Decoding Neural Signals with Computational Models: A Systematic Review of Invasive BMI

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There are significant milestones in modern human’s civilization in which mankind stepped into a different level of life with a new spectrum of possibilities and comfort. From fire-lighting technology and wheeled wagons to writing, electricity and the Internet, each one changed our lives dramatically. In this paper, we take a deep look into the invasive Brain Machine Interface (BMI), an ambitious and cutting-edge technology which has the potential to be another important milestone in human civilization. Not only beneficial for patients with severe medical conditions, the invasive BMI technology can significantly impact different technologies and almost every aspects of human's life. We review the biological and engineering concepts that underpin the implementation of BMI applications. There are various essential techniques that are necessary for making invasive BMI applications a reality. We review these through providing an analysis of (i) possible applications of invasive BMI technology, (ii) the methods and devices for detecting and decoding brain signals, as well as (iii) possible options for stimulating signals into human's brain. Finally, we discuss the challenges and opportunities of invasive BMI for further development in the area.
INTRODUCTION

Over the centuries, our understanding of human brain has increased significantly. Psychology and cognitive science are relatively new fields that have become involved in some of the most competitive research areas in contemporary times. Scientific approaches for treating, manipulating, and simulating human behavior have advanced by leaps and bounds in recent years. The brain's complex and multiple functions such as perceptual interpretation, organs' functions regulation, and information processing capabilities, have long been acknowledged by academia. Recent progresses, especially in computer science and electrical engineering, allow the behavior of neurons to be easily captured, analyzed and decoded. Such information can be used for creating real world applications that can take our lives into a much higher level of comfort. From creating intelligent robot assistants for people with disabilities, to efficiently curing brain damages or psychological disorders, the invasive Brain Machine Interface (BMI) technology will definitely play a vital role in human's lives in the near future.

Since the introduction of electronic computers, the human brain has been increasingly seen as an organic carbon-based computer, rather than today's silicon-based electronic systems. This analogy has sparked a significant amount of study to create an analog computer of human consciousness [1]. Even the most elementary behavioral reactions are produced by the integrative activity of large networks in cortical and sub-cortical brain systems [2]. The central nervous system (CNS) has developed to provide efficient hormonal and muscle outputs, and to keep pace in behaviour adjustments continuously throughout life. BMIs provide the CNS with extra synthetic outputs generated from brain impulses [3].

Despite being decades away from developing true artificial intelligence (AI) or possibly uploading the contents of a human brain to an electronic equivalent, a new stage of human evolution known as “AI Symbiosis” has been reached, indicating the development of mutually beneficial relationships between humans and AI. Identifying the way electronic activities take place within the brain cells enables us to understand biological intelligence in humans. This has enabled us to design BMI, an engineered system that can potentially replicate most of capabilities of a human's brain. To understand the need of BMIs in research and development, we provide a brief review of their relatively young history and initial development.

Recent developments in machine learning make it possible to interpret neuron signals and perform a wide variety of tasks such as speech synthesis [4], motor imagery [5], emotion recognition [6], etc. Not only beneficial for patients with severe medical conditions, this technology can significantly impact different technologies and almost every aspects of human's life. Such a deep understanding of neuron communications and human's mind can lead to a societal evolution and potentially initiate another civilization milestone. Despite it's significant advantages, similar to all other emerging technologies, BMI comes with numerous challenges. The viability and reliability of this technology are highly dependant on the accuracy of collected brain signals. However, the sensitivity of brain's neural network in one hand, and limitations on BMI devices on the other hand, make data collection from neuron signals a challenging task for scientists. In addition to health related risk factors, privacy concerns, and the accuracy of different decoding methods, the brain signals are also other barriers that slow down the progress in this domain. In fact, these are the key issues that are emerging or are becoming hot research topics in this area.

Although the study of brain signals started in 1804, understanding and decoding its signals using BMI technol-
| Ref. | Survey title                                                                 | Year  | Highlight                                                                 | A                      | B                      | C                      | D                      |
|------|------------------------------------------------------------------------------|-------|---------------------------------------------------------------------------|------------------------|------------------------|------------------------|------------------------|
| [7]  | Recent Advances in Electrical Neural Interface Engineering: Minimal Invasiveness, Longevity, and Scalability | 2020  | • large-scale, long-lasting neural recording                               | ✓                      | ×                      | ×                      | ✓                      |
| [8]  | Neural implants: A review of current trends and future perspectives          | 2022  | • neural prosthetics and their applications in treating neurological disorders their different types of BCI | ✓                      | ✓                      | ✓                      | ×                      |
| [9]  | Signal Generation, Acquisition, and Processing in Brain Machine Interfaces: A Unified Review | 2021  | • signal generation within the cortex, signal acquisition                 | ✓                      | ✓                      | ×                      | ✓                      |
| [10] | Recent Approaches on Classification and Feature Extraction of EEG Signal: A Review | 2021  | • using invasive, non-invasive, or hybrid techniques, and the signal processing domain challenges and possible solutions | ✓                      | ×                      | ✓                      | ✓                      |
| [11] | Signal Generation, Acquisition, and Processing in Brain Machine Interfaces: A Unified Review | 2022  | • using invasive, non-invasive, or hybrid techniques, and the signal processing domain challenges and possible solutions | ✓                      | ✓                      | ✓                      | ×                      |
| [12] | Implantable brain-machine interfaces: first-in-human studies, technology challenges and trends | 2020  | • advances in BCI applications, their challenges and future               | ×                      | ✓                      | ✓                      | ✓                      |
| [13] | Review of machine learning techniques for EEG based brain computer interface | 2022  | • Machine learning techniques applied in the brain computer interface     | ✓                      | ×                      | ✓                      | ✓                      |
| Our paper | Artificial Decoding Neural Signals with Computational Models: A Systematic Review of Invasive BMI | 2022  | • Anatomy and physiology of the brain                                    | ✓                      | ✓                      | ✓                      | ✓                      |

...technology can open many opportunities for developing novel technologies in different domains. Decoding brain signals can be done via learning and classification methods. We dived into the cutting-edge machine learning models that are applied to different invasive and non-invasive neural signal interpretations. We studied supervised, unsupervised, semi-supervised, and other Reinforcement Learning methods as well as Federated Learning, to investigate opportunities in these areas that are not covered in other surveys. We have also dug the literature to review all existing works that covered classification models. The main contributions of this paper include:

- a comprehensive coverage of background knowledge, enabling technologies, and state-of-the-art scientific development on the applications of invasive BMI,
- analyzing the brain structure and its signals from biological and engineering perspectives,
- a comprehensive review and analysis of possible applications of invasive BMI technology,
- an overview of different methods, including machine learning based methods, and devices for detecting and decoding brain signals, and possible options for stimulating signals into human’s brain,
- a discussion of challenges and opportunities of invasive BMI.

To have a clear understanding of the topics, we first discussed the brain structure and its signals from biological and engineering perspectives. Two major nervous systems, i.e. the central nervous system and peripheral nervous systems, have been reviewed both functionally and anatomically, as well as action potentials in synapse formation. For the neural signal detection, we focused on invasive methods due to the advancements in neurosurgery and minimized side effects of required operations. The related sections cover different aspects of brain signal processing, including signal generation, detection, acquisition, noise filtering, signal enrichment, feature extraction, decoding, encoding, and stimulation.

Signal decoding models can be divided into two main categories: learning and classification. We systematically reviewed these models from invasive and non-invasive signal decoding perspectives. In the learning methods, we...
delved into some cutting-edge algorithms that are applied to different tasks and resulted in the state of the arts accuracy. To the best of our knowledge, such methods are not fully covered in the existing surveys.

Different BMI applications might require different signal detecting, decoding, or stimulating mechanisms. Therefore, we provide an overview and prediction of possible BMI applications in future, most importantly in the field of medicine. As an example, we will look into the possibilities that BMI can offer to patients with spinal cord injuries and other nervous system related disabilities. We also discuss opportunities and threats of utilizing AI in areas such as learning, memory access, communications, virtualization, etc.

Table 1 highlights the main contributions of this survey and compares them with seven other surveys in this domain. We considered (A) noise filtering, (B) Invasive and non-invasive models, (C) Machine Learning, (D) Applications and challenges in our comparison. As it is illustrated in the Table, none of the existing survey papers provided such comprehensive review of related concepts in BMI technology. In the noise filtering and signal enrichment parts, we discussed some methods, ranging from classical to deep learning-based models. It should be noted that due to the lack of significant works on invasive signals, we studied noise filtering models in non-invasive BMI. Also, in the security and challenges section, adversarial attacks are primarily studied on non-invasive signals, whereas they are not studied very well on invasive signals. A list of abbreviated terms and their definitions are provided in Table 3. The rest of the paper is organized as follows. The human’s brain structure is discussed in Section 2. A brief overview of artificial synapse technology is provided in Section 3. Section 4 discusses invasive and non-invasive methods. Reviewing and analyzing possible applications of invasive BMI are provided in Section 5. Conducted techniques in generation, detection, and acquisition of brain signals are discussed in section 6. In Section 9, we discuss and compare various methods and devices for brain signal encoding, followed by ethical and implementation related challenges of invasive BMI in Section 10. We finally conclude the paper in Section 11.

## 2 | HUMAN NERVOUS SYSTEM

The human nervous system consists of two main systems: 1- central nervous system (CNS), and 2- peripheral nervous system (PNS). Both systems synchronously work together, for example, the PNS receives surrounding stimulation via many different types of sensors and transmits the sensation to the CNS. The CNS store and interpret sensation stimulation. As well as sending interpretation messages, it transmits CNS messages to the target regions throughout the body by motor neurons. The anatomy of the CNS consists of the brain and, spinal cord. The brain is divided into three main regions: the forebrain, the brainstem, and the cerebellum. The forebrain is the largest part of the brain that includes the cerebrum and diencephalon. The diencephalon is composed of the thalamus and hypothalamus. Moreover, the large left and right cerebral hemispheres have formed by the cerebrum which includes the cerebral hemisphere, and constitute 4 main lobes: the frontal, temporal, parietal, and occipital lobes [14] which is shown in Figure 1.

### 2.1 | The Brain Neural Network

Neurons and glial cells, also known as supporting cells, are the two main biological components of the nervous system. The building block of the functionally human neuron system is a neuron which is an electrical and chemical signaling cell. A neuron has specialized membrane extensions called axons, dendrites, and tiny protrusions known as dendritic spines. Axons convey information, while dendrites and tiny protrusions receive information. Between neurons, for example, axon to axon, axon to dendrites, and dendrites to dendrites, is a cleft known as neuron synapses, which plays
an important role during neural electrical activity. Several ion channels are involved in this process [14]. Ion transport across neuronal surface membranes is essential for neuronal signaling and computation. The multiple input stimulation is received by each neuron via activating and inhibiting ion transports. The multiple simulations are combined to decide whether the neuron will fire an action potential, which sends the neuron message output to its target neurons. Thus, extracellular currents and voltage gradients are produced by all of these membrane currents and all neural electrical activity called action potential. In the production of action potentials, the Na⁺/K⁺ channels are crucial. The Na⁺ channel undergoes a conformational shift followed by a dramatic increase in Na⁺ permeability after a local depolarization of the membrane of approximately –20 mV to a threshold value of –70 mV. As a result, the membrane potential approaches the Na⁺ resting-state potential (approximately +40 mV). Within 1 millisecond of the preceding events, the Na⁺ channels are deactivated. Meanwhile, the K⁺ channels begin to open and efflux K⁺ from neurons as a result of resting membrane potential. The membrane is entirely refractory to a fresh depolarization during the interval of inactivation of the Na⁺ channels (absolute refractory phase) and afterward somewhat refractory. After a membrane potential overshoots (hyperpolarization), the original equilibrium resurfaces (Figure 2). Finally, firing one neuron interacts with several neighboring neurons chemically and electrically [16]. Chemical and electrical synaptic transmission are the two main processes by which neurons interact.

