), 869-883.

[117] Mahmoud, M. E., Abdullah, M., Ayad, M., & ElDeftar, M. (2023). Bone Marrow Mesenchymal Stem Cells-Loaded Chitosan/Bioglass Scaffold For Reconstruction Of Segmental Bone Defect. Al-Azhar Journal of Dental Science, 26(4), 493-501.

[118] Hassan, K., Madkour, M. A., & Nouh, S. A. (2023). A REVIEW OF SECURITY CHALLENGES AND SOLUTIONS IN WIRELESS SENSOR NETWORKS. Journal of Al-Azhar University Engineering Sector, 18(69), 914-938.

[119] Castagnola, E., Zheng, X. S., & Cui, X. T. (2023). Flexible and soft materials and devices for neural interface. In Handbook of Neuroengineering (pp. 79-139). Singapore: Springer Nature Singapore.

[120] Halawa, A. S., Gamalel-Din, S., & Nasr, A. A. (2023). Semantic Segmentation of Educational Videos for Micro Learning Objects in Adaptive E-Learning. Journal of Al-Azhar University Engineering Sector, 18(69), 900-913.