An fNIRS Study on Obsessive-Compulsive Disorder Detection

A Thesis

Submitted in the partial fulfilment of the requirement for the award of the Degree of

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By

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This is to certify that the dissertation entitled **"An fNIRS Study on Obsessive-Compulsive Disorder Detection"** has been carried out by **Priyanka Mitra** (University Registration No:**160230** of 2021-2022, Examination Roll No: **M6IAR24011**) under my guidance and supervision and be accepted in partial fulfillment of the requirement for the Degree of Master of Technology in Intelligent Automation and Robotics offered by Department of Electronics and Tele-communication engineering. The research results presented in the thesis have not been included in any other paper submitted for the award of any degree to any other University or Institute.

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PREFACE

Obsessive-compulsive disorder (OCD) is a disorder in which people have recurring, unwanted thoughts, ideas or sensations (obsessions). To get rid of the thoughts, they feel driven to do something repetitively (compulsions). The repetitive behaviors, such as hand washing/cleaning, checking on things, and mental acts like (counting) or other activities, can significantly interfere with a person's daily activities and social interactions.

fNIRS is an optical, noninvasive neuroimaging technique that allows the measurement of brain tissue concentration changes of oxygenated (HbO2) and deoxygenated (HbR) hemoglobin following neuronal activation.

Using fNIRS, brain activity is measured by using near-infrared light to estimate cortical hemodynamic activity which occur in response to neural activity. Alongside EEG, fNIRS is one of the most common non-invasive neuroimaging techniques which can be used in portable contexts. The signal is often compared with the BOLD signal measured by fMRI and is capable of measuring changes both in oxy- and deoxyhemoglobin concentration, but can only measure from regions near the cortical surface. fNIRS may also be referred to as Optical Topography (OT) and is sometimes referred to simply as NIRS.

The major objective of the thesis is to use fNIRS to detect whether a person is healthy or suffering from Obsessive Compulsive Disorder which is being classified using Convolutional Neural Network (CNN).

This thesis comprises five chapters, each addressing crucial aspects of machine learning, deep learning, Brain computer interface (BCI) and Obsessive-Compulsive Disorder (OCD). Chapter 1 provides a comprehensive introduction to Brain Computer Interface (BCI), and its types like EEG, fMRI, fNIRS, ECoG etc. It also gives us the Literature Survey of the previous works. Lastly, it gives us a brief idea about the scope of the thesis. Chapter 2 talks about the detailed description on OCD and the visual stimuli used to detect if a patient is healthy or not. It talks about Eriksen Flanker task and how it identifies a healthy individual and an OCD suffering individual. Chapter 3 deals with detailed information about different classifiers in AI that is Machine learning and its types like Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K- nearest neighbor (KNN) and basics of CNN. It also talks about Deep Learning and its applications. Chapter 4 illustrates the results of the experiment. It illustrates the block diagram of the system, gives detailed information about CNN along with its equations. Then we show how the experiment is conducted using fNIRS electrodes, and the number of participants performing the experiment looking at the instruction set and their results. We also find out the Classification Analysis percentage to find out the highest percentage. Chapter 5 synthesizes the findings from the thesis, distilling key conclusions drawn from the experiment and talking about the advantages of CNN and finding out the future scope of the experiment that we performed along with its applications.

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CHAPTER 1

Introduction to the Thesis

1. INTRODUCTION TO BCI

A brain–computer interface (BCI), sometimes called a brain–machine interface (BMI), is a direct communication pathway between the brain's electrical activity and an external device, most commonly a computer or robotic limb. Their sensors capture electrophysiological signals transmitted between the brain's neurons and relay that information to an external source, like a computer or a robotic limb, which essentially lets a person turn their thoughts into actions. These brain chips go over the scalp in a wearable device, get surgically placed under the scalp or even get implanted within brain tissue. The idea is that, the closer the chip is to the brain's neural network, the clearer, or "high definition," a signal can be interpreted. BCIs are often directed at researching, mapping, assisting, augmenting, or repairing human cognitive or sensory-motor functions. They are often conceptualized as a human–machine interface that skips the intermediary component of the physical movement of body parts, although they also raise the possibility of the erasure of the discreteness of brain and machine. Implementations of BCIs range from non-invasive (EEG, MEG, MRI) and partially invasive (ECoG and endovascular) to invasive (microelectrode array), based on how close electrodes get to brain tissue.

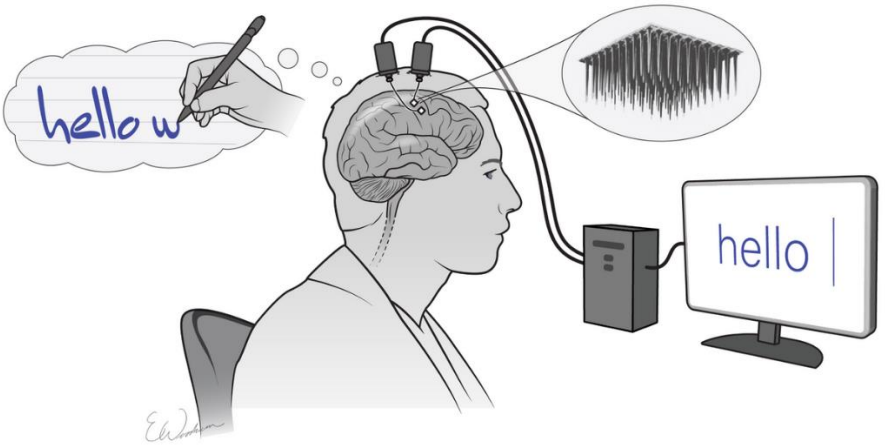


Figure 1.1 Brain computer interface

A brain-computer interface (BCI) is a device that lets the human brain communicate with and control external software or hardware, like a computer or robotic limb. Despite decades of research, many BCIs remain in the experimental phase, and their main application involves moving a cursor by thought. But the promise of this technology has scientists envisioning more

advanced purposes for BCIs. Patients with paralysis, muscle atrophy and other conditions could leverage BCIs to regain motor functions. Rehabilitation services could also adopt BCIs to accelerate patients' recovery from injuries.

Once a cyborgian sci-fi trope that turned into reality at the dawn of the 2000s, the possibilities of brain-computer interfaces continue to generate excitement. This has led to a $1.74 billion market that's expected to grow to $6.2 billion by the end of the decade. As healthtech research progresses and demand grows, start-ups are stepping up to pioneer the new wave of human-computer interaction. Ramses Alcaide, CEO of neurotech start-ups Neurable, which develops non-invasive brain-computer interfaces in the form of headphones, sees potential for BCI-enhanced devices to become an everyday item for the average person. "If we can make brain-computer interfaces accessible and seamless enough then they can be integrated into our daily lives, just as we use smartphones or laptops today," Alcaide told Built In. "But in order to truly become a ubiquitous tool, they need to be comfortable, intuitive and reliable enough that people can use them without consciously thinking about them — similar to how we use a mouse or keyboard to interact with a computer. "Research on BCIs began in the 1970s by Jacques Vidal at the University of California, Los Angeles (UCLA) under a grant from the National Science Foundation, followed by a contract from DARPA. Vidal's 1973 paper marks the first appearance of the expression brain–computer interface in scientific literature.