2.1.1 | Chemical Connection

Chemical synapses are the most common type of synapses in the adult human nervous system. Chemical synapses are differentiated by the existence of a synaptic cleft, presynaptic vesicles near active zones, which serve as sites of neurotransmitter (NT) release, and postsynaptic membrane specializations. Extracellular matrix proteins are found in the cleft of many chemical synapses, and transmembrane proteins produced by the presynaptic neuron can bind to partner on the postsynaptic cell across the synapse. The presynaptic electrical signal is turned into a chemical signal mainly NT, that binds to postsynaptic receptors and causes a response in the postsynaptic cell, which is typically an electrical signal, in chemical synapses (Figure 3). Because there are multiple metabolic stages involved, synaptic transmission at chemical synapses is slower than electrical signals with a range from 0.5 to 3.0 milliseconds. However, having biochemical stages has the advantage of making chemical synapses more flexible. The reaction can
be amplified, the electrical response’s sign can be reversed, second messengers can be involved, and the response can be short-term or long-term. At chemical synapses, two forms of transmission can happen: Fast/direct synaptic transmission, and Slow/indirect transmission. Fast/direct synaptic transmission is caused by NT binding to ionotropic receptors, which causes fast changes in the postsynaptic membrane potential. Slow/indirect transmission (also known as neuromodulation) occurs when NT binds to metabotropic receptors, causing G proteins and second messengers to be activated, which can modify ion channels and/or cause long-term changes in excitability, metabolism, and gene expression. Because neurons contain both metabotropic and ionotropic receptors for NT, several NTs participate in both modes of transmission, whereas other NTs solely work through metabotropic receptors [14].

FIGURE 2  Permeability of potassium and sodium ions during an action potential[17]

FIGURE 3  Structure of Neuron and Synapse[18]
2.1.2 | Electrical Connection

Electrical synapses are the simplest and quickest synaptic transmission type. Electrical synapses have been discovered in the retina, hypothalamus, and hippocampus and are thought to synchronize groups of neurons. The synaptic cleft in an electrical synapse has one or more domains where the postsynaptic and presynaptic plasma membranes are near enough to produce a gap junction (-3-4 nm). Gap junctions, which include gap junction channels, link many different types of cells in the body. A transmembrane protein complex called connexon in the presynaptic membrane links to a connexon in the postsynaptic membrane to produce the gap junction channel that joins the cytoplasm of the two neurons in electrical synapses. Current (ions) and second messengers can pass from the presynaptic to the postsynaptic neuron through these connexon channels. Because tiny ions diffuse quickly, the delay between presynaptic and postsynaptic reactions is only 0.1 millisecond. Electrical synaptic transmission has restrictions, despite being exceedingly fast. Because there is no conversion or gain, the postsynaptic reaction is always less than, and has the same sign as, the presynaptic response [14].

3 | ARTIFICIAL SYNAPSE TECHNOLOGY

The term “memristor” or “memory resistance” refers to an artificial synapse unit that was first described in 1808 by Sir H. Davy and in 1960 by B. Following that, León Chua explored a new element of two-terminal circuits with a link between the electrical charge and the magnetic flux after a series of technical experiments. Modern memristors can mimic the synaptic mechanism and be tailored to the technical needs of neuromorphic computing systems. Nowadays some company started investigating on development of an experimental neurochips like Neuralink based on the features of current memristors that can interpret brain activity via functional measurements of millions of neurons and their synapsis, allowing communication with the outside world. The technology is capable of translating nervous system activity into real-world interaction, such as providing a sense of touch or proprioception to modify the movement of a human prosthetic limb [19].

4 | IMPLANTATION OF THE DEVICES

Today, research and applications of the brain-computer interface and the brain-machine interface are one of the most exciting interdisciplinary fields in science and technology. BMIs are divided into two categories: invasive and non-invasive. There are several types of invasive, non-invasive and recording-stimulus technologies. Non-invasive methods do not require opening the skull of the implantation receiver. They act on the surface of the skin and can record an average of millions of neurons. However, non-invasive techniques are not able to detect the distinctive features of neurophysiological diseases in real time, therefore, one has to insert electrodes in certain areas of the brain to detect such features. In invasive procedures, the electrodes are placed directly on the surface of the cortex. Useful signals can be recorded, which are the average activity of thousands of neurons. Authors in [20] discussed further information on all types of BMI.

The aggressive technologies are extremely interesting. Before we move on, let’s discuss the neural network. The neural network (a phrase coined by novelist Ian M. Banks in 2000) is made up of arrays of microscopic electrodes that are attached to polymer wires or threads and injected into the brain. Neuralink has produced arrays of these strands, each of which is claimed to be considerably thinner than a hair and has 3072 electrodes dispersed among 96 strands. It has also built a neurosurgery robot that can connect six strands together, injecting 192 electrodes into the brain each
minute while also preventing blood vessels from bleeding (this has yet to be tested on humans) [20].

5 | APPLICATIONS

Nowadays, the BMI technology is mostly used in different medicine areas to monitor the neural communications. The majority of BMI advancements are done through academic research and are not yet available to the general public. In this section, we discuss applications of BMI in different areas which are expected to be among the most advanced technologies of the 21st century.

5.1 | Medical

Currently, the BMI devices are widely used to monitor the brain signals, and among them, the non-invasive ones are more common than the implanted type due to their simplicity and easier installation procedure. However, this technology is not yet a first choice of practitioners to treat patients with related medical conditions due to its numerous limitations [20]. In this section we discuss a few examples to show how BMI technology can make a revolution by boosting the human’s health up to a much higher level.

5.1.1 | Disease Prediction

It is possible to imagine a world without the majority of current diseases, if they can be predicted by BMI devices and prevented from occurring or effecting human’s body. Brain signals that are produced via chemical and electrical communication of neurons, can be recorded, decoded and learned to prevent diseases prematurely.

5.1.2 | Pain Elimination

Perhaps, the pain phenomena that is caused by injuries, burns or illness, is one of the most important reasons for human’s survival. Although it’s existence is highly crucial for our health, it can be minimised or completely eliminated during the treatment process as the cause of pain is already known. However, almost all of pain killer medicines come with different side effects [21]. BMI technology makes it possible to communicate with brain and send signals to eliminate the pain.

5.1.3 | Therapeutic

There is a wide range of medical conditions that can be treated using neural interfaces, also known as ‘Electroceuticals’. This is a new category of therapeutic agents which target the neural circuits of organs. Such therapies involve mapping the neural circuitry and transmitting neural impulses to these specific organs [22]. Some remedies have been provided for many years in medical practice such as implanting cochlear which many people with hearing impairment have benefitted from, Stimulants to help with stroke recovery, and deep brain stimulation (DBS) to improve crucial tremors in Parkinson’s disease and dystonia [23]. Other remedies such as transcranial direct current stimulation (tDCS) for depression are still under investigation in the laboratory. Others are in the trial or initial phases of medical application. For instance, DBS for epilepsy or the Mollii Suit is a body cloth that provides electrical stimulation to people who have muscle spasticity as a result of stroke or cerebral palsy [24].
In general, when conditions are resistant to drugs, interface treatments are frequently followed. For example, it is estimated that 20–30% of epilepsy patients are drug-resistant. These electroceuticals can be more efficient than drugs because they exactly target a specific part of the brain or body and also they don’t have undesirable effects which are caused by ingesting chemical drugs [20]. Below, we discuss several practical examples.

- **Spinal cord injury (SCI):** is a destructive occurrence, with symptoms ranging from loss of motor and sensory function to shortened life expectancy, with SCI survivors typically reliant on medical resources and social assistance [25]. The goal of many brain-computer (neural bypass) interfaces is to transform cerebral signals into peripheral motor responses, effectively bypassing spinal cord injuries. Transcutaneous spinal cord stimulation is being investigated as a less invasive approach for activating local spinal circuitry. For neuromodulation, electrodes are inserted on the skin and direct current stimulation is employed. As a result of this finding, researchers have worked to build algorithms that depend on non-invasive scalp electroencephalography (EEG) inputs [26]. However, due to the poor signal-to-noise ratio (SNR) of these signals, they are susceptible to artefact contamination. Electro-corticography (ECoG) signals obtained from the brain surface have been used in subsequent research. Because of the clinical justifications for ECoG (eg, seizure mapping), these more recent attempts have been confined to brief implantation. Generally, research on the properties of brain signals (invasive and non-invasive) such as ERDs (event-related desynchronizations) and other frequency features is at the forefront of current efforts for various end-organ applications, including the manipulation of a computer cursor and the movement of paralyzed muscles [26].

- **Parkinson's disease (PD):** is characterized by a gradual impairment of voluntary motor control caused by the buildup of α-synuclein-containing Lewy bodies in the brain's substantia nigra pars compacta and the death of dopaminergic neurons, resulting in a decrease in dopamine levels. [27, 28]. Deep brain stimulation (DBS) can be used to treat it. A tiny electrode wire must be implanted in the area of the brain that causes aberrant movement via surgery. An Implantable Pulse Generator (IPG) battery can be implanted in the belly or under the collarbone, requiring a second surgical surgery. The IPG sends electrical impulses to the brain, which can aid in the control of various motor symptoms [29].

- **Autism:** is a neurodevelopmental disease that has a significant impact on verbal and nonverbal communication, as well as social interaction [30]. TMS has also shown promise in aiding autistic people in improving their social skills [20]. Transcranial direct current stimulation (tDCS) has been presented as a novel ASD therapeutic approach with the potential to improve cognitive, motor, and social communication abilities by addressing particular underlying neural abnormalities [31].

- **Body parts replacements:** After losing a limb, a person's life can be transformed by bionic limbs. These devices communicate directly with the remaining neurological or neuromuscular system. There has been a long history of making bionic limbs for disabled people due to the need to improve their lives [32]. When the user flexes, a bionic limb, such as an arm, recognizes minuscule impulses generated by the body. Recently, the Neuralink company showed how their app converts residual limb muscles into movements using the bionic limb. On the other hand, advanced BMIs can use this technique a step further by allowing us to use “the brain to transmit our intentions, without having to go through an extra, physical step of converting those intentions into text, speech, or gestures”. It is possible to make interactions easier, faster, and more natural [29].

- **Epilepsy:** In 2005, the International League Against Epilepsy (ILAE) suggested a conceptual definition of epilepsy as a brain illness marked by an enduring susceptibility to create epileptic seizures and its psychosocial repercussions [33]. Brain-machine interfaces (BMIs) can be used to diagnose and cure neurological problems as well as expose brain functioning. Karageorgos et al [34] have presented HALO (Hardware Architecture for LOW-power
BCIs), an architecture for implanted BCIs that can be used to treat illnesses like epilepsy. HALO also collects and analyses the information that can be utilized to better understand the brain. Epilepsy is characterized by uncontrolled and excessive electrical activity in neurons, which results in epileptic seizures. Seizures are predicted by analyzing neuronal signals [35]. The brain requires inhibitory synapses to tone down and regulate the activity of other cells when brain stimulation increases. BMIs then use electrical stimulation to reduce the intensity of seizures. The period between seizure initiation and stimulation, on the other hand, must be very short, in the tens of milliseconds range. Low-power hardware is also required for long-term implantation. The Neuralink BMI chip is based on prior methods, however, it provides better bandwidth brain connection in real-time while using less power [29].

