Integration of Brain-Computer Interface (BCI) and Artificial Intelligence (AI)

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***Abstract*—A brain-computer interface (BCI) allows for the bidirectional and real-time connection of actuators and living brains. There has been an AI revolution in the analysis and decoding of neural activities in the BCI ELD. That means, for around ten years BCI with AI support has been used for different purposes. This has led to many developments such as smart BCI that improved clinical results by improving PWD quality of life, increasing average people's athletic abilities, and enhancing neurophysiology endings besides accelerating colonization. Nevertheless, despite all these technological progressions, long training times, real-time feedback mechanisms, and monitoring BCI are today still major challenges being faced (Brunner et al., 2011). The authors of this article outline the current position of AI related to BCI technologies; they also highlight recent developments in BCI applications including their challenges. According to the results of the experiments, brain-computer interface (BCI) can assist impaired people in regaining their physical abilities, improving their quality of life. Its impact on several industries, including gaming and entertainment, automation and control systems, learning and education processes, brain-based marketing organizations and sectors, and ergonomic neuroscience, is illustrative. It is simply an interface between computers allowing communication even without anybody's movement. By connecting several house appliances with one switch only users can use this system. Part of a BCI is what is called EEG. This EEG sensor captures information on brain activity. The signal from the brain regarding any subject can be captured from this EEG sensor. This then becomes the command for operating home appliances like lights, fans, etc. Researchers have done studies showing that even paralyzed persons use homes can be automated using the Brain Computer Interface system. Paralysis is among the common disabilities. A good number of persons are paralyzed yet their brains are fully functioning. This way, therefore, they can rely on this BCI to control many of their home appliances and also have a very independent life. The new authors of this article are presenting several existing BCI systems as well as proposing another one for home care provision to disabled persons.**

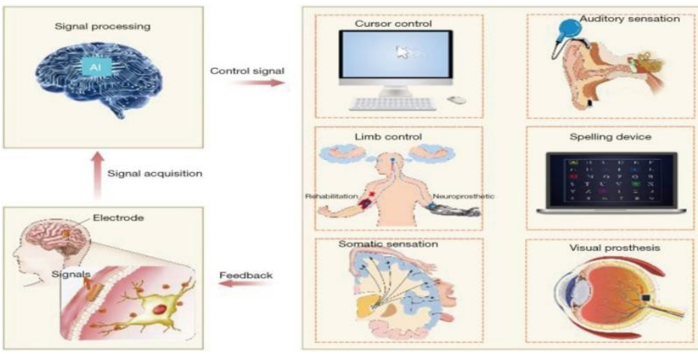
***Keywords*—BCI, EEG, P300, Home care, Home automation, Disable, DPE OLE BCI(Brain-Computer Interface), artificial intelligence (AI), prosthesis, encoding and decoding, computational neuroscience, machine learning, Artificial Intelligence Applications Challenges Technology Machine learning.**

I. Introduction

In normal life, humans use their peripheral nerves and muscles to act in ways that they want while dealing with the surrounding physical environments. For people with severe neurological disorders like ALS and brain stem stroke, this is quite expensive. Consequently; sometimes others have to help them because they cannot use external devices on their own which might be impossible[1,2]. This has led to the invention of BCI (Brain-Computer Interface) technology by scientists and researchers that relies on brain signals to do human activities without using the peripheral nerves or muscles as runners(3). Brain-computer interface (BCI) also known as Brain-Machine Interface (BMI), facilitates a direct interaction between the brain and external devices like computers or robot limbs[4,5]. It connects the electrical activity of brains with the world outside eliminating customary modes for different tasks like speech, vision, and movement to augment human capabilities of relating with the environment[7,8,9]. BCI make it possible to access neural coding required for controlling applied devices or any other forms of communicating systems, processing, analyzing, manipulating, or translating them without resorting to muscle-based channels of communication (10). The AI effect however refers to machines doing more than humans calling it AI (11). However, Teller's theorem reveals another important idea about artificial intelligence: "Artificial Intelligence is whatever hasn't been done yet."For instance, Optical Character Recognition technology, which was once novel, now falls under things that are not considered artificially intelligent. The technological boom has narrowed the gap between humans and machines. Machines have made possible what was once referred to as 'mind control' [12,13,14]. This is because of Brain-computer interfaces (BCI) and Artificial intelligence (AI) which are considered cutting-edge technologies in this area. BCI were developed and utilized independently of AI experimental paradigms until recently when scientists suggested that they should be combined with AI so that electric signals generated by the brain can be used more efficiently for controlling external devices[15,16,17,18]. The advancement of BCI may be one of the greatest technological breakthroughs for severely paralyzed individuals in years (19). BCI technology interacting with the central nervous system, and neural sensory organs can provide an alternative communication pathway for patients suffering neurodegenerative diseases such as motor neuron diseases or acquired brain injuries [20,21,22]. The history of BCI dates back to efforts aimed at developing new electrophysiologist methods capable of recording extracellular electrical activity initiated by a difference in electric potential carried by ions across neuronal membranes[23,24]. Different approaches to describing various techniques employed to follow different types of brain signals can be characterized: as invasive or non-invasive. Electroencephalography (EEG), and magnetoencephalography are also included in this section, fMRI and near-infrared spectroscopy are common examples of noninvasive systems that do not hurt tissue or take time to set up[25,26,27,28]. Electrophysiologist techniques make BCI feasible because they read out information about brain function, but also write it back through manipulation of activity in specie regions or whole-brain interactions aiming regionally-restricted modulation of global cognitive state. Though there are limitations regarding BCI development; still, little information has been effectively passed despite the extensive use of extracellular multiple electrodes. From background electrical activity recorded in the brain neuroscientists cannot sure out a person's intentions and then match them with robotic arm actions either. Hence, a pre-prosthetic signal processing helper could become an ideal specialty for AI[29,30,31,32,33].