1. 1 How Do Brain-Computer Interfaces Work?

While brain-computer interfaces differ in type and approach, they are all modelled after the electrophysiology of a brain's neural network. When we make a decision or even think about making a decision — electrical chemical signals spark. This phenomenon is located in our nervous system; more specifically, in the gaps between neurons, known as synapses, as they communicate back and forth.

In order to capture this brain activity, BCIs place electrodes proximal to these conversations. These sensors detect voltages, measuring the frequency and intensity of each "spike" as they fire or potentially fire. "It's like a microphone; but in this case, we're listening to electrical activity instead of sound," said Craig Mermel, the president and chief product officer at Precision Neuroscience, a start-up developing a semi-invasive, reversible neural implant. "We're picking up the electrical chatter of the brain's neurons communicating with each other."

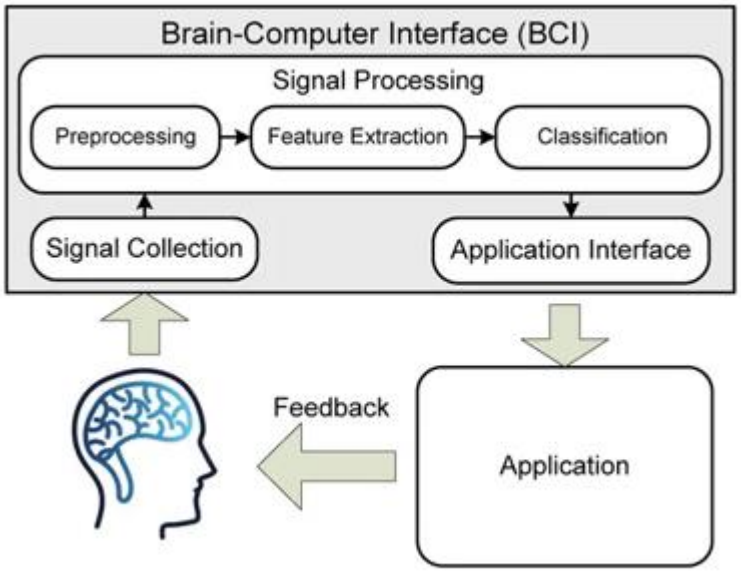


Figure 1.2 BCI Signal Processing

That information is then fed through local computer software, where it's translated in a process known as neural decoding. This is where a variety of machine learning algorithms and other artificial intelligence agents take over, converting complex data sets collected from brain activity into a programmable understanding of what the brain's intention might be.

1.2 History

The history of brain–computer interfaces (BCIs) starts with Hans Berger's discovery of the electrical activity of the human brain and the development of electroencephalography (EEG). In 1924 Berger was the first to record human brain activity by means of EEG. Berger was able to identify oscillatory activity, such as Berger's wave or the alpha wave (8–13 Hz), by analysing EEG traces. Berger's first recording device was very rudimentary. He inserted silver wires under the scalps of his patients. These were later replaced by silver foils attached to the patient's head by rubber bandages. Berger connected these sensors to a Lippmann capillary electrometer, with disappointing results. However, more sophisticated measuring devices, such as the Siemens double-coil recording galvanometer, which displayed electric voltages as small as one ten thousandth of a volt, led to success. Berger analysed the interrelation of alternations in his EEG wave diagrams with brain diseases. EEGs permitted completely new possibilities for the research of human brain activities.

Although the term had not yet been coined, one of the earliest examples of a working brain-machine interface was the piece Music for Solo Performer (1965) by the American

composer Alvin Lucier. The piece makes use of EEG and analog signal processing hardware (filters, amplifiers, and a mixing board) to stimulate acoustic percussion instruments. To perform the piece one must produce alpha waves and thereby "play" the various percussion instruments via loudspeakers which are placed near or directly on the instruments themselves.

UCLA Professor Jacques Vidal coined the term "BCI" and produced the first peer-reviewed publications on this topic. Vidal is widely recognized as the inventor of BCIs in the BCI community, as reflected in numerous peer-reviewed articles reviewing and discussing the field (e.g. A review pointed out that Vidal's 1973 paper stated the "BCI challenge" of controlling external objects using EEG signals, and especially use of Contingent Negative Variation (CNV) potential as a challenge for BCI control. The 1977 experiment Vidal described was the first application of BCI after his 1973 BCI challenge. It was a non-invasive EEG (actually Visual Evoked Potentials (VEP)) control of a cursor-like graphical object on a computer screen. The demonstration was movement in a maze. After his early contributions, Vidal was inactive in BCI research, and BCI events such as conferences, for many years. In 2011, however, he gave a lecture in Graz, Austria, supported by the Future BNCI project, presenting the first BCI, which earned a standing ovation. Vidal was joined by his wife, Laryce Vidal, who previously worked with him at UCLA on his first BCI project.

n 1990, a report was given on a closed loop, bidirectional adaptive BCI controlling computer buzzer by an anticipatory brain potential, the Contingent Negative Variation (CNV) potential.[19][20] The experiment described how an expectation state of the brain, manifested by CNV, controls in a feedback loop the S2 buzzer in the S1-S2-CNV paradigm. The obtained cognitive wave representing the expectation learning in the brain is named Electroexpectogram (EXG). The CNV brain potential was part of the BCI challenge presented by Vidal in his 1973 paper.

Studies in 2010s suggested the potential ability of neural stimulation to restore functional connectively and associated behaviours through modulation of molecular mechanisms of synaptic efficacy. This opened the door for the concept that BCI technologies may be able to restore function in addition to enabling functionality. Since 2013, DARPA has funded BCI technology through the BRAIN initiative, which has supported work out of the University of Pittsburgh Medical Center, Paradromics, Brown, and Synchron, among others.