- **Depression:** is one of the most common mental health conditions and almost one-third of depression cases are treatment resistant. Due to their severe side effects such as weight gain and decreased libido, mental health medications are not the best option. While BMIs also come with challenges, they are much safer than drugs [29]. High frequency repetitive transcranial magnetic stimulation (rTMS) to the left dorsolateral prefrontal cortex (DLPFC) is an authorized therapy for depression based on its safety and effectiveness factors [36]. On the other hand, it has side effects, such as discomfort at the head site, magnet effects on the muscles, etc. Advanced BMI technologies can stimulate neurons of the frontal cortex to release dopamine hormones which can directly target neurons related to depression with fewer side effects rather than rTMS.

### 5.2 Hybrid Human

With the advancements of Machine Learning and Artificial Intelligence (AI), robotics moved to a much higher level in the last few decades. In 1997 Gary Kasparov the world Chess champion was defeated by an IBM supercomputer in a highly publicized match. Since then, we have witnessed how fast robots replaced humans in different sectors. They become faster and more intelligent while getting cheaper year by year, as their CPU power gets doubled every two years based on Moore’s law. Although such advanced computers make our lives much easier, they can become threats. The well-known theoretical physicist, Stephen Hawking warned once about the rise of AI that if we are not careful they can be the worst thing that’s ever happened to us. There is no doubt that robots are much faster and more intelligent than humans today. With the current exponential development pace, theoretically they can reach a point where they won’t need our programs and will be able to reproduce themselves.

In any competitions against them, the relatively super slow humans will be defeated readily. In many ways, AI could outperform and replace us, but there is no possible global governance model for the shift from Artificial Narrow Intelligence (ANI) to Artificial General Intelligence (AGI). If they do not establish the first situation correctly, an Artificial Super Intelligence (ASI) might come out of AGI and our future may be endangered. So as an alarm we have to investigate an international rules for transitions [37]. This also urges the need for a more advanced BMI that enables humans using machines to empower their decision making system, and paying more attention to establish a consensus internationally about shifting [38].

Not only in theory, combined biological brain and AI systems are already developed and passed their initial trials. Neuralink’s BMI chip for example, can connect our brain to a synthetic neocortex, so we can be merged with an AI based machine. Such models may result in the birth of hybrid species. Transhumanists anticipate that new technologies will improve the human condition by providing them more intellectual ability and longer life, endless memory, and faster communication. Mankind may evolve into post-human, and the human era may come to an end by 2045 [38].
5.3 | Virtualization

Researchers believe that the investment and speed of development in the gaming world enable these technologies to thrive with benefits for a variety of applications among people with severe disabilities. Invincibility on the next generation, such as the decline of social skills and drowning in online and cyberspace, is advancing very fast. In the past few years, we have witnessed great advancements in the context of entertainment. From Virtual Reality (VR) and Augmented Reality (AR) to 3D holography, each have taken this experience one step beyond. Playing a video game with virtual/augmented reality or holding a conference with a holographic projection of remote people has been a thrilling experience. As another example, we have experienced looking into our desired house to buy or going on a virtual tour of Louvre museum with VR.

However, the sky is the limit for our future possibilities. In the near future there will be no need for above technologies because advanced BMI technologies such as Link (i.e, the Neuralink chip) promises a different experience, a whole new experience to be specific.

Consider there are cloud-based games designed specifically for Link. In this case just a 5G or fiber internet connection would be enough for players around the world to not only play together, but also share their feelings, emotions, intentions and decisions. Additionally, we will be able to have the exact five senses of sight, smell, hearing, taste and touch in the context of a virtual tour of for example a zoo, museum or even the International Space Station (ISS). just having someone in charge of doing our desired actions would be enough as it seems. Apparently we are much closer than expected to experience everything we have seen in Sci-Fi movies.

5.4 | Communications

Advanced BMIs such as Link allow communicating with a messenger app without typing or even touching a button. This possibility is already available for disabled people to help them communicate easily. While typing is not straightforward for them, they can think about the message they are about to send, and their Link system will handle the rest in milliseconds. They could even be enabled to be active on social media platforms, web surfing, and email responding. This capability becomes even more interesting when we understand that the high rate of data transfer can accelerate their routine jobs dramatically.

This amazing possibility can even encourage us to think about developing custom-designed apps only for the human brain. Instead of making use of a messenger app control feature of Link, we can develop special apps only for this goal. Consider there are many cloud-based servers hosting these apps around the world, and humans can connect to them in order to connect to a mesh of millions or billions of Links. In this case, we will be enabled not only to face a whole new social life, but we can share what we see, feel or experience with our peers simultaneously.

5.5 | Advanced Education

BMIs can provide opportunities to improve the entire brain's functionality. Our memories and decision making abilities could be enhanced significantly when our brain is empowered by AI. This will enable us accessing different memory layers and solving much more complex problems in a very short time. Information could be encoded into neuron signals and uploaded to our brain and become our new memories. We could easily upload new skills to brain, similar to the Neo Matrix movie, instead of practicing hard for a long time. Students can benefit from neural interfaces in order to achieve educational goals by learning better and focusing more. All our knowledge which in fact is memorized information could be safely encoded to digital signals and stored on digital devices or uploaded to the cloud safely.
Education sector will be one of those areas that benefits the most from advanced BMI as it enables us to transfer not only data and information to our brains, but experience, knowledge and wisdom as well. Consider a very special situation, when several air-craft pilots are needed and due to the time and geography constraints summoning registered pilots is not an option. Theoretically, it is viable to train pilots using advanced BMIs in a very short period of time as all necessary tools for knowledge transmission to brain are available. However there is always a downside for every innovation. While currently it requires years of hardworking, patience and persistence to learn a particular skill, any changes in this traditional learning process can change the definition of morality and social values. We will discuss such challenges with more details in Section 10.

5.6 | Civilization Shift

The extraction of information and knowledge associated with the help of artificial intelligence is often biased. Technology influences individual decision-making, and this will have implications for the future of community democracy. We must be able to use technology to democratize processes through the digital platforms that build communities. The ability of machines and artificial intelligence to solve problems quickly is one of their greatest advantages, which has already surpassed human capabilities. It is predicted that humans and super-intelligent creatures will live together in the future [39]. The relationship between humans and robots can be balanced by a cyber minister, and the future society may consist of a combination of human-machine systems, a community of forces brought together by the machine-human environment [38]. However, human civilization has evolved gradually over thousands of years and such changes will cause a huge impact on many components of our civilization including our cultures, languages, and the entire industry.

6 | SIGNALS AND DEVICES

The five BMI steps—signal collection and processing, feature extraction, data categorization, and control interfaces—are covered in this section (Figure 4 shows an observation of these steps). We also cover the methods for generating, detecting, and acquiring signals, as well as their underlying concepts. Additionally, it explores the comparison of spatial and temporal resolution for BMI methods, both invasive and non-invasive. Figure 6 shows an overview of these methods.

6.1 | Signal Generation

Electrical signaling is a cardinal feature of the nervous system and endows it with the capability of quickly reacting to changes in the environment. Although synaptic communication between nerve cells is perceived to be mainly chemically mediated, electrical synaptic interactions also occur. Two different strategies are responsible for electrical communication between neurons. One is the consequence of low resistance intercellular pathways, called "gap junctions", for the spread of electrical currents between the interior of two cells. The second occurs in the absence of cell-to-cell contacts and is a consequence of the extracellular electrical fields generated by the electrical activity of neurons [40].

The first attempts to translate neuronal activity into commands to control external devices were made in monkeys in the 1960s. After that, during 1960-1970, the biological feedback was realized in monkeys, to provide voluntary
control of the firing rate of cortical neurons [41]. We also distinguish recording and stimulating activities. Recording, also mentioned as brain-to-computer interface (BCI), attempts to read brain signals and interpret them. Stimulating, also mentioned as computer-to-brain interface (CBI), goes in the opposite direction and tries to stimulate or control the brain [29]. These intelligent systems can decipher brain signals using five consecutive stages: signal acquisition, pre-processing, feature extraction, classification, and control interface as shown in Figure 4.

6.2 | Signal Detection

Synchronization of neuronal activity in the brain underlies the emergence of neuronal oscillations termed “brain waves”, which serve various physiological functions and correlate with different behavioral states. It has been postulated that at least ten distinct mechanisms are involved in the formulation of these brain waves, including variations in the concentration of extracellular neurotransmitters and ions, as well as changes in cellular excitability [43].

6.3 | Signal Acquisition

Since the first electroencephalography (EEG) recording in 1938, numerous neural implants to stimulate and record electrical activity in the brain have been developed [44]. Over the past years, number of technologies have been developed to measure the activity of the human brain. Some of the techniques measure the variation of the electrical activities related to the different states of the brain while some other techniques measure other parameters. Available modalities can be classified under the two categories based on their invasiveness: non-invasive and invasive. The major difference between these two techniques is that invasive techniques require surgery to implant electrodes within the brain's cortex while non-invasive techniques rely on recordings over the skull. Generally non-invasive methods have poor spatial resolution but show reasonable temporal resolution. Also, signal attenuation is a big problem in such techniques due to limited electrical conductivity of skull [45]. Recently, another class of BMIs has also emerged, utilizing the benefits of both invasive and non-invasive techniques, appropriately termed as hybrid BMIs [46]. Figure 5 provides a hierarchical classification of BMIs.
6.3.1 | Invasive Techniques

To precisely record neuronal data with a higher degree of freedom for neuroprostheses, the development of BMIs will require invasive recording techniques [47] such as electrocorticography (ECoG) and intracortical electrodes. Figure 6 clearly depicts that the invasive techniques have far better spatial and temporal resolutions than non-invasive techniques.

The ECoG technique requires surgery to place electrodes in extracortical areas either inside or outside dura mater, called subdural ECoG, and epidural ECoG, respectively [48]. This technique is like EEG but with a higher SNR as the electrode grid is placed directly above the cortex surface avoiding skull. The brain’s electrical activity can be recorded intracellularly and extracellularly depending on the position of the electrode. Extracellular activities of neurons can be called APs. Also in nervous and other tissues, local field potentials (LFPs) arise from the summation of and synchronization of the electrical activity of individual neurons. ECoG records an average of thousands of neurons, and can also be referred as local field potentials (LFPs), however, it is not suitable for obtaining deep brain signals [49]. However, AP readings from a group of functionally linked single neurons are required for high precision and increased data fidelity [50]. To achieve this, microelectrodes are used to record single unit activity (SUA) as well as multi-unit activity (MUA). Though even with SUA, a specific number of neurons must be recorded to derive some consistent and trustworthy meaning from the readings. Although Opinions vary, but a good estimate for minimum number of readings can be anywhere between 15 and 30 neurons [51]. Hence, intracortical SUA and MUA recordings using microelectrodes are very important.

6.3.2 | Non-invasive Techniques

One of the most used neural recording techniques is EEG, in which electrodes are simply placed on the surface of scalp at specific points to record averaged neuronal signals from different intracortical regions [52]. EEG based systems are
portable and are usually cheap. They have good temporal resolution as they directly measure the neural activity while it lacks in spatial resolution as the signal has to pass through a number of physical barriers including skull, scalp, and cerebrospinal fluid (CSF) [52, 53]. Also EEG recordings are susceptible to artifacts that can be mechanical, electromyographic, or electrooculographic in nature [54]. Magnetoencephalography (MEG) is another technique which records postsynaptic activity of neurons using magnetic fields. Its spatial resolution is reasonably better than EEG and has a high temporal resolution [55]. Functional magnetic resonance imaging (fMRI) is a method used widely in medical science to create 3D maps of brains. As a result of neuronal activity, it detects changes in magnetic field caused by changes in hemoglobin oxygenation levels. The signal generated by fMRI is also called “blood oxygen level dependence” (BOLD) [56]. It can be used to obtain full brain scans covering all brain areas unlike EEG or MEG [57].