II. Literature review

From the late 1990s to the 21st century, AI researchers began working on medical diagnosis, logistics, and data mining-related issues. By enhancing processing power, cooperating AIs, and creating economy models that use statistical modeling and mathematics to handle these issues, researchers have added to the relevance of AI in significant ends. Deep Blue, a computer program, defeated chess champion Garry Kasparov in 1997. We looked into BCI research trends based on data provided by Scopus. Scopus provided us with metadata that enabled us to study some patterns and trends of BCI research. The exponential growth of BCI literature is noticeable, with China publishing the highest number of papers starting in 2019, followed by the USA within these years. Nevertheless, this observation means that the significance of BCI may be greater for people, but at the same time, it raises crucial questions about possible BCI dangers. AI is an array of general approaches that allow computers to emulate intelligent behavior with minimal human intervention until their performance even matches or exceeds human potential in task-specie applications[36,37,38]. During BCI operation, AI algorithms continuously receive internal parameters such as pulse durations, amplitudes, stimulation frequencies, energy consumption, stimulation or recording densities, and electrical properties of neural tissues. These algorithms identify useful parts and logic in the data before producing desired functional outcomes. However, these studies remain largely under investigation without transitioning into clinical practice. We noticed a tendency in the early stage of the technology revolution to combine BCI with AI. In this paper, we discuss current applications reviewing BCI' status quo based on AI. Figure1



(Figure 1)[1]

BCI through which AI functions are illustrated schematically. BCI have opened vast new possibilities for use such as cursor control, auditory perception, limb control, spelling devices, somatic sensation, and visual prostheses. Brief, circuitry entails: one microelectrode receives signals from the human cerebral cortex that are then transmitted to the AI, where signal processing is done including feature extraction and classification; eventually the processed signals are output to perform above mentioned tasks. Finally, feedback is sent to adjust the function of the human cortex. BCI Brain-computer interfaces; AI Artificial intelligence. (41)

III. APPLICATIONS OF BCI

BCI technology allows paralyzed individuals to control mechanical devices with their minds. This Benet offers such people an insight into the real world where they can carry out different activities without relying on healthy individuals(42).

A. Thoughts Decoding

Our thoughts and the feelings they create, our awareness of touch, breath, hearing, movement and activity, hunger or thirst, when we are cold or sweat a lot and ND it difficult to sleep through the night.

B.Communication through telepathy

Combining BCI with CBI is purported to enable communication by thought alone, a phenomenon often referred to today as telepathic communication. Our thoughts and the feelings they create, our awareness of touch, breath, hearing, movement and activity, hunger or thirst, when we are cold or sweat a lot and ND it difficult to sleep through the night. BCI which is currently in its early development stages will be part of the BBB interface when fully integrated with CBI.

C. Automation and Control

These transformations may also impact the automation and control sector (Birnbaum et al., 2008). Currently, some home automation systems are built employing BCI technology. Thus, individuals with physical handicaps can mechanize household activities to become more autonomous in their lives. An increase in the number of BCI applications may lead to better outcomes for manufacturing processes later.