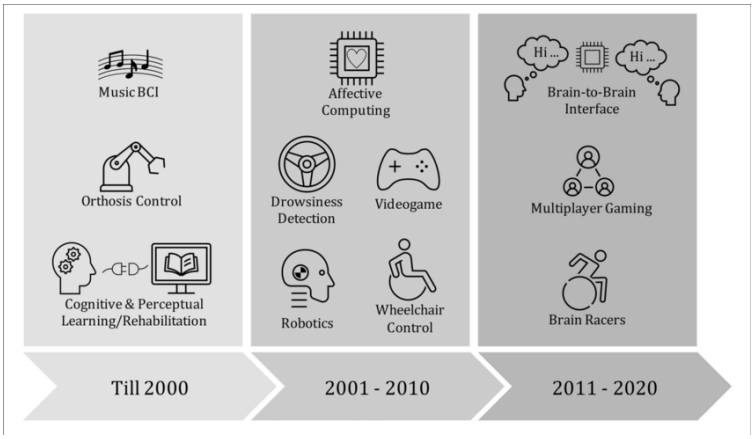


Figure 1.3 History of BCI

Versus neuroprosthetics

Neuroprosthetics is an area of neuroscience concerned with neural prostheses, that is, using artificial devices to replace the function of impaired nervous systems and brain-related problems, or of sensory organs or organs itself (bladder, diaphragm, etc.). As of December 2010, cochlear implants had been implanted as neuroprosthetic device in approximately 736,900 people worldwide. There are also several neuroprosthetic devices that aim to restore vision, including retinal implants. The first neuroprosthetic device, however, was the pacemaker.

The terms are sometimes used interchangeably. Neuroprosthetics and BCIs seek to achieve the same aims, such as restoring sight, hearing, movement, ability to communicate, and even cognitive function. Both use similar experimental methods and surgical techniques.

1.3 Animal BCI research

Several laboratories have managed to record signals from monkey and rat cerebral cortices to operate BCIs to produce movement. Monkeys have navigated computer cursors on screen and commanded robotic arms to perform simple tasks simply by thinking about the task and seeing the visual feedback, but without any motor output.[28] In May 2008 photographs that showed a monkey at the University of Pittsburgh Medical Center operating a robotic arm by thinking were published in a number of well-known science journals and magazines. Sheep too have been used to evaluate BCI technology including Synchron's Stentrode. In 2020, Elon Musk's Neuralink was successfully implanted in a pig, announced in a widely viewed webcast. In 2021, Elon Musk announced that he had successfully enabled a monkey to play video games using Neuralink's device.

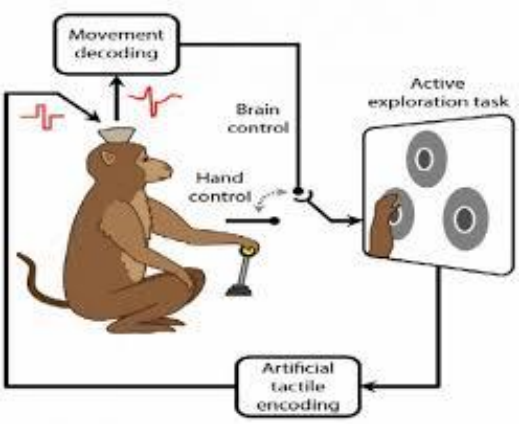


Figure 1.4 Rhesus monkey

1.4 Early work

In 1969 the operant conditioning studies of Fetz and colleagues, at the Regional Primate Research Center and Department of Physiology and Biophysics, University of Washington School of Medicine in Seattle, showed for the first time that monkeys could learn to control the deflection of a biofeedback meter arm with neural activity. Similar work in the 1970s established that monkeys could quickly learn to voluntarily control the firing rates of individual and multiple neurons in the primary motor cortex if they were rewarded for generating appropriate patterns of neural activity.

Studies that developed algorithms to reconstruct movements from motor cortex neurons, which control movement, date back to the 1970s. In the 1980s, Apostolos Georgopoulos at Johns Hopkins University found a mathematical relationship between the electrical responses of single motor cortex neurons in rhesus macaque monkeys and the direction in which they moved their arms (based on a cosine function). He also found that dispersed groups of neurons, in different areas of the monkey's brains, collectively controlled motor commands, but was able to record the firings of neurons in only one area at a time, because of the technical limitations imposed by his equipment.

There has been rapid development in BCIs since the mid-1990s. Several groups have been able to capture complex brain motor cortex signals by recording from neural ensembles (groups of neurons) and using these to control external devices.

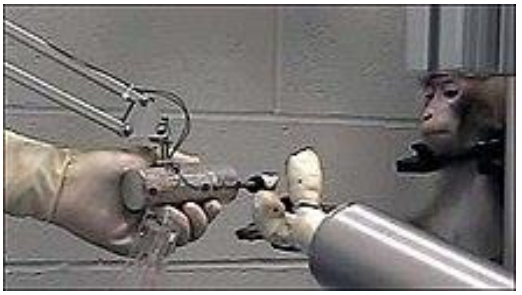


Figure 1.5 Monkey operating a robotic arm with brain–computer interfacing (Schwartz lab, University of Pittsburgh)

- **Kennedy and Yang Dan**

Phillip Kennedy (who later founded Neural Signals in 1987) and colleagues built the first intracortical brain–computer interface by implanting neurotrophic-cone electrodes into monkeys.

In 1999, researchers led by Yang Dan at the University of California, Berkeley decoded neuronal firings to reproduce images seen by cats. The team used an array of electrodes embedded in the thalamus (which integrates all of the brain's sensory input) of sharp-eyed cats. Researchers targeted 177 brain cells in the thalamus lateral geniculate nucleus area, which decodes signals from the retina. The cats were shown eight short movies, and their neuron firings were recorded. Using mathematical filters, the researchers decoded the signals to generate movies of what the cats saw and were able to reconstruct recognizable scenes and moving objects. Similar results in humans have since been achieved by researchers in Japan



Figure 1.6 Yang Dan and colleagues' recordings of cat vision using a BCI implanted in the lateral geniculate nucleus

- **Nicolelis**

Miguel Nicolelis, a professor at Duke University, in Durham, North Carolina, has been a prominent proponent of using multiple electrodes spread over a greater area of the brain to obtain neuronal signals to drive a BCI.

after conducting initial studies in rats during the 1990s, Nicolelis and his colleagues developed BCIs that decoded brain activity in owl monkeys and used the devices to reproduce monkey movements in robotic arms. Monkeys have advanced reaching and grasping abilities and good hand manipulation skills, making them ideal test subjects for this kind of work.

By 2000, the group succeeded in building a BCI that reproduced owl monkey movements while the monkey operated a joystick or reached for food.[37] The BCI operated in real time and could also control a separate robot remotely over Internet Protocol. But the monkeys could not see the arm moving and did not receive any feedback, a so-called open-loop BCI.