Other than using electrical signals, neural data can be obtained using photons in the wavelength range of 650–900 nm that can penetrate cortical areas and show contrasts based on oxygenation/deoxygenation of hemoglobin. The method is called near infrared spectroscopy (NIRS) [58]. Functional near infrared topography (fNIRT) is another modification of NIRS that renders 3D images of the brain [59]. Some other known methods include positron emission tomography (PET), single positron emission computed tomography (SPECT), and computer axial tomography [60, 61].

Non-invasive techniques are widely used and well established, however, the major shortcomings of almost all the non-invasive techniques are low signal specificity, low signal to noise ratio (SNR), and signal distortion. The hindrance due to skull and intermediate brain layers between the cortex and the electrodes reduces the SNR of the recordings, leading to an average signal of millions of neurons. Moreover, any of the above-mentioned techniques cannot record a single or even a few hundred neurons, which is highly critical for practical BMI applications. Hence, a logical step forward for obtaining a specific high-resolution signal is to put electrodes directly outside or inside the cortex.

6.4 Invasive vs Non-invasive

Electrical activity in brain cells is regulated by ionic currents, the superposition of which is called the local field potential (LFP) which is recorded by an electrode and is dominated by populations with substantial synaptic processes. The main sources are action potentials (AP) and synaptic transmission. There is a widespread belief that high-frequency components (more than 500 Hz) originate from APs and low-frequency components from synaptic transmissions. Brain
tissue exhibits different types of impedance. Although brain tissue is usually thought to have high-pass properties, there are signs that it may also have low-pass properties.

BMI technologies allow us to record APs up to local field potentials. Neurons can make connections by electric synapses, spikes change LFPs with synaptic input. These electric fields can influence the LFPs. Information in the LFPs and APs can be different [62]. But there is a misunderstanding that information between invasive and non-invasive are the same and obstacles cannot affect non-invasive BMI. This may have been influenced by studies that showed similar performance for intracortical BMIs based on APs versus LFPs [63]. Although invasive and non-invasive signals may originate from the same source, there are differences. Several factors are involved, such as the fact that some neuronal clusters are difficult to detect or record with EEG. Additionally, tissue acts as a low pass filter that reduces high frequency signals to bury them in the background noise [64]. Additionally, the electrophysiological properties of extracellular media influence how LFPs propagate in extracellular spaces [65, 66]. Through EEG, these limitations cannot be overcome. EEG however can monitor neural activity in areas adjacent to the neurocranium with a low cost and without risk. Invasive recordings, however, can be deeper, but do not cover the entire neocortex, as they require surgical intervention.

7 | SIGNAL DECODING

The most important component of BMI technology is the signal translation and decoding. After collecting a massive amount of brain signals, it’s time to understand them using different decoding and signal processing methods that are reviewed in this section.

7.1 | Noise Filtering & Signal Enrichment

For achieving better results during processing data, identifying noises generated by different sources during the data collection process is crucial. These are usually caused by natural factors, such as muscle movements located near the brain, the effect of environmental signals or internal movements, interrupting sensations, hardware, and data collection. However, sometimes noises can be created intentionally by someone to attack the device, which is related to the security and privacy of BMI devices. We will dive robustness of models against the attacks in Section 8.3. The goal of noise filtering applications is that leverage brain signals to enhance them through noise filtering and signal enhancement so that devices and applications utilizing brain signals are more accurate and robust.

A variety of different methods have been proposed to remove artifacts. For general noise filtering and signal enhancement, lots of work has been done in signal processing using classical methods (like wavelet, PCA, etc.) and Neural network-based models. Obviating noisy segments manually results in missing information on these segments. Two main methods of automatic signal removal [67]:

1. estimating using the reference channel and
2. decomposition of the brain signal into other domains.

The lack of research into invasive signal filtering led us to discuss invasive and non-invasive denoising and enrichment techniques in this section. Methods applied to non-invasive signals can be applied to invasive signals. In the following, we discuss invasive and non-invasive noise filtering methods with available methods ranging from classical to deep learning-based algorithms.
Non-Invasive

For denoising non-invasive signals, both classical and deep learning methods are used. In the following, we will review them.

7.1.1 Classical methods

Classical methods include regression [68], blind source separation (BSS) [69], empirical-mode decomposition (EMD) [70], wavelet transform algorithm [71], as well as hybrid methods such as canonical correlation analysis (CCA) [72], empirical mode decomposition (EMD), blind source separation (BSS), and EMD-BSS, EEMD-CCA [67]. One of the most common methods researchers use is the common average reference (CAR) spatial method, which filters common noises out [73]. However, this method may share noises between channels that can cause significant signal interference.

7.1.2 Deep learning methods

Nowadays, Deep learning methods emerge state-of-the-art (SOTA) results in various tasks. SOTA algorithms for signal denoising, use deep learning algorithms to accomplish one of these tasks. Most of the recent works used Autoencoder-Decoder and Generative Adversarial Networks (GANs), which we will describe in the following.

A well-known denoising architecture is deep convolutional autoencoders. This method is used in [74, 75] which were previously, used for music and voice enrichment. Also, from another perspective, signal denoising can be designed for a specific task in order to prevent reducing accuracy. For instance, [76] tries to improve the quality of EEG signals to avoid reducing the performance of Steady-state visually evoked potential (SSVEP)-based BMI against noises using autoencoders. As a recommendation for improving the results of these algorithms, data augmentation could be helpful to compensate for training data shortages.

Another algorithm used for signal decoding is GAN. [77] uses a GAN-based denoising method to denoise the multichannel EEG signals, and also defines a new loss function to ensure that the filtered signal can retain as much effective original information and energy as possible.

invasive

The number of studies conducted on noise filtering and signal enrichment is limited due to problems like lack of data, and no available public dataset. In the following, some recent works will be discussed, as well as suggestions for solving problems in this field.

For detecting Local Fields Potentials (LFP) artifacts, [78] attempted to solve this issue by an Adaption of Alexnet [79]. Also, [80] solved the problem using LSTM neural network architectures. SANTIA [81] is a tool that tries to simplify machine learning training steps for offline artifact identification in invasive signals.

There has been little work in this area because of the lack of datasets for signal noise enrichment and filtering. Adding different types of noises to signals can be considered a solution to this problem which is a data augmentation technique. In addition, works like [74] show that by applying speech noise filtering methods to brain signals, accurate results could be achieved.
7.2  Feature extraction

BMI systems perform much better when the appropriate feature extraction technique is employed. The main goal of feature extraction is to make it easier to identify patterns and improve the accuracy of the BMI using supervised or unsupervised methods. Another related goal is data dimensionality reduction. An overview of the popular methods used to extract features in signal processing is presented in Figure (7). The majority of these feature extraction techniques have different domains such as time, frequency, time-frequency, and spatial as discussed below:

7.2.1  Time Domain Features

Using time domain features will allow employing signal values at distinct intervals of time. Following the pre-processing of lowpass filtering, bandpass filtering, and down sampling, the time domain features are extracted. These features are used to quantify the temporal variations in time-locked brain signal amplitudes.

- **Hjorth Parameters**: Hjorth parameters allow computing the Activity, Mobility, and Complexity of time-varying signals [82].
- **Statistical Features**: The signals’ time series are characterized by a variety of statistical metrics. Energy, Entropy, Mean, Standard Deviation, Skewness, and Kurtosis are six statistical parameters commonly employed in BMI investigations [83].
- **Fractal Dimension**: The Fractal Dimension (FD) is a statistical metric that measures signal’s self-similarity across a given spatial or time interval. The nature of brain signals is fractal, hence fractal pieces can be used to determine the features [84, 85].
- **Kalman Filter**: It is important for BMI to represent the uncertainty associated with an estimation before committing to a decision in order to prevent potentially disastrous actions based on poor estimations. Signal properties and their uncertainty can be estimated statistically using Bayesian filtering techniques. One of the most well-known Bayesian filtering algorithms is the Kalman filter [86].
• **Particle Filter:** In non-linear non-Gaussian processes, particle filters are used in order to derive a posterior distribution over the hidden state. Human signals are nonlinear, so linear regression models will not reflect the nonlinearity of those signals. Particle filter as an alternative nonlinear decoding model, can be used to overcome this problem [87].

### 7.2.2 Frequency Domain Features

Frequency domain features describe the signal power at a particular frequency band. Some of most important features listed below:

- **Discrete Fourier Transform:** Decomposing a signal into a weighted sum of sinusoidal and cosine waves of different frequencies is known as Fourier analysis. Fourier decomposition, rather than expressing a signal in terms of time, does it in terms of frequency content. The original signal can be reconstructed using the Inverse Fourier Transform (IFT). For BMI applications, brain signals are frequently recorded at discrete periods. In the Discrete Fourier Transform, the Fourier series is changed and applied to discretely sampled data (DFT) [88].

- **Fast Fourier Transform:** The Fast Fourier Transform (FFT) effectively computes the DFT with fewer calculations, making processing more efficient. Many BMI systems use characteristics collected from the power spectrum of a brain signal across time, such as EEG or Electrocorticography (ECoG). Welch's approach (based on FFT) is a frequently used method for power spectrum estimate, and the power of a certain frequency band is utilised as a spectral characteristic in subsequent analysis such as classification [89].

### 7.2.3 Time-Frequency Domain Features

Time-frequency methods can be useful in understanding brain signals that are non-stationary, because they consider dynamic changes to provide useful information.

- **Matched Filtering(MF):** a feature extraction approach that detects a specific pattern from unknown signals by comparing it to known signal templates [90].

- **Autoregression Model (AR):** a type of statistical modeling that uses a natural tendency of the signals to correlate over time or across various dimensions such as space. Thus, it is possible to predict the future measurements based on a few historical values [91].

- **Short Time Fourier Transform:** The Fourier transform represents an original signal with basis functions namely, sines and cosines of different frequencies. The Fourier transform, however, does a poor job of capturing signals that are finite and non-periodic or having sharp peaks and discontinuities since sines and cosines have an indefinite temporal breadth. However, the assumption of a stationary signal in Fourier analysis is broken by brain signals which are often non-stationary (i.e., statistical features change with time). One solution is to perform Fourier analysis over short-time windows, a procedure known as short-term Fourier transform (STFT). The STFT addresses the issue of window size, where tiny windows offer high temporal resolution and poor frequency resolution, and wide windows offer superior frequency resolution but worse temporal resolution. This insight produces the wavelet transform, which successfully balances temporal and frequency resolution[92, 93].

- **Wavelet:** Wavelet transform modifies the shape of the simple sine and cosine functions of the Fourier transform. In a Wavelet, the Mother Wavelet function is finite in time in contrast to Fourier where sine and cosine run from (−∞, +∞). Unlike a Fourier decomposition which always uses complex exponential basis functions, a wavelet
decomposition uses a time-localized oscillatory function as the analyzing or mother wavelet [94].

7.2.4 | The Common Spatial Pattern

The Common Spatial Pattern (CSP) is a prominent feature extraction approach that emphasizes differences while minimizing similarities between classes. CSP finds spatial filters which can transform the input data into resulting feature vectors that enhance the discriminability between classes. Although CSP was primarily designed to handle multichannel data related to two-class problems, a few extensions have also been proposed for multi-class BMI data. Additionally, the spatial resolution influences CSP performance since the few electrode positions, offer more discriminating data for specific brain activity compared to others. Considering these issues, the following strategies for improving CSP performance have been proposed: Common Sparse Spectral-Spatial Pattern (CSSP), Common Spatio-Spectral Pattern (CSSP), and Wavelet Common Spatial Pattern (WCSP) [95, 96].