D. Energy Harvesting from Brains

The brain normally consumes about 20% of the total body's energy despite representing only 2% of our body mass as adults. This proportion is why it ranks as the third most energy-consuming organ after the heart and liver. Nonetheless, BCI techniques, among other advanced technologies, can make it possible to tap into this enormous power supply, thereby fueling low-energy external devices. How much cerebral electricity can a conventional BCI system harness? There is a need for further research on this subject. Intelligence Exchange: Can the human mind be reprogrammed using BCI together with CBI so that thinking becomes shared among people? Although scientists may consider it action, the basic principles of BCI imply that these brains are artificially programmed. Nevertheless, reaching this milestone would require a deep understanding of what our brains are like (Tucker & Johnson, 2011). We are still far from such a level today.

E. Affective Computing, Gaming, Robotics, and Other Miscellaneous Applications

To evolve computers into not just assisting but decision-making beings, they are believed to require emotional and perceptual capabilities (Picard, 2000). They should recognize underlying affective conditions based on physiological or behavioral measures. However, recent studies indicate that BCI could be useful in investigating affective states, hence relying on psychology (PICO and Ahmadi, 2018; Song et al., 2018; Huang et al., 2019). Huang et al. presented an EEG-based BCI designed to detect both positive and negative emotions evoked by video stimuli (Huang et al., 2019). [43,44,45,46]

IV. APPLICATIONS OF AI

A. AI in Astronomy

To solve universal problems, artificial intelligence can be used. Artificial intelligence tools and techniques can help us learn about the principles that govern the workings and origin of the universe.

AI for Healthcare: Over the years, healthcare industries have used AI-based systems and tools more frequently. This is going to make a big difference when it comes to delivering health services. The diagnostic service provided by AI algorithm-based systems is better than that offered by human beings: It helps doctors understand patients' cases that are critical enough to call for emergency medical attention.

B. AI for Finance

Better services may be delivered by financial institutions in collaboration with artificial intelligence while achieving their financial objectives. Algorithmic deployment of chatbots, trading, automation, machine learning, etc., are playing a vital role here.

C. AI for Data Security

It has become an important aspect of data security for businesses worldwide.The growing popularity among enterprise units for using AI algorithms in software for detecting bugs and recognizing cyberattacks signees this trend.

D. AI for Social Media

There are several user proles and products on various social platforms. However, these platforms pose difficulties for people as they try to cope with such large amounts of information. The latest market trends in data management are possible through AI technology.

E. AI for Travel & Transport

Popularity is increasing regarding the implementation of AI in the travel industry as well as the transportation industry since people have started realizing its significance there too. These systems suggest hotels or rights and manage orders using AI technologies. Business units deploy chatbots based on AI technology to efficiently interact with customers.

F. AI for the Automotive Industry

Some major industries employ virtual assistant bots to help their customers. Designed by Tesla company, real-time assistance service via Tesla Bot is available now. As we speak several organizations are working towards the development of self-driven cars which offer safer journeys as compared to traditional driving.

G. AI for Robotics

With the aid of artificial intelligence, some tasks can be executed by robots using their previous experience. However, traditional non-specialized robots execute repetitive actions. However, AI integration can improve the thinking capabilities of such robots. Another example of this is humanoid AI where an AI algorithm is used to control a robot designed in human form. Robots like Sophia and Erica can act and talk like human beings.

H. AI for Gaming

AI system based on Deep Blue can play games as well. If we consider a chess game with its powerful AI. It creates algorithms that seek several possible moves from the opposing side concerning each step in one's move.

I. *Artificial Intelligence in E-commerce*

AI tools in the ecommerce departments of industries can generate better product mixes that give a combination of size, color, and brand attributes. The comments and analysis from reviewers also help to determine if a product would be suitable for that user using the internet.[47,48,49,50]

V. APPLICATIONS OF AI-BASED BCI

A. An application for cursor movement control

Initially, the rst tests involved quadriplegic people using brain-computer interfaces to control their PC mouse pointers, which was a very possible way through. These are generally composed of neural recording sensors, movement intention decoders, and an external interface that interacts with the computer cursor. For example, the P300 matrix speller and rapid serial visual presentation (RSVP) based on scalp EEG, and synchronous evoked potentials are BCI systems developed for controlling cursors. The Brain Gate consortium commenced the RST clinical trial in humans using motor BCI by recording signals from BlackRock 96-channel MEA implanted at the M1 arm area in a tetraplegia patient due to cervical spinal cord injury. They achieved the two-dimensional movement of a cursor on a screen and subsequently used this "neural cursor" to direct the movement of a robotic limb.