Later experiments by Nicolelis using rhesus monkeys succeeded in closing the feedback loop and reproduced monkey reaching and grasping movements in a robot arm. With their deeply cleft and furrowed brains, rhesus monkeys are considered to be better models for human neurophysiology than owl monkeys. The monkeys were trained to reach and grasp objects on a computer screen by manipulating a joystick while corresponding movements by a robot arm were hidden. The monkeys were later shown the robot directly and learned to control it by viewing its movements. The BCI used velocity predictions to control reaching movements and simultaneously predicted hand gripping force. In 2011 O'Doherty and colleagues showed a BCI with sensory feedback with rhesus monkeys. The monkey was brain controlling the position of an avatar arm while receiving sensory feedback through direct intracortical stimulation (ICMS) in the arm representation area of the sensory cortex.

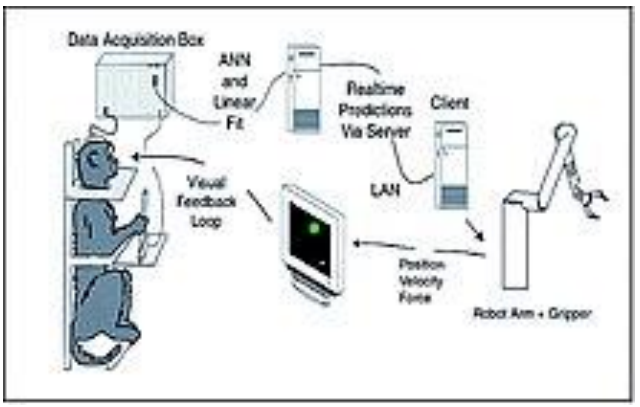


Figure 1.7. Diagram of the BCI developed by Miguel Nicolelis and colleagues for use on rhesus monkeys.

- ***Donoghue, Schwartz and Andersen***

Other laboratories which have developed BCIs and algorithms that decode neuron signals include the Carney Institute for Brain Science at Brown University and the labs of Andrew Schwartz at the University of Pittsburgh and Richard Andersen at Caltech. These researchers have been able to produce working BCIs, even using recorded signals from far fewer neurons than did Nicolelis (15–30 neurons versus 50–200 neurons).

John Donoghue's lab at the Carney Institute reported training rhesus monkeys to use a BCI to track visual targets on a computer screen (closed-loop BCI) with or without assistance of a joystick. Schwartz's group created a BCI for three-dimensional tracking in virtual reality and also reproduced BCI control in a robotic arm. The same group also created headlines when they demonstrated that a monkey could feed itself pieces of fruit and marshmallows using a robotic arm controlled by the animal's own brain signals.

Andersen's group used recordings of premovement activity from the posterior parietal cortex in their BCI, including signals created when experimental animals anticipated receiving a reward.



Figure 1.8 BCIs are a core focus of the Carney Institute for Brain Science at Brown University.

In addition to predicting kinematic and kinetic parameters of limb movements, BCIs that predict electromyographic or electrical activity of the muscles of primates are being developed. Such BCIs could be used to restore mobility in paralyzed limbs by electrically stimulating muscles.

Miguel Nicolelis and colleagues demonstrated that the activity of large neural ensembles can predict arm position. This work made possible creation of BCIs that read arm movement intentions and translate them into movements of artificial actuators. Carmena and colleagues programmed the neural coding in a BCI that allowed a monkey to control reaching and grasping movements by a robotic arm. Lebedev and colleagues argued that brain networks reorganize to create a new representation of the robotic appendage in addition to the representation of the animal's own limbs.

In 2019, researchers from UCSF published a study where they demonstrated a BCI that had the potential to help patients with speech impairment caused by neurological disorders. Their BCI used high-density electrocorticography to tap neural activity from a patient's brain and used deep learning methods to synthesize speech. In 2021, researchers from the same group published a study showing the potential of a BCI to decode words and sentences in an anarthric patient who had been unable to speak for over 15 years.

The biggest impediment to BCI technology at present is the lack of a sensor modality that provides safe, accurate and robust access to brain signals. It is conceivable or even likely, however, that such a sensor will be developed within the next twenty years. The use of such a sensor should greatly expand the range of communication functions that can be provided using a BCI.

Development and implementation of a BCI system is complex and time-consuming. In response to this problem, Gerwin Schalk has been developing a general-purpose system for BCI research, called BCI2000. BCI2000 has been in development since 2000 in a project led by the Brain–Computer Interface R&D Program at the Wadsworth Center of the New York State Department of Health in Albany, New York, United States.

A new 'wireless' approach uses light-gated ion channels such as Channelrhodopsin to control the activity of genetically defined subsets of neurons in vivo. In the context of a simple learning task, illumination of transfected cells in the somatosensory cortex influenced the decision-making process of freely moving mice.

The use of BMIs has also led to a deeper understanding of neural networks and the central nervous system. Research has shown that despite the inclination of neuroscientists to believe that neurons have the most effect when working together, single neurons can be conditioned through the use of BMIs to fire at a pattern that allows primates to control motor outputs. The use of BMIs has led to development of the single neuron insufficiency principle which states

that even with a well-tuned firing rate single neurons can only carry a narrow amount of information and therefore the highest level of accuracy is achieved by recording firings of the collective ensemble. Other principles discovered with the use of BMIs include the neuronal multitasking principle, the neuronal mass principle, the neural degeneracy principle, and the plasticity principle.[54]

BCIs are also proposed to be applied by users without disabilities. A user-centered categorization of BCI approaches by Thorsten O. Zander and Christian Kothe introduces the term passive BCI. Next to active and reactive BCI that are used for directed control, passive BCIs allow for assessing and interpreting changes in the user state during Human-Computer Interaction (HCI). In a secondary, implicit control loop the computer system adapts to its user improving its usability in general.

Beyond BCI systems that decode neural activity to drive external effectors, BCI systems may be used to encode signals from the periphery. These sensory BCI devices enable real-time, behaviourally-relevant decisions based upon closed-loop neural stimulation

- **The BCI Award**

The Annual BCI Research Award is awarded in recognition of outstanding and innovative research in the field of Brain-Computer Interfaces. Each year, a renowned research laboratory is asked to judge the submitted projects. The jury consists of world-leading BCI experts recruited by the awarding laboratory. The jury selects twelve nominees, then chooses a first, second, and third-place winner, who receive awards of $3,000, $2,000, and $1,000, respectively.

1.5 Invasive vs. Non-Invasive BCIs

Brain-computer interfaces come in two main types: invasive and non-invasive.

Invasive BCIs are directly connected to a patient's brain tissue and are implemented through surgical procedures. Because there are major risks that come with surgery, invasive BCIs are more appropriate for patients looking to recover from severe conditions like paralysis, injuries and neuromuscular disorders. The Intraparenchymal signal is taken directly implanting electrodes in the cortex.