8 | MACHINE LEARNING

The purpose of this section is to provide an overview of machine learning techniques that are relevant for signal decoding (classification and learning methods) as well as adversarial attacks. As part of signal decoding, we consider different methods for classifying signals, ranging from classical to Deep Learning-based models. Various learning strategies are also discussed for learning representations in the various conditions from data, such as learning from unlabeled data, lack of labeled data, learning representations of data without supervision, privacy, etc. In the adversarial attack part, we challenge the robustness of machine learning-based models against different attacks on BMI signals.

8.1 | Signal decoding: Classifications methods

The next stage of the functional model is to decode a BMI signal into meaningful representations in order to learn a model for a specific task. Signal decoding is important to understanding relationships between neural signals and the world. It can be used to determine how much information neural activity contains about an external variable (e.g., sensation or movement) [98], and how this information differs across brain areas [99], experimental conditions [100], disease states [101], speech recognition and speech synthesis [102, 103] sleep spindle identification [104, 105], emotion recognition [106], etc. When the goal is to determine how much information a neural population has about an external variable, regardless of the form of that information, then using ML will generally be beneficial. It is extremely
important to be careful with the scientific interpretation of decoding results, both for ML and other models [107]. Decoding can tell us how much information a neural population has about a variable X. However, high decoding accuracy does not mean that a brain area is directly involved in processing X, or that X is the purpose of the brain area [108].

Different classifiers are used to translate the features extracted from brain signals to control commands. These classifiers range from the simplistic linear classifiers to complex non-linear classifiers. Some of the commonly used classifiers are: (i) K-Nearest Neighbor (KNN), (ii) Linear Discriminant analysis (LDA), (iii) Support Vector Machines (SVM), (iv) Artificial Neural Networks (ANN), (v) Extreme Learning Machine (ELM), and (vi) Naive Bayes (NB). These classifiers are discussed in detail below, highlighting their suitability for specific situations, and example usage from the literature.

- **K-Nearest Neighbor (KNN):** In KNN, training samples are identified and classified into the dominant class based on their proximity to an unobserved point. Nearest neighbors for BMI are often found using a distance measure. The Euclidean distance metric was used in [109] to calculate the distance between the target sample and other samples using the below equation:

\[
d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}
\]

where \(n\) is the number of features, \(x_i, y_i\) is the sample’s \(i^{th}\) feature, and \(d(x, y)\) indicates the distance between \(x\) and \(y\) samples.

KNN was used to classify EEG signals in [110, 111, 112], and employed in [113, 114] for categorizing ECOG signals. In order to classify the signals, Euclidean distance was calculated between them, and a further majority class was assigned to the test signal among its K neighbors. In [115, 116, 117], The KNN approach provided better accuracy for classification tasks with improved specificity and sensitivity percentages by non-invasive techniques for detecting epileptic seizures. Moreover, in [118, 113, 117] by invasive technique KNN compared with another classifiers was more efficient for motor imagery (MI) tasks and decoding finger movements. A subspace KNN technique was used for MI classification in [119]. At each time an arbitrary subspace was chosen, the subspace KNN scheme calculated a new set of KNN. Aggregating K near neighbors in each chosen subspace was used to conduct the majority voting on the test sample’s class membership. Recent research [120] used combined method recurrent neural network (RNN) and KNN algorithm in human emotion recognition.

- **Linear Discriminative Analysis (LDA):** LDA is a type of linear classifier. The major benefits of using LDA are as follows. Firstly, the computational complexity of LDA is less, and hence the time taken for the classification is reduced. This is useful when using the algorithm in an online session. Secondly, LDA is a simple classifier to use and visualize. Linearity can be a limitation while handling non-linear data. On the other hand, simpler techniques like LDA are suitable when small training data set is available. LDA is used in a number of BMI-controlled humanoid applications for classification. For LDA, decision boundary are singly connected and convex. Figure 8(a) denotes 3 class classification in which the colour of the region denotes the class being predicted.

LDA was used by the authors in [121, 122] to categorize EEG signals and in [123, 124] to categorize acquited ECOG signals by invasive technique.

LDA as an efficient classifier was used in [125] to decoding hand flexion and extension and also in [123] to epileptic seizures detection based on ECOG signals. In [126], an aggregated sparse LDA method was used to classify ERP data. By exploiting the conformity between least-squares regression and LDA, the aggregated sparse
LDA acquired several discriminant vectors for classification. This method outperformed the traditional LDA and produced superior results for single-test ERP categorization.

- **Support vector Machine (SVM):** SVM is a non-linear classifier. It is useful in cases when the training data is less. Most of the time it generalizes better and this makes its use advantageous for BMI systems as the classifiers once trained, classify brain signals for multiple sessions. The features generated during multiple sessions may vary even for a single user. Hence the models which are less sensitive to over-fitting may perform better. SVM also performs well with high dimensionality data. However, SVM are sometimes slower than other classifiers, which becomes an issue while dealing with large data. Decision boundary with maximising margin between the classes is shown in Figure 8(b).

SVM was employed in [111, 112, 127] for classifying EEG signals. The authors in [128, 129, 130] used SVM approach for the identification of children with autism spectrum disorder, seizure detection, and for decoding pilot behavior consciousness based on EEG, respectively. EEG signals linked with random words and right and left body movements were classified robustly in [131] using the multi-class SVM approach. The authors in [132] employed a fuzzy kernel-SVM approach for classifying EEG signals. EEG signals were classified by radial basis function (RBF) Kernel with the SVM approach in [133].

To categorize ECOG-based signals [134, 135, 136] used SVM algorithm. SVM for hand and motor imagery recognition shows a significant increment in accuracy in [137, 138, 139] compared with other methods such as k-nearest neighbor, Fisher linear discriminant analysis, naïve Bayes classifier, gradient boosting, etc. It was also employed in [140, 141] for finger movement detection based on invasive signals. The authors in [142] utilized SVM for an efficient automated localization of ECoG electrodes in CT images via shape analysis using Gaussian support vector machine (G-SVM) to recognize the actual electrodes among all metal objects.

- **Artificial Neural Networks (ANN):** ANN is also a type of non-linear classifier. The classifier is inspired by the neuron structure of the brain. It is used to approximate non-linear functions. Using ANN is generally computationally intensive and requires a number of parameters to be configured. It is more complex in terms of usage as compared to LDA and the computational time taken to generate the output is also longer. However, ANNs are highly adaptive and can be applied on a wide variety of use-cases. Unfortunately, ANNs are prone to over-fitting, and thus the selection of the parameters/architecture and regularization needs to be done carefully. The decision boundary of ANN can be seen in Figure 8(c), in which the non-linearity of the function is evident. The figure shows two classes, one represented using red colour and the other one using a blue colour that has been classified using ANN [143], [144].

The authors in [112] employed ANNs for EEG signal categorization and in [145, 124] for ECOG signal categorization. It was noticed that the ANNs provided superior classification outputs than other compared techniques. Authors in [146] compared ANN with other classifiers(KNN, LDA, Naive Bayes, SVM) which is ANN consequences much better accuracy. In [147], ANNs trained using a classical back-propagation scheme was exploited for categorizing EEG signals connected with diverse mental tasks such as math, baseline, figure rotation, visual counting, and letter composing. In [145, 148] ANN was used for decoding of finger movement and activation from ECoG data and it outperformed linear models such as Linear Regression Model (LRM). In [149], ANNs were used for categorizing six distinct emotions, namely, satisfied, pleasant, happy, frustrated, sad, and fear along with different ML schemes such as KNN, naive Bayes, and SVM. The ANN structure employed 6 output and 10 hidden layers for classifying distinct emotional states. Results signified that among the exploited ML schemes, ANN displayed good classification performance by providing greater accuracy.

- **Naive Bayes:** In naive Bayes, features are assumed to be independent in every class. It forecasts the class $C$ of an arriving instance $Z$ consisting of features $[z_1, \ldots, z_n]$ through estimating the highest probability using Equation
\[
p(C_i|Z) = \frac{p(C_i) \prod_{j} p(z_j|C_j)}{p(Z)}. \tag{2}
\]

The naive Bayes method was mainly used in [150, 149] for classifying non-invasive signal like EEG data and in [151, 152] for classifying EGOG data of invasive technique. It applying for classifying Motor Imagery (MI) in [153, 154]. The probabilistic naive Bayes (NB) method was employed in [155] for limb movement classification. In [151, 152], multinomial naive Bayes (Multinomial NB) classifier was used as one of the classification method to Seizure detection and Prediction of motor and somatosensory function, respectively. The authors in [156] used a weighted naive Bayes algorithm to classify EEG-MI signals by assigning a weight for every extracted feature where this approach performed better than various competing techniques in existing works. In [157], the Gaussian Naive Bayes (GNB) method was used to categorize EEG-MI signals. By using the naive Bayes and the Gaussian distribution, the EEG-MI signals were classified. The experimental assessment reported that GNB showed better performance than two other classical classifiers, namely, SVM and LDA.

8.2 | Signal Decoding: Learning methods

Machine learning, a subset of computational intelligence, relies on patterns in the data extracted by algorithms to explore a specific task without using explicit instructions. Machine learning tasks are generally categorized into several models, such as supervised learning, semi-supervised learning, unsupervised learning, self-supervised learning, reinforcement learning, federated learning, etc. The training data for unsupervised machine learning does not have any classifications or labels. An input function or learned representation of data to describe hidden structures, such as clustering or grouping, consists only of input data. The following sections discuss different strategies for learning data from different perspectives, starting with learning from labeled data to unlabeled data. This section will explore learning strategies that can be applied with little labeled data, such as semi-supervised learning, self-supervised learning, and unsupervised learning. The reinforcement learning section focuses on the interaction between an agent and brain signals, as well as recent advancements in reinforcement learning. Due to sensitivity to the privacy of users, we will also discuss some work done on privacy preserving federated learning opportunities in the federated learning area. Throughout this section, we will discuss various learning strategies and their applications.

• **Supervised Learning:** With supervised learning, classification and regression tasks can be performed based on the results of the training stage with labeled examples, now that the new data (testing data) has been processed to identify types of events or predict future events. In general, supervised machine learning approaches can be divided into classical algorithms (like linear regression, SVM, etc) and Deep learning based approaches that are using neural networks.

Some tasks such as emotion recognition [4, 106], detecting neurodegenerative diseases [158, 159] are examples of classification tasks, and also others like speech synthesis [102, 103] and signal enrichment [74, 75, 80, 78] are examples of regression tasks.

• **Deep Learning:** In the traditional neural network, weights of the model have to be chosen very carefully. This is a major obstacle in the effective use of the neural network in many applications of BMI. In recent studies, researchers have been using deep learning approach as deep neural network has high descriptive power and thus improves the accuracy of the system. Deep learning has successful performance in the field of computer vision and in recent years has also been applied in classification of motor imagery tasks [160], [161].
Deep learning algorithms play an important role in decoding brain signals in tasks such as classification, regression, etc. These algorithms can be used for recognition and speech synthesis [102, 103], sleep spindle identification [104, 162, 105], emotion recognition [4, 106], and for categorizing neurodegenerative diseases [158, 159].

Nowadays, researchers use many deep learning-based architectures such as DNN, CNN [163], LSTM [164], RNN [165, 166], Transformers [167], etc. Classical algorithms require fewer data and low computation resources compared to deep learning-based models, but they are not as accurate as deep learning-based models. On the other hand, deep learning-based models are more accurate and have more parameters to consider more data features. But training these parameters requires more computation resources and data.

The use of deep learning faces several challenges. To develop a reliable model, the parameters need to be more precise, high-quality features need to be included, and a real dataset is needed. Deep learning models especially require large labeled datasets for training. Creating a dataset with high-quality labels is difficult, expensive, or time-consuming to obtain. However, these issues can be addressed by alternative solutions, which are discussed in the following paragraphs.

- **Semi-Supervised Learning:** The supervised model cannot be efficiently trained without expert labeling, which is one of the major limitations. It is a time-consuming analysis of multiple human experts that is necessary to produce labels, especially for medical tasks that need expensive machinery. By using a few labeled samples, it is difficult to build a successful learning system. Building a successful learning system with a few labeled sample samples is a challenging task. Comparatively, unlabeled data are publicly available and can be obtained easily or inexpensively. Learning performance can be enhanced by using a large amount of unlabeled data and few labeled samples. Using semi-supervised learning training strategies can be helpful in such cases, these algorithms are at the forefront of research in the recent years [168, 169, 170].

  The difference in existing Approaches is on what information to gain from the structure of the unlabeled data. There are many standards for evaluating semi-supervised learning algorithms. In one common approach, we start with a labeled dataset; keep only a few percentages of the labels, and treat the rest as unlabeled. Even though this method does not guarantee realistic settings for semi-supervised learning [171], it continues to be the standard evaluation methodology for semi-supervised learning. Recent studies show that adding discrepancy between predictions made on perturbed unlabeled data points to loss function can improve results on standard baselines [172].

  Hence collecting labeled invasive data is very expensive and labelling them requires neurologists, it is a time-consuming process, but there are lots of unlabeled invasive signals, as such using this method can improve the accuracy of models. For example, [173] uses this method for train an electrographic seizure classifier. On the other hand, this method is widely used for BMI applications using non-invasive signals for tasks such as abnormal signal classification [174], spelling [175], emotion recognition [6], motor imagery recognition [5], effective computing [176], etc.

- **Unsupervised Learning:** Extracting meaningful information from data without supervision or target labels is a challenging area in machine learning. Basic algorithms mostly can be divided into two categories: clustering algorithms (like Kmeans, DBSCAN, etc), and dimension reduction methods (PCA, ICA, t-SNE, etc). The objective of clustering algorithms is to cluster data that are similar to each other, and the objective of dimension reduction methods is to reduce dimension of data with keeping important information under many constraints.

  A number of breakthroughs have been achieved in machine learning benchmarks as a result of the rise of deep neural networks. Typically, successful models are trained through supervised learning, which requires large datasets annotated for the specific task at hand. The cost of obtaining annotated data can often be prohibitive or even im-
possible in some cases. As such, there has been increasing attention being paid to unsupervised learning in recent years [177, 178]. These methods mainly try to maximize mutual information between the input and output of the model. There are various techniques to learn neural networks, latent representation of data in unsupervised manner, such as Autoencoder, Contrastive Learning, to name but a few. Although these type of learning can be helpful for applications of BMI but few projects done using this strategy. There are lots of invasive and non invasive unlabeled data, these methods can be applied on them, especially for invasive data for which collecting labeled records is hard. Here we mention some works that were done for non invasive data sets. In EEGFuseNet, [179] authors presented an unsupervised hybrid convolutional recurrent generative adversarial network-based characterization and fusion of EEG features. The EEGFuseNet is trained unsupervised, and its spatial and temporal capabilities are automatically characterized. The performance of this model evaluated in an unsupervised emotion recognition application. As a method for determining latent factors from multichannel EEGs, [180] proposed utilizing an unsupervised deep generative model based on variational autoencoders. By using a sequence modeling approach, we examine how well we can recognize emotions based on latent factors we have learned.

- **Self-Supervised Learning**: Nowadays self supervised learning is a common technique, because data labeling is expensive and thus high-quality labeled dataset is limited and expensive. Hence learning a good representation of data structure makes it easier to transfer useful information to a variety of downstream tasks as downstream task has only a few examples and it can be used for Zero-shot transfer to new tasks. There have been impressive advancements in self-supervised learning (SSL) methods on a wide range of tasks, including vision [177, 182, 183, 184, 185, 186], speech [187], graphs [188, 189], natural language processing [190, 191], and reinforcement learning [192, 193].

Self-supervised learning makes use of the underlying data structure to obtain supervisory signals from the data itself. Predicting any unseen or hidden component (or property) of the input from any visible element of the input is the general approach of self-supervised learning. For instance: from the current frames in a video (observed data), we can also predict previous or future frames. Self-supervised learning may employ a range of supervisory...
signals for a variety of co-occurring modalities and for big data sets without depending on labels by utilizing the structure of the data itself. It is important to note that self-supervised learning requires a much greater number of feedback signals than standard supervised learning does, despite its unsupervised nature [194]. Figure 9 illustrates different existing methods of self-supervised learning on brain signals.

Various methods are available for self-supervised learning, and here we discuss some of them. The BERT method [191] randomly masks words of document and tries to predict masked words given the context of document and tries to predict next sentence in the training procedure. In GPT [195] training mechanism tries to predict next word in document, in an auto-regressive way. In MYOW [196], an adaptive selection technique is presented to obtain additional similar views by fitting examples from the entire dataset for augmentation of neural population activity. An augmentation can take two forms: temporal jitter (coupling samples with close timing) and dropout (masking a subset of input channels randomly). The Swap-VAE [197] disentangles the latent representations of multi-unit neural recordings from nonhuman primates according to the latent representations of their augmentation-based self-supervised information maximization latent representations.

Data collection (and labeling) is one of the most challenging tasks in neuroscience. While plentiful labeled data exist, it is rarely clear that these variables - such as behavior or environment - truly reflect an individual’s underlying brain state. This is why self-supervised learning appeals to neuro scientists in two ways: it has the capacity to represent brain activity robustly without labels, and it can unbiasedly predict an unknown (rather arbitrary) set of variables [181].

Brain signals, as contrast to multicellular recordings, which records the activity of individual neurons, measure general activity in a variety of brain locations. To create representations of these macro-scale brain data, authors in [198] examined various physiological datasets using augmentation and adversarial training techniques, including electroencephalography (EEG) [199]. Another work examined a variety of temporal pretext tasks used with EEG for patient pathology screening and sleep decoding [200]. Authors in that work proposed a cross-modal deep clustering approach constructs representations of EEG, ECoG, and behavior in a self-supervised way. Transformer-based models such as BENDR [201] computes latent representations of EEG signals using self-supervised sequence modeling approaches like wave2vec 2.0 [202].

- **Reinforcement Learning** Reinforcement learning (RL) is learning procedure characterized by trial-and-error search and delayed reward. The goal of reinforcement learning is to optimize a reward signal by learning what to do in situations and how to take actions. By trying various activities, the learner, instead of being told which actions to take, learns which ones yield the maximum reward. Actions may not only affect the immediate reward, but also the next situation and, through that, all following rewards [203].

In [204] a framework is presented for integrating a deep reinforcement learning (DRL) model with an implicit human feedback mechanism (with EEG signals) in a practical and sample-efficient way. For the purpose of human-assisted RL algorithms, [204] takes a game as a proxy for a real-life environment. Authors in [205] use EEG signals as features of a Q-learning based system in order to recommend music as music therapy to improve clinical depression and anxiety. For controlling games, error-related potentials (ErrPs) are used in [204] as feedback of the reinforcement learning algorithm. Authors in [204] propose and validate an experimentally zero-shot method of learning ErrPs, where ErrPs can be learned for one game and then transferred to other unseen games. The intersection of Reinforcement learning and BMI has various applications which can help humans in various applications such as controlling robots, controlling emotions, Virtual reality, etc. Existing works mainly use non invasive signals as input, however, since invasive signals have better quality and they can capture specific zone of of brain and neurons connections, the use of invasive signals can therefore lead Reinforcement Learning based agents to reach better results.
• Federated learning:
  Federation learning (FL) is a machine learning setting where multiple entities work together under the supervision of a central provider or server to solve a machine learning problem. In order to accomplish the learning objective, focused updates destined for immediate aggregation are used instead of exchanging or transferring raw data between clients. To reduce data consumption, focused updates have a high degree of focus on the minimum necessary information for the particular learning task at hand. As soon as possible, aggregation is performed as early as possible to minimize data usage. According to this definition, federated learning from fully decentralized (peer-to-peer) learning techniques are different. FL can mitigate many systemic privacy risks and costs associated with traditional, centralized machine learning through focused collection and data minimization. Due to this feature of FL, there has been a significant increase in research and applications in this area in recent years [206].

  Success of Deep learning based BCI models are restricted by the lack of large datasets. Because of high cost of collecting brain signal data and privacy concerns, it is difficult to create a large enough dataset by combining multiple small datasets. Considering that brain signals can reflect brain activity from multiple angles, abuse of brain data can result in serious privacy violations. Thus, organization data exchanges without explicit user approval are prohibited by regulations like the General Data Protection Regulation (GDPR) [207]. In order to protect privacy while analyzing brain signals, it is important to conduct a joint analysis. Thus, federated learning frameworks may be used to solve this problem [208, 209]. Machine learning can be trained using data from multiple sources without any actual sharing of data due to federated learning, which is a powerful and emerging technique [210]. According to [210], a deep learning architecture is proposed based on the spatial correlation matrix of EEGs. To protect data privacy, it was adapted to multi-device learning settings based on federated learning frameworks. Analysis of PhysioNet EEG Motor Movements/Imagery Data set [211] is also done subject-specifically and subject-adaptively. The results show that Federated learning can achieve the same classification accuracy as state-of-the-art methods without sharing EEG data with others.

  Federated learning can be also applied to invasive signals. Furthermore, existing deep learning models can be trained by the FL strategy. As we know invasive brain data is very sensitive, therefore, due to serious concerns on these data such as data privacy, it is an important learning strategy to learn from multiple devices and protect privacy of users’ data.

8.3 Adversarial Attacks

  A BCI provides direct access to external devices via brain signals, typically recorded using brain activity. Those with severe paralysis can use it to communicate or to assist in rehabilitation [212]. In addition to medical applications, recent advancements in devices have made BCIs adaptable for consumer equipment, may provide stress relief [213], or Emotiv headsets that may control ground vehicles and drones [214]. A failure of a BCI system could result in misdiagnoses, user frustration, or even physical harm while driving a wheelchair or operating a drone [215, 216].

  Even though deep learning models have state-of-the-art performance, recent studies have demonstrated their vulnerability against adversarial examples, which can degrade the performance of a well-trained model by adding small imperceptible perturbations. For example, in a classification task, an adversarial perturbation can be attached to the other labels sometimes that are irrelevant to data, and the attacker does this in order to cause disorder or crash the system [217]. Using adversarial examples to classify images can deceive a deep learning model into giving incorrect labels for images [218, 219]. In addition to speech recognition and malware classification, semantic segmentation and many other techniques have also been subjected to adversarial attacks [220, 221, 222].

  Adversarial attacks can be divided into two classes, white-box and black box attacks. In the white-box attack,
the attacker has full control of the model architecture and parameters. A gradient-based strategy or an optimization-based strategy can, therefore, be used to attack by adding perturbations to the calculated direction. Various algorithms have been proposed to generate adversarial examples, including the fast gradient sign method (FGSM) [218], the C&W method [223], L-BFGS [219], the basic iterative method [224], Deep Fool [225], etc. In the black-box attack scenario, the attacker only observes how a target model responds to inputs but does not know anything about the model’s architecture, parameters, and training data. In order to generate adversarial examples, the attacker must limit the magnitude of perturbations and limit the number of queries. They were however inefficient when it came to querying: to build a substitute model sufficiently similar to the target model, they typically required a large number of queries. Based on the transferability, authors in [226] presented an adversarial attack method for creating black-box substitute models and attacking black-box target models.

Some works have been done in order to attack non-invasive based models, due to lack of invasive data and hard to access to invasive data set there is not such work in models that take invasive signals as input, but attacks in invasive devices can cause dangerous affects, especially when the device stimulates brain neurons. Next, we review some related work on models that exploit non-invasive signals.

According to [227], adversarial examples for black-box attacks on EEG-based BCIs can be done using unsupervised fast gradient sign methods (UFGSM). Authors in [228] introduces a query synthesis-based active learning strategy to transferability-based black-box attacks of EEG-based BCIs. Authors in [229] provide a practical adversarial example. An EEG trial can be preprocessed with this signal before the square-shaped signal is added. An interesting aspect of the attack is that it is described as a backdoor key, which implies that the attacker could have access directly to the training dataset and pollute it with adversarial examples. According to authors of [230], their attack algorithm generates smooth adversarial examples based on the signals. Based on a realistic head model, the derivative models the spreading over the scalp, taking into account the attack source and the electrical and physical properties of the conducting tissues.

9 | SIGNAL ENCODING AND STIMULATION

Electrical brain stimulation and other neuromodulation techniques can be used as a treatment for a variety of neurological disorders including movement disorders, pain, and epilepsy. These therapies are carried out by activating or inhibiting the brain with electricity. The electricity can be induced by either implanting electrodes directly in the brain or placing them on the scalp. Also, applying magnetic fields to the head can induce brain neurons. Although these types of therapies are less frequently used than medication and psychotherapies, they hold promise for treating certain mental disorders that do not respond to other treatments.

There are some methods for brain stimulation including Electroconvulsive therapy [231], vagus nerve stimulation (VNS) [232], repetitive transcranial magnetic stimulation (rTMS) [233, 234], magnetic seizure therapy (MST) [235], and deep brain stimulation (DBS) [236]. A summery of method and side effects of these devices an be found in Table 2.

- **Electroconvulsive therapy:**
  
  Electroconvulsive therapy (ECT) is an electric current is used to treat mental disorders using electroconvulsive therapy. Typically, this type of treatment is used when all other treatments (such as antidepressant medications or psychotherapy) have failed to improve the patient’s condition. On the other hand this therapy has some side effects such as headache, upset stomach, muscle aches, memory loss.

  ECT is a non-invasive procedure that uses electrodes placed at specific sites on the head. A current of electricity
TABLE 2

| Device                          | side effects                                      | method   |
|--------------------------------|---------------------------------------------------|----------|
| Electroconvulsive therapy      | headache, upset stomach, muscle aches, memory loss| non-invasive |
| Repetitive Transcranial Magnetic Stimulation | some patients actually get worse, voice changes, hoarseness, cough or sore throat, neck pain, difficulty swallowing discomfort in the area where the device is implanted, breathing problems, discomfort at the head site, mild headaches, brief lightheadedness, or seizure | non-invasive |
| Repetitive Transcranial Magnetic Stimulation | during the treatment, the scalp, jaw, or face muscles may contract with the magnet and have some effects on them. | non-invasive |
| Magnetic Seizure Therapy       | Same as ECT, MST has risks that can be caused by anesthesia exposure and the induction of a seizure. | non-invasive |
| Deep Brain Stimulation         | side effects form of brain surgery. Bleeding in the brain or stroke, infection, disorientation or confusion, unwelcome mood changes, movement difficulties, lightheadedness, and difficulty sleeping are all possible | invasive |
| Neuralink                      | side effects form of brain surgery.               | invasive |

passes through the electrodes into the brain causing a seizure that lasts less than a minute [231]. Figure 10 shows a visualization of this method.

- **Vagus Nerve Stimulation:**
  Vagus Nerve Stimulation (VNS) works through a device implanted under the skin that sends electrical pulses through the left vagus nerve, half of a prominent pair of nerves that run from the brainstem through the neck and down to each side of the chest and abdomen. The vagus nerves carry messages from the brain to the body's major organs (e.g. heart, lungs and intestines) and to areas of the brain that control mood, sleep, and other functions. Figure 11 shows a visualization of this method.

  Electrical pulses are sent to the left vagus nerve through a device which is inserted under the skin to deliver the therapy. A major function of the nervous system is sending signals to the body's organs and to various parts of the brain related to moods, sleep, and other functions. For this therapy, a small device is surgically implanted in the upper left side of the chest called a pulse generator. There is an electrical lead wire connected to the left vagus nerve to drive the pulse generator [232].

  VNS treatment is used to reduce symptoms of depression, some patients will not respond to this method, and some actually get worse. Also, VNS has some side effects such as voice changes or hoarseness, cough or sore throat, neck pain, discomfort or tingling in the area where the device is implanted, breathing problems, especially during exercise, difficulty swallowing [231].

- **Repetitive Transcranial Magnetic Stimulation:**
  This method is a non-invasive method that tries to stimulate the brain by using a magnate. Repetitive transcranial magnetic stimulation (rTMS) has been studied as a treatment for depression, psychosis, anxiety, and other disorders.

  This treatment includes holding a coil against the forehead near the area of the brain associated with mood control. The magnetic pulses, that are transmitted from the coil, easily pass through the skull and cause small electrical flows that stimulate nerve cells in the targeted brain region [233]. During the treatment, scientists can select which parts of the brain will be affected and which will not be. The magnetic field in this treatment has the same strength as that of a magnetic resonance imaging (MRI) scan. An rTMS session usually lasts between 30 and 60 minutes without requiring anesthesia. Figure 12 shows a visualization of Vagus Nerve Stimulation method.
In some cases, the patient may have discomfort at the head site, especially at the place of the magnet, and during the treatment, the scalp, jaw, or face muscles may contract with the magnet and have some effects on them. Also, my result the Mild headaches, brief lightheadedness, or seizure, however, long-term side effects are unknown. The main advantage of this method over ECT is rTMS can be targeted to a specific region in the brain. Because focusing on a specific part of the brain decreases the chances of side effects associated with ECT [231].

- **Magnetic Seizure Therapy:**
  Magnetic seizure therapy (MST) is an alternative to ECT that may not adversely affect memory. Magnetic seizure therapy (MST) tries to keep the effectiveness of ECT and reduce its cognitive side effects. This method is like both ECT and rTMS, for stimulating a specific target in the brain, uses magnetic pulses instead of electricity, and aims to induce a seizure-like ECT. Hence the pulses have a higher frequency than that used in rTMS. Therefore, like ECT, in order to prevent movement and muscle relaxation, the patient should be anesthetized. Same as ECT, MST has risks that can be caused by anesthesia exposure and the induction of a seizure. MST produces fewer memory side effects, shorter seizures, and allows for a shorter recovery time than ECT [231, 235].

- **Deep Brain Stimulation (DBS):**
  DBS was developed for treating Parkinson’s disease symptoms such as tremors, stiffness, walking difficulties, and uncontrollable movements. In this method, a generator that is inserted in the chest controls a pair of electrodes implanted in the brain, sending out continuous signals customized to fit the individual (Figure 13).
  During DBS, the brain is surgically shaved and then attached to a sturdy frame to prevent the head from moving. During the procedure, the head is fixed to this frame and the patient is awake to give feedback to the surgeon. Two holes are drilled into the head, then, a thin tube is threaded into the brain by the surgeon to place electrodes on either side of a specific brain area. This is followed by general anesthesia. In the chest, electrode wires are attached to battery-operated generators and transmit electrical pulses to brain electrodes [241].
  DBS comes with similar risk factors as any other form of brain surgery. Bleeding in the brain or stroke, infection, disorientation or confusion, unwelcome mood changes, movement difficulties, lightheadedness, and difficulty
sleeping are all possible side effects of the operation. Other adverse effects that haven't been documented yet are possible because the method is currently being researched. Long-term benefits and adverse effects have yet to be determined [231].

- **Neuralink Chips:**

  Elon Musk unveiled Neuralink's implantable brain chip, the Link version 0.9, in 2019 [242]. It's undoubtedly, the most advanced brain computer interface designed to be implanted directly into the brain by a surgical robot (Figure 14(a)). The chip plugs into many areas of brain directly by tiny microscopic threads (Figure 14(d)). They are about $1/20^{th}$ of the width of a human hair. Link can process, stimulate and transmit brain signals wirelessly. The entire operation is done by the robot with tiny arms (Figure 14(b), 14(c)) precisely instead of human hands to completely eliminate associated risks. Same day surgery without a big incision or general anesthesia. They remove about a coin sized piece of skull and the person can walk around right after the surgery. [243]

  Neuralink enables its users to control their phone, keyboard, and mouse directly with the brain by recording
and analyzing brain signals with the smartphone applications. For doing these process they built an application exercise for users to control the device [242]. Many strategies meant to control the activity of whole-brain regions, rather than to transport information to and from the brain, have been considered. As a result, they have fewer electrodes (fewer than 10) and are substantially thicker than Neuralink threads. For example, DBS leads have just 4-8 electrodes and are 800 times thicker. With over 1024 channels of input from the brain, Neuralink can deliver unparalleled scalable data. The Link will also detects spikes in real-time on each channel, and this information will be relayed wirelessly.

10 | CHALLENGES

The development and deployment of BMI applications face non-technical as well technical challenges. Ethical concerns are major non-technical hindrances of development and deployment of technology that directly interact with human body, BMI is no exception. Implementation challenges include cost, data privacy, machine capability, etc. We elaborate these challenges next.

10.1 | Ethical Challenges

AI is gradually merging with neurotech and has the potential to have an impact on quality of life, particularly for someone suffering from diseases such as from spinal cord injury, Parkinson, Paralysis, etc., but also with the development of new technologies, ethical concerns are rising about whether the technology will serve medical and industrial sector or like other technology being involved in the privacy, security and stability concerns. Combining current advances in technology with neuroscience may lead to progress in different areas of human existence and may lead to global uniform regulation.
The Neuralink robot inserts needles precisely where the neurosurgeon wants them, with fine needles so small that they cannot be seen by the naked eye [243]
10.1.1 | Bias

The development of these technologies have seen some limitations. The challenges are due to their first target markets, or their training data may lead their applications to biases such as gender or race bias, especially in the AI-based applications. For example, an application may work well on men but do not perform as well on women. These may be because of their training data or their brain structure, etc. Recent research projects have focused on finding ways to remove or prevent these biases in various applications. In addition, we suggest that potential users be involved in the development of algorithms and devices to ensure prejudice is discussed from the very beginning of their development which should lead to greater acceptability, particularly for those who are already marginalized.

10.1.2 | Privacy & Security

Today, Due to the sensitivity of brain-related data sets can raise concerns about information misuse, protecting the privacy of users is a challenging task. When neuro data of a person is protected from seeing, intrusion, analysis, and accumulation, or interference by third parties or unlicensed neurotech gadgets, it is called “brain shielding” [244]. Applications should be designed to access information only to persons whom they give them permission, such as doctors. However storing these data sets is another changing problem due to their volume, transferability, and other factors. The information is useful for training models or someone who wants their neuron's activities. It is better for Applications to adapt these activities to the users on the device without any connection from the other servers or sources. Additionally, companies can use federated learning methods instead of directly collecting data, and applications can be designed to encrypt the information on the device for security.