B. Application of neuroprosthetics and limb rehabilitation

In the beginning, these experiments were based on moving cursors on a computer screen in two or three dimensions, which later developed into more natural movements like reaching to grab objects with hands rather than through BCI-bi manual arm movements, etc. The best part is watching a quadriplegic person holding a cup of coffee using an artificial arm that is connected to his/her brain using an interface. This approach involves placing different types of electrodes either on or inside his/her motor cortex which is responsible for planning and performing actions. Therefore, when he/she thinks about moving their hand, for example, it is possible to record the individual's brain waves and use them as commands for guiding an artificial limb.

C. *Application in somatosensation*

Somatosensory feedback from senses that function through the movement of our body parts is an essential tool for paralysis patients. There are various types of somatosensory feedback employed in motion control such as mechanoreceptive afferent signals and proprioceptive information. This way, we can know where our skin comes into contact with objects and also get to know how hard it is to grasp it. The lack of limb motion dynamics planning is due to loss of proprioception. That's why somatosensation matters and it is crucial to develop bidirectional BCI. For example, by stimulating sensors on the prosthesis one may activate neurons with receptive ends appropriate for touch. It states brief that this AI shows how prosthesis-induced pressures exerted on objects relate to ICS pulse magnitudes more effectively than ever before. Random forests constitute practical and convenient non-linear classier in non-invasive sensorimotor rhythm BCI whereas FukuyamaKoontz transform-based feature extraction has been widely used for somatosensory evoked potential-based BCI to improve performance from 70% -75%.

D. *Application in auditory perception*

The cochlear implant is the most frequently used and oldest type of BCI(55). On the other hand, according to the FDA, This functions as a good example of a successful efferent interface that will slow down hearing loss for about 200,000 people worldwide by December 2010. It goes around damaged ear parts, turning sound waves into electric currents and sending them directly to the sensory epithelium of the basilar membrane to simulate hearing. The implants can be put in between the cochlear nerve and the pons after auditory nerves are destroyed; or in the lateral foramen of Lusaka, which belongs to such a structure as the cochlear nucleus. However, if it is given to the cortex rather than the auditory nerve, sensory input has improved resolution[51,52,53,54,55].

VI. DISCUSSION

The review that follows considers current studies on BCI within the AI ELD, which have grown at a fast pace during the last teen years. A combination of BCI and AI may be an extraordinary way to study the brain this will give direct access and control over the neurons that control behavior leading to a better understanding of the human brain and advancements in rehabilitation medicine. One of the tenets machine learning offers BCI is its possibility to do real-time or near modulations of training parameters, so that any changes done are a result of active feedback in real-time. Also, algorithms generate decisions predicated on past data learned from and act as signposts for users meaning they don't have to spend much time rewinding what worked or did not work for them in previous trials. Frequently patients as well as healthy subjects exhibit great variability or even an inability to self-regulate their brains since it is difficult to use BCI devices [56,57,58]. The entire driving principle behind AI is based on an algorithm that most people are not aware of. The involvement of AI-based algorithms and application development is limited to a few researchers or manpower only. This is due to the need to include new technological metrics when making AI-based systems. Improved skills in data science and analytics among researchers will result in better utilization within the AI domain. Various ethical issues and social problems should be examined and talked about in the future days when brain-computer incorporation technologies are becoming more complex than ever before. For instance, there might be certain types of BCI that can be very expensive thereby raising questions about affordability and practicality, especially for those with severe disabilities who require such devices as assistive technology. Besides, BCI having AI software integrated into decision-making devices implanted into the human brain raises concerns about human autonomy. Additionally, others can exploit brain data as digitalized neural information that is stored on computers to ND out what we remember, our intentions, our conscious and unconscious interests, or the way we react emotionally. Finally, it has also been noted that some people with Parkinson's disease who go through deep-brain stimulation become hypersexual or develop other impulse-control disorders[59,60,61].

VII. CONCLUSION

On the other hand, AI may represent a branch of knowledge that mainly focuses on creating and employing smart machines; it is an expanding area that embraces medicine and neuroscience. Nevertheless, most previous research aimed at evaluating AI-based BCBS has not been thoroughly formed for reproducibility or generalization even though these devices are meant to improve functionality as well as quality of life among patients with paralysis, spinal cord injury (SCI), amputation, blindness due to head injury or other causes acquired post-birth, deafness from environmental noise or hearing loss due to aging or disease, memory dysfunction after stroke and epilepsy. It has also been reported that normal motor/sensory/cognitive function could be enhanced by carefully manipulating them. Therefore, prior technical advancement of BCI's widespread use in clinical practice requires clinical trials to be approved appropriately by competent authorities.

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