Non-invasive BCIs involve wearing a device with electrical sensors that serve as two-way communication channels between a patient's brain and a machine. These types of brain-computer interfaces produce weaker signals since they're not directly connected to brain tissue.

As a result, non-invasive BCIs would be better suited for purposes like virtual gaming, augmented reality and guiding the actions of robots and other technologies. The EEG signal is taken placing electrodes on the scalp, so on the most external part.

Semi-invasive: the ECoG signal is taken from electrodes placed in the dura or in the arachnoid.

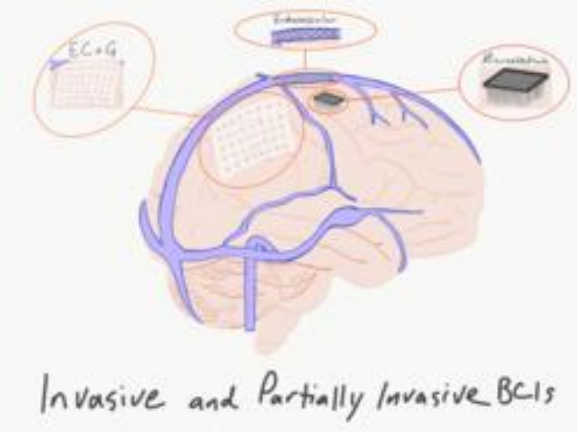


Figure 1.9 Illustration of invasive and partially invasive BCIs: electrocorticography (ECoG), endovascular, and intracortical microelectrode.

1.6 Human BCI research

1.6.1 Invasive BCIs

Invasive BCI requires surgery to implant electrodes under the scalp for communicating brain signals. The main advantage is to provide more accurate reading; however, its downside includes side effects from the surgery including scar tissue, which can make brain signals weaker. In addition, according to the research of Abdulkader (2015), the body may not accept the implanted electrodes and this can cause a medical condition. There are single unit BCIs, which detect the signal from a single area of brain cells, and multiunit BCIs which detect from multiple areas. Electrodes have different lengths, for example, up to 1.5 mm (Utah, Blackrock Microsystems) or 10 mm (FMA, MicroProbes) in a MEA. The quality of the signal is the highest, but the procedure has several problematics, as for example the risk of forming scar tissues. The body reacts to the foreign object and builds the scar around the electrodes, which cause deterioration in the signal. Because neurosurgery can be a risky and expensive process, the target of invasive BCI are mainly blind and paralyzed patients.

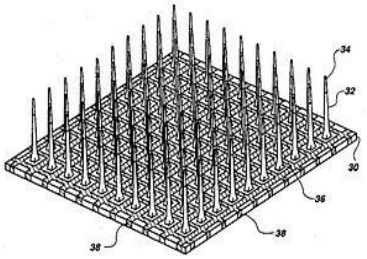


Figure 1.10 The micro-electrodes are placed directly into the cortex, measuring the activity of a single neuron.

1.6.1.1 Vision

Invasive BCI research has targeted repairing damaged sight and providing new functionality for people with paralysis. Invasive BCIs are implanted directly into the grey matter of the brain during neurosurgery. Because they lie in the grey matter, invasive devices produce the highest quality signals of BCI devices but are prone to scar-tissue build-up, causing the signal to become weaker, or even non-existent, as the body reacts to a foreign object in the brain.

In vision science, direct brain implants have been used to treat non-congenital (acquired) blindness. One of the first scientists to produce a working brain interface to restore sight was private researcher William Dobelle.

Dobelle's first prototype was implanted into "Jerry", a man blinded in adulthood, in 1978. A single-array BCI containing 68 electrodes was implanted onto Jerry's visual cortex and succeeded in producing phosphenes, the sensation of seeing light. The system included cameras mounted on glasses to send signals to the implant. Initially, the implant allowed Jerry to see shades of grey in a limited field of vision at a low frame-rate. This also required him to be hooked up to a mainframe computer, but shrinking electronics and faster computers made his artificial eye more portable and now enable him to perform simple tasks unassisted.

In 2002, Jens Naumann, also blinded in adulthood, became the first in a series of 16 paying patients to receive Dobelle's second generation implant, marking one of the earliest commercial uses of BCIs. The second-generation device used a more sophisticated implant enabling better mapping of phosphenes into coherent vision. Phosphenes are spread out across the visual field in what researchers call "the starry-night effect". Immediately after his implant, Jens was able to use his imperfectly restored vision to drive an automobile slowly around the parking area of the research institute. Unfortunately, Dobelle died in 2004 before his processes and developments were documented. Subsequently, when Mr. Naumann and the other patients in the program began having problems with their vision, there was no relief and they eventually

lost their "sight" again. Naumann wrote about his experience with Dobelle's work in Search for Paradise: A Patient's Account of the Artificial Vision Experiment and has returned to his farm in Southeast Ontario, Canada, to resume his normal activities.

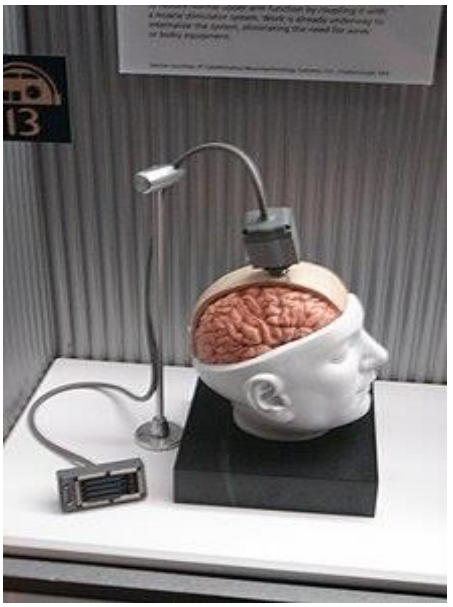


Fig 1.11 Dummy unit illustrating the design of a BrainGate interface

1.6.1.2 Movement

BCIs focusing on motor neuroprosthetics aim to either restore movement in individuals with paralysis or provide devices to assist them, such as interfaces with computers or robot arms.

Researchers at Emory University in Atlanta, led by Philip Kennedy and Roy Bakay, were first to install a brain implant in a human that produced signals of high enough quality to simulate movement. Their patient, Johnny Ray (1944–2002), developed 'locked-in syndrome' after having a brain-stem stroke in 1997. Ray's implant was installed in 1998 and he lived long enough to start working with the implant, eventually learning to control a computer cursor; he died in 2002 of a brain aneurysm.