Another challenge of the applications is the model robustness, especially application that is based on machine learning are noise sensitive. They can be fooled by noises as discussed in Adversarial attacks. Neuro-implants with impaired or disabled functionality may have disastrous effects, so data security is essential. "Brainjacking" or malicious changes in the algorithms may be caused by exploiting several vulnerabilities in the system. Models can be robust by various techniques that are discussed in the machine learning literature. These attacks can be done in a targeted way to force or encourage users distributing their actions.

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Neuro-data protection is a set of technologies, standards, and guidelines that protect neuro-data and data inferred from neurotech from unapproved users' entry, disclosure, alteration, or damage [244]. Creating justice in protecting the privacy of individuals leads to gaining popularity and legal acceptance in all countries of the world.

10.1.3 | Human Identity

Personal, complicated, and dynamic manifestation of different fields of human reality is not restricted to biology, culture, ecology, experiences, and historic sociopolitical situations, all these things build each persons distinct concept about meaning, in relation with people and the world, as well as self-concepts and possession, a phenomenon which is both special and literally imprinted within the nervous system while also being affected by outer pressure and societal constructs [244].

10.1.4 | Fairness

This technology could be available to every person in the world and be treated fairly and justly. Products designed for neurotech can’t be designed to meet the needs of a specific social class. There can be limitations that make it difficult
for neurotech capabilities and participation in neurotech design to be accessed. Neurotech gives solutions to those limitations and neuro data explanation is another factor that causes discrimination [244].

10.1.5 | Accuracy and Efficiency

Even though applications can be helpful, they can also be harmful, especially in the applications that stimulate the brain or can lead the user in dangerous situations. Applications can misclassify signals or encode them incorrectly. This can stimulate neuron signals completely wrong resulting in chromatic nerves or even irreparable damages and the user's death.

When assessing neuro data, Neurotech [244] provides explanations, as well as code designed by them to modify the nervous system. They are forthright and honest about neurotechnology’s capabilities and their application of neuro data, as well as any conclusions that are drawn.

10.1.6 | Well-Being

When designing or implementing neurotech (or using related neural data) products, should satisfy the user to a physical and mental state (including health, safety, happiness, and comfort) as a priority. It is very important to be able to create this feeling of satisfaction in people who use this technology.

10.1.7 | Social Issues

Interaction with machines increases as a result of BMI which leads to a diminishing interactions among people. Moreover, as technology tends to widen inequalities in the society, BMIs will do the same, by providing benefits to those who can afford them [29].

10.2 | Implementation Challenges

Clearly, all of the above-mentioned ideas come with their design and implantation issues. We are at the early stages of development currently, however, this fascinating project drives us to come up with mind-blowing ideas that require managing of the implementation challenges to use the technology for human benefits.

10.2.1 | Cost

Gradually, with the advancement of this technology and the emergence of newer and more expensive versions, it may cause class distance and at the same time lead to the domination of the richer group to other classes due to affordability of the newer versions. The manufacturers of this technology should support their software from older models that may reduce this domination.

10.2.2 | Implant Monitoring

Data security, data ownership, and handling large amounts of data are some of the challenges in this field. When 250 channels are recorded at 30 kHz, micro-electrode recordings generate 115GB of data per hour which is a significant volume [245]. This amount of data is beyond the capacity of many hospital systems currently in place.
performance computing (HPC) systems and cloud-based computing may provide solutions that scale with increasing data storage and processing demands [245]. The use of distributed algorithms or federated learning algorithms (as discussed in Section 8.2) in device computing cores is another solution.

### 10.2.3 | Chips

The little electrical impulses that each electrode records must be transformed by The Link into current neuronal information. High-performance signal amplifiers and digitizers are required for the Link since the neural signals in the brain are tiny (micro-volts). Additionally, when the number of electrodes rises, the amount of information included in these raw signals is too large to upload using low power devices. These technologies must be able to identify and characterize brain spikes on real-time basis in the chip. While significantly decreasing per-channel chip size and power consumption in comparison to the existing technologies, Link’s customized chips can achieve such real time analysis [243].

### 10.2.4 | Hermetic Packaging

It is important to keep the fluid and salts in the brain away from the Link. An enclosure made from biocompatible materials, replacing the skull physically, and having over 1,000 electrical channels can be challenging to make waterproof, but the challenge is multiplied when it is made from biocompatible materials, replaces the skull, and has over 1,000 electrical channels. Neuralink is developing cutting-edge techniques to construct and seal each significant component of the package. By creating components as a single component, it can reduce device size and remove failure points by replacing the connection between several components [243].

### 10.2.5 | Neural Decoding

In order to use brain spikes for computer control, the spikes must first be decoded. Scientists in academic labs have created computer programs that decode hundreds of neurons’ activity to control a virtual computer mouse. This technology will enable electrical gadgets to be controlled more accurately and realistically by capturing more neurons. Through this method, they seek to increase the effectiveness and robustness of neural decoding by leveraging current developments in statistics and algorithm design. The implanted device is controlled using these algorithms in real-time. A challenging aspect of designing adaptive algorithms is ensuring, that they remain reliable and stable while improving over time [243].

### 10.2.6 | Mechanical Damage

Although current devices have considered many aspects, mechanical damage to electrodes, stems, ligaments, and other implant components still needs to be considered. Recent reports show evidence of mechanical damage to parts of the recording system during or after planting. Crisp materials are more prone to failure, so it is recommended to use harder and more flexible materials [42]. The first barrier to new achievements is their so-called "adaptive decoding algorithm"; the algorithm is implemented on the device itself with the task of processing action potentials in real-time. Algorithm time and battery usage optimization can increase its efficiency dramatically. Another challenge they face is security issues because all of the device’s connections are based on Bluetooth wireless communication technology; from charging the link to its outside connections[243].
CONCLUSION

Invasive BMI is an emerging technology that has an enormous potential beyond the obvious applications, such as, improving the lives of patients with spinal cord injury, or Parkinson's disease. Beyond the medical applications, this technology can provide immense benefits in other applications, such as advanced AI based education, communication among human-machine systems, etc. To develop innovative applications of invasive BMI, understandings of biological and engineering key concepts that underpin this technology are necessary. In this review paper, we highlighted the recent developments in the field of BMI by analyzing recent literature. Specifically, we have provided the developing signal sensing technologies and discussed applying computational approaches to interpret and decode brain signal data. In this paper, we systematically surveyed the recent advancements in dry sensors, wearable devices, signal enhancement, signal decoding, deep learning, etc., for BMIs. We focused on explaining the brain structure and studied computational methods and strategies, especially machine learning based methods, for decoding brain signals with a focus on invasive signals. Furthermore, we addressed brain signal stimulation, and discussed challenges of implementing these technologies including ethical issues. The various computational intelligence approaches enable us to learn reliable brain cortex features and understand human knowledge from signals. We summarized the recent brain signal encoding and decoding methods, followed by discussing dominant machine learning-based models for BMI applications. We also provided an overview of healthcare applications and pointed out the open challenges and future directions.

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| Number | Abbreviations   | Definition                      | Number | Abbreviations   | Definition                      |
|--------|-----------------|---------------------------------|--------|-----------------|---------------------------------|
| 1      | AI              | Artificial Intelligent          | 42     | EMD             | Empirical-Mode Decomposition    |
| 2      | BMI             | Brain Machine Interface         | 43     | CCA             | Canonical Correlation Analysis  |
| 3      | CNS             | Central Nervous System          | 44     | CAR             | Common Average Reference        |
| 4      | PNS             | Peripheral Nervous System       | 45     | GAN             | Generative Adversarial Network  |
| 5      | BCI             | Brain Computer Interface        | 46     | SSVEP           | Steady State Visually Evoked Potential |
| 6      | DBS             | Deep Brain Stimulation          | 47     | LFP             | Local Fields Potential          |
| 7      | tDCS            | transcranial Direct Current Stimulation | 48     | LSTM            | Long Short Term Memory          |
| 8      | SCI             | Spinal Cord Injury              | 49     | FD              | Fractal Dimension               |
| 9      | EEG             | Electroencephalography          | 50     | IFT             | Inverse Fourier Transform       |
| 10     | ECoG            | Electrocorticography            | 51     | DFT             | Discretely Sampled Data         |
| 11     | ERD             | Event-Related Desynchronization  | 52     | FFT             | Fast Fourier Transform          |
| 12     | PD              | Parkinson's Disease             | 53     | MF              | Matched Filtering               |
| 13     | IPG             | Implantable Pulse Generator     | 54     | STFT            | Short-Time Fourier Transform    |
| 14     | TMS             | Transcranial Magnetic Stimulation | 55     | CSP             | Common Spatial Pattern          |
| 15     | ASD             | Autism Spectrum Disorder        | 56     | CSSP            | Common Sparse Spectral-Spatial Pattern |
| 16     | ILAE            | International League Against Epilepsy | 57     | WCSP            | Wavelet Common Spatial Pattern  |
| 17     | DLPFC           | Dorsolateral Prefrontal Cortex  | 58     | LDA             | Linear Discriminant Analysis    |
| 18     | rTMS            | repetitive Transcranial Magnetic Stimulation | 59     | SVM             | Support Vector Machines         |
| 19     | ANI             | Artificial Narrow Intelligence  | 60     | ANN             | Artificial Neural Networks      |
| 20     | AGI             | Artificial General Intelligence | 61     | LDA             | Linear Discriminant Analysis    |
| 21     | ASI             | Artificial Super Intelligence   | 62     | NN              | Neural Network                  |
| 22     | HMM             | Hidden Markov Model             | 63     | DNN             | Deep Neural Network             |
| 23     | MS              | Multiple Sclerosis             | 64     | KNN             | K-Nearest Neighbor              |
| 24     | CBI             | Computer-to-Brain Interface     | 65     | MI              | Motor Imagery                   |
| 25     | NIRS            | Near Infrared Spectroscopy      | 66     | RNN             | Recurrent Neural Network        |
| 26     | fMRI            | functional Magnetic Resonance Imaging | 67     | ERP             | Event-Related Potential         |
| 27     | PET             | Positron Emission Tomography    | 68     | RBF             | Radial Basis Function           |
| 28     | SNR             | Signal to Noise Ratio           | 69     | LRM             | Linear Regression Model         |
| 29     | LFP             | Local Field Potential          | 70     | GNB             | Gaussian Naive Bayes            |
| 30     | AR              | Augmented Reality              | 71     | ICA             | Independent Component Analysis  |
| 31     | SUA             | Single Unit Activity           | 72     | t-SNE           | t-distributed Stochastic Neighbor Embedding. |
| 32     | MUA             | Multi-Unit Activity            | 73     | SSL             | Self-Supervised Learning        |
| 33     | CSF             | Cerebrospinal Fluid            | 74     | DRL             | Deep Reinforcement Learning     |
| 34     | MEG             | Magnetoencephalography         | 75     | RL              | Reinforcement Learning          |
| 35     | BOLD            | Blood Oxygen Level Dependence   | 76     | ErrP            | Error-related Potential         |
| 36     | fNIR           | functional Near Infrared Topography | 77     | GDPR            | General Data Protection Regulation |
| 37     | SPECT           | Single Positron Emission Computed Tomography | 78     | FGSM            | Fast Gradient Sign Method       |
| 38     | AP              | Action Potential               | 79     | UFGSM           | Unsupervised Fast Gradient Sign Methods |
| 39     | VR              | Virtual Reality                | 80     | VNS             | Vagus Nerve Stimulation         |
| 40     | PCA             | Principal Component Analysis   | 81     | MST             | Magnetic Seizure Therapy        |
| 41     | BSS             | Blind Source Separation        | 82     | ECT             | Electroconvulsive Therapy       |
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