Tetraplegic Matt Nagle became the first person to control an artificial hand using a BCI in 2005 as part of the first nine-month human trial of Cyberkinetics's BrainGate chip-implant. Implanted in Nagle's right precentral gyrus (area of the motor cortex for arm movement), the 96-electrode BrainGate implant allowed Nagle to control a robotic arm by thinking about moving his hand as well as a computer cursor, lights and TV. One year later, professor Jonathan Wolpaw received the prize of the Altran Foundation for Innovation to develop a Brain Computer Interface with electrodes located on the surface of the skull, instead of directly in the brain.

More recently, research teams led by the BrainGate group at Brown University and a group led by University of Pittsburgh Medical Center, both in collaborations with the United States Department of Veterans Affairs, have demonstrated further success in direct control of robotic prosthetic limbs with many degrees of freedom using direct connections to arrays of neurons in the motor cortex of patients with tetraplegia

1.6.1.3 Communication

In May 2021, a Stanford University team reported a successful proof-of-concept test that enabled a quadriplegic participant to input English sentences at about 86 characters per minute and 18 words per minute. The participant imagined moving his hand to write letters, and the system performed handwriting recognition on electrical signals detected in the motor cortex, utilizing hidden Markov models and recurrent neural networks for decoding.

A report published in July 2021 reported a paralyzed patient was able to communicate 15 words per minute using a brain implant that analysed motor neurons that previously controlled the vocal tract.

In a recent review article, researchers raised an open question of whether human information transfer rates can surpass that of language with BCIs. Given that recent language research has demonstrated that human information transfer rates are relatively constant across many languages, there may exist a limit at the level of information processing in the brain. On the contrary, this "upper limit" of information transfer rate may be intrinsic to language itself, as a modality for information transfer.

In 2023 two studies used BCIs with recurrent neural network to decode speech at a record rate of 62 words per minute and 78 words per minute

1.6.1.4 Technical challenges

There exist a number of technical challenges to recording brain activity with invasive BCIs. Advances in CMOS technology are pushing and enabling integrated, invasive BCI designs with smaller size, lower power requirements, and higher signal acquisition capabilities. Invasive BCIs involve electrodes that penetrate brain tissue in an attempt to record action potential signals (also known as spikes) from individual, or small groups of, neurons near the electrode. The interface between a recording electrode and the electrolytic solution surrounding neurons has been modelled using the Hodgkin-Huxley model.

Electronic limitations to invasive BCIs have been an active area of research in recent decades. While intracellular recordings of neurons reveal action potential voltages on the scale of hundreds of millivolts, chronic invasive BCIs rely on recording extracellular voltages which typically are three orders of magnitude smaller, existing at hundreds of microvolts. Further adding to the challenge of detecting signals on the scale of microvolts is the fact that the electrode-tissue interface has a high capacitance at small voltages. Due to the nature of these small signals, for BCI systems that incorporate functionality onto an integrated circuit, each electrode requires its own amplifier and ADC, which convert analog extracellular voltages into digital signals. Because a typical neuron action potential lasts for one millisecond, BCIs measuring spikes must have sampling rates ranging from 300 Hz to 5 kHz. Yet another concern is that invasive BCIs must be low-power, so as to dissipate less heat to surrounding tissue; at the most basic level more power is traditionally needed to optimize signal-to-noise ratio. Optimal battery design is an active area of research in BCIs.

Challenges existing in the area of material science are central to the design of invasive BCIs. Variations in signal quality over time have been commonly observed with implantable microelectrodes. Optimal material and mechanical characteristics for long term signal stability in invasive BCIs has been an active area of research. It has been proposed that the formation of glial scarring, secondary to damage at the electrode-tissue interface, is likely responsible for electrode failure and reduced recording performance. Research has suggested that blood-brain barrier leakage, either at the time of insertion or over time, may be responsible for the inflammatory and glial reaction to chronic microelectrodes implanted in the brain. As a result, flexible and tissue-like designs have been researched and developed to minimize foreign-body reaction by means of matching the Young's modulus of the electrode closer to that of brain tissue.

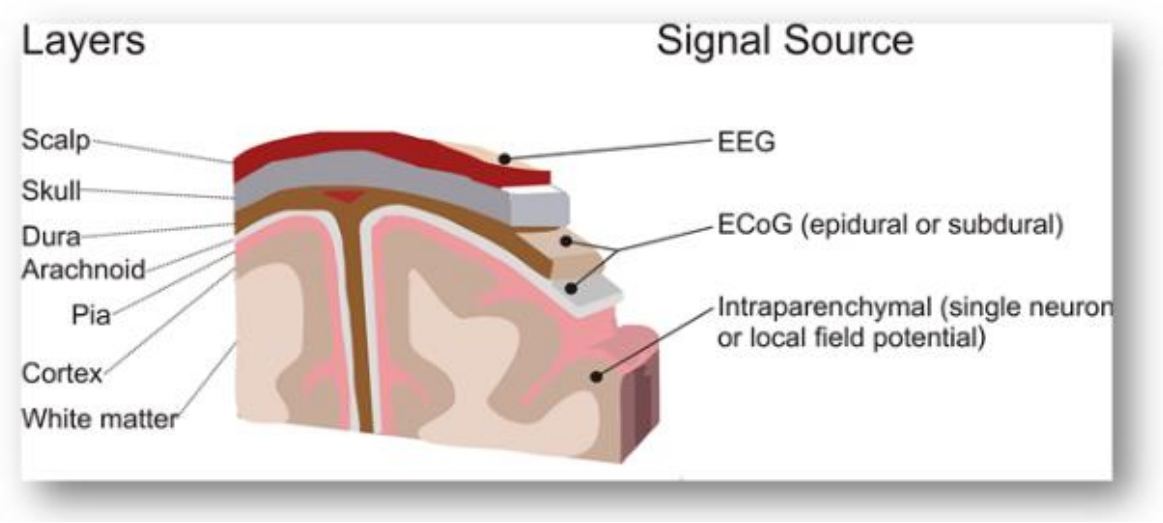


Figure 1.12 The following image shows the different layers of the brain and where the signal is taken from.

1.6.2 Partially invasive BCIs

Partially invasive BCI devices are implanted inside the skull but rest outside the brain rather than within the grey matter. They produce better resolution signals than non-invasive BCIs where the bone tissue of the cranium deflects and deforms signals and have a lower risk of forming scar-tissue in the brain than fully invasive BCIs. There has been preclinical demonstration of intracortical BCIs from the stroke perilesional cortex.

1.6.2.1 Endovascular

Endovascular surgery describes minimally invasive procedures to diagnose and treat vascular disease. In endovascular surgery, our vascular surgeons use catheters (long, thin, flexible tubes) to access arteries and veins. This allows them to diagnose and treat a variety of vascular conditions anywhere in the body.

Endovascular procedures are less invasive than traditional open surgical techniques and can offer benefits such as:

- No incisions
- Shorter hospital stay
- Less pain
- Lower risk of complications
- Shorter recovery time

A systematic review published in 2020 detailed multiple studies, both clinical and non-clinical, dating back decades investigating the feasibility of endovascular BCIs.

In recent years, the biggest advance in partially invasive BCIs has emerged in the area of interventional neurology. In 2010, researchers affiliated with University of Melbourne had begun developing a BCI that could be inserted via the vascular system. The Australian neurologist Thomas Oxley (Mount Sinai Hospital) conceived the idea for this BCI, called Stentrode, which has received funding from DARPA. Preclinical studies evaluated the technology in sheep.

The Stentrode, a monolithic stent electrode array, is designed to be delivered via an intravenous catheter under image-guidance to the superior sagittal sinus, in the region which lies adjacent to motor cortex. This proximity to motor cortex underlies the Stentrode's ability to measure neural activity. The procedure is most similar to how venous sinus stents are placed for the treatment of idiopathic intracranial hypertension.The Stentrode communicates neural activity to a battery-less telemetry unit implanted in the chest, which communicates wirelessly with an external telemetry unit capable of power and data transfer. While an endovascular BCI benefits from avoiding craniotomy for insertion, risks such as clotting and venous thrombosis are possible.

First-in-human trials with the Stentrode are underway. In November 2020, two participants with amyotrophic lateral sclerosis were able to wirelessly control an operating system to text, email, shop, and bank using direct thought through the Stentrode brain-computer interface, marking the first time a brain-computer interface was implanted via the patient's blood vessels, eliminating the need for open brain surgery. In January 2023, researchers reported no serious adverse events during the first year for all four patients who could use it to operate computers.

- **Conditions We Treat with Endovascular Surgery**

Our vascular specialists use endovascular procedures to treat a variety of conditions throughout the body, including:

- Conditions affecting the aorta (the body’s largest artery, which carries blood from the heart), such as aneurysms or dissection
- Cardiovascular diseases such as atherosclerosis, the build-up of cholesterol and other fats (plaque) inside artery walls that causes narrowed or blocked arteries

- Carotid artery disease: Narrowing or blockage of arteries that supply blood to the brain
- Chronic venous insufficiency: Damaged valves and/or weakened veins that are unable to efficiently send blood from limbs back to the heart
- Critical limb ischemia: Narrowing or blockage of arteries that carry blood to the arms or legs
- Deep vein thrombosis (DVT): Blood clots that develop in large, deep veins, usually in the legs
- Peripheral vascular disease: A complication of diabetes, caused by atherosclerosis in arteries that carry blood to the legs
- Pulmonary embolism: Blood clots that develop in leg or arm arteries and travel to the lung arteries
- Renal vascular disease, such as narrowing or blockage in arteries and veins of the kidneys
- Stroke: Partially or completely blocked blood flow to the brain, which can be caused by a blood clot blocking an artery or an artery that ruptures in the brain
- Tumours, both cancerous and noncancerous
- Varicose veins: Visibly enlarged, bulging veins, typically in the legs, that can cause leg swelling and other symptoms
- Vascular malformations: Clusters of abnormal, enlarged arteries, veins, or lymph vessels caused by hereditary disorders.

➢ **<u>Endovascular Surgery Techniques</u>**

Endovascular procedures use catheters to help diagnose and treat vascular and other conditions, sometimes during the same procedure. The doctor makes a small incision in the groin area to access a blood vessel and carefully threads a catheter into the vessel. The doctor then injects dye through the catheter to show the blood vessel on imaging.

Using imaging such as ultrasound or fluoroscopy (X-ray video), the doctor guides the catheter to the area for diagnosis or treatment. Medical instruments in the catheters enable the doctor to view the area in question and perform procedures such as widening arteries or removing blockages.

Our vascular surgeons and interventional radiologists offer the latest, minimally invasive techniques for endovascular surgery, such as:

- Ablation: Use of intense heat to seal off varicose veins
- Artery bypass: Use of a graft (plastic tube or section of blood vessel from the patient's body) to reroute blood flow around a section of blocked artery
- Balloon angioplasty and stenting: Inflation of a tiny balloon at the end of the catheter to open narrowed or blocked arteries, often with a stent (tiny wire mesh tube) that is implanted to keep the artery open
- Blood clot procedures: Removal of a large blood clot or injection of medications that dissolve the clot
- Carotid endarterectomy: Removal of plaque in neck arteries that carry blood to the brain
- Embolization: Use of medications or synthetic substances to block blood flow to a small, specific area to treat aneurysms, vascular malformations, or cancerous or noncancerous tumours
- Exclusion: Repair of an aneurysm by blocking off the weakened section of artery and rerouting blood flow
- Vena cava filter placement: Implantation of a filter in the vena cava, the body's largest vein, to prevent blood clots from getting into the lungs

1.6.2.2 ECoG

Electrocorticography (ECoG) measures the electrical activity of the brain taken from beneath the skull in a similar way to non-invasive electroencephalography, but the electrodes are embedded in a thin plastic pad that is placed above the cortex, beneath the dura mater. ECoG technologies were first trialled in humans in 2004 by Eric Leuthardt and Daniel Moran from Washington University in St. Louis. In a later trial, the researchers enabled a teenage boy to play Space Invaders using his ECoG implant. This research indicates that control is rapid, requires minimal training, and may be an ideal trade-off with regards to signal fidelity and level of invasiveness.

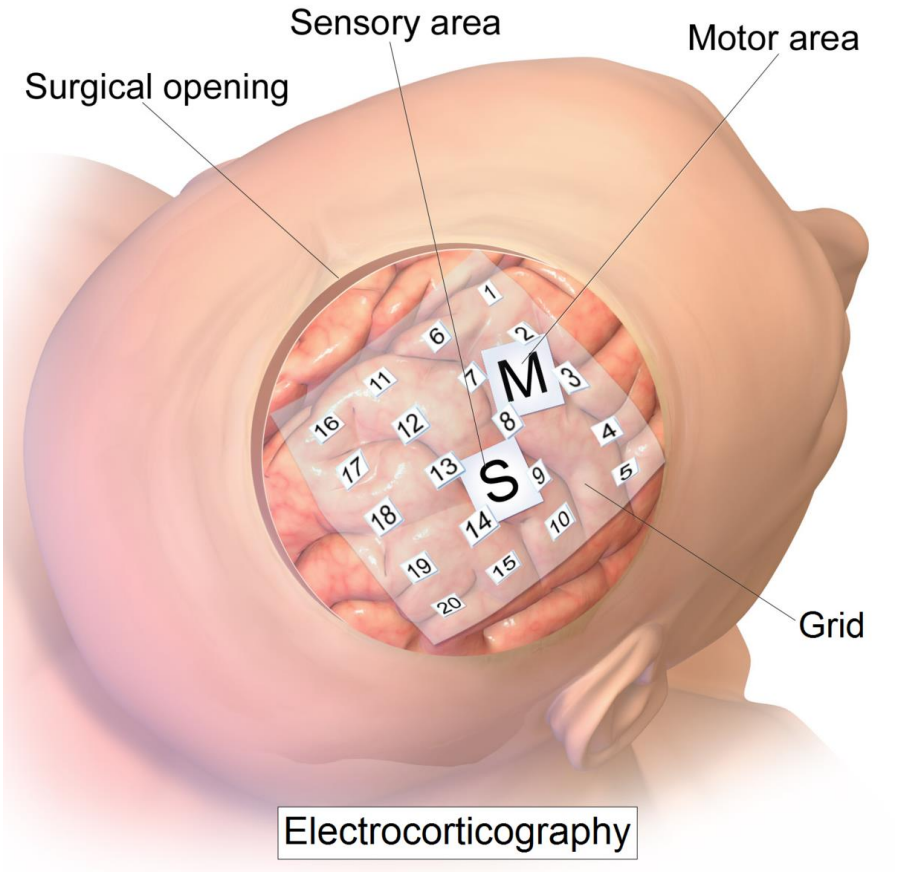


Figure 1.13 Electrocorticography

Electrocorticography uses electrodes placed on the exposed surface of the brain to measure electrical activity from the cerebral cortex. It has been used for the first time in the 1950s at the Montreal Neurological Institute. It is called semi-invasive but it still requires a craniotomy to implant the electrodes. For this reason, it is used only when surgery is necessary for medical reasons (epilepsy for example).

The electrodes may be placed outside the dura mater (epidural) or under the dura mater (subdural). The strip or grid electrodes covers a large area of the cortex (from 4 to 256 electrodes), allowing a diverse range of cognitive studies.

Signals can be either subdural or epidural, but are not taken from within the brain parenchyma itself. It has not been studied extensively until recently due to the limited access of subjects. Currently, the only manner to acquire the signal for study is through the use of patients requiring invasive monitoring for localization and resection of an epileptogenic focus.

ECoG is a very promising intermediate BCI modality because it has higher spatial resolution, better signal-to-noise ratio, wider frequency range, and less training requirements than scalp-

recorded EEG, and at the same time has lower technical difficulty, lower clinical risk, and may have superior long-term stability than intracortical single-neuron recording. This feature profile and recent evidence of the high level of control with minimal training requirements shows potential for real world application for people with motor disabilities. Light reactive imaging BCI devices are still in the realm of theory.

Recent work published by Edward Chang and Joseph Makin from UCSF revealed that ECoG signals could be used to decode speech from epilepsy patients implanted with high-density ECoG arrays over the peri-Sylvian cortices. Their study achieved word error rates of 3% (a marked improvement from prior publications) utilizing an encoder-decoder neural network, which translated ECoG data into one of fifty sentences composed of 250 unique words.

The positive characteristics of ECoG are:

- high spatial resolution and signal fidelity
- resistance to noise
- lower clinical risk and Robustness over long recording period
- higher amplitude

Spatial resolution

A benefit of the ECoG over EEG, is that the spatial resolution is much higher because the signal doesn't have to travel to reach the scalp. The spatial resolution in ECoG is tenths of milli-meters, while it is centi-meters in EEG

Resistance to noise

ECoG signal is not impacted by noise and artifacts as for example EMG (electromyographic - caused by muscles movements) and EOG (electrooculographic - caused by eyes movements)

Lower clinical risk

The electrode arrays don't need to penetrate into the cortex, which makes it safer than invasive recording

Higher amplitude

ECoG recordings are 50–100 μV maximum versus 10–20 μV

1.6.3 Non-invasive BCIs

- MEG magnetoencephalography

- PET positron emission tomography
- fMRI functional magnetic resonance imaging
- fNIRS near-infrared spectroscopy
- EEG Electroencephalography

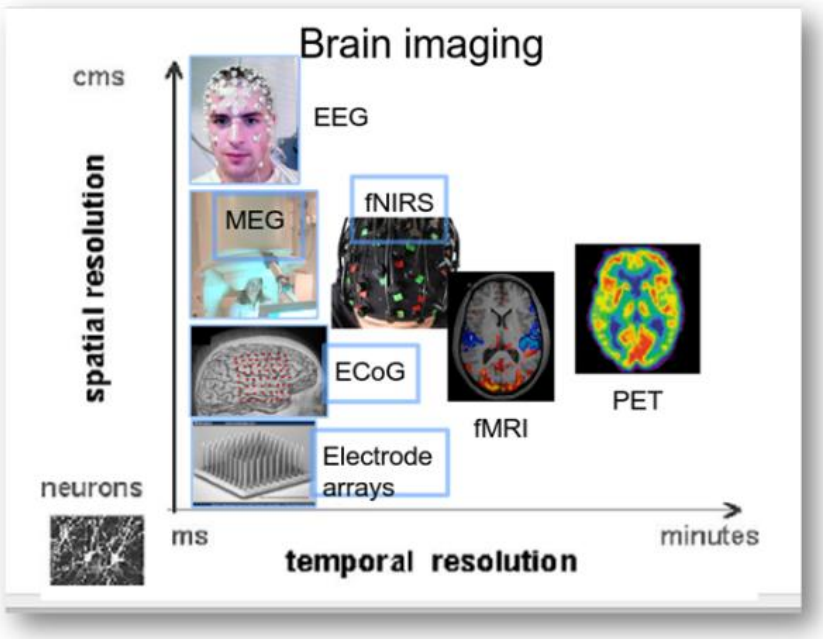


Figure 1.14 Different brain imaging techniques, compared by spatial and temporal resolution

There have also been experiments in humans using non-invasive neuroimaging technologies as interfaces. The substantial majority of published BCI work involves non-invasive EEG-based BCIs. Non-invasive EEG-based technologies and interfaces have been used for a much broader variety of applications. Although EEG-based interfaces are easy to wear and do not require surgery, they have relatively poor spatial resolution and cannot effectively use higher-frequency signals because the skull dampens signals, dispersing and blurring the electromagnetic waves created by the neurons. EEG-based interfaces also require some time and effort prior to each usage session, whereas non-EEG-based ones, as well as invasive ones require no prior-usage training. Overall, the best BCI for each user depends on numerous factors.

A non-invasive brain-computer interface (BCI) is a device that allows users to send messages or commands to devices, friends, family, or others through direct, non-invasive measures of brain activity. Non-invasive BCIs record information from sensors placed on or very close to the head. No surgery is required to implant recording devices, and non-invasive BCIs do not use any painful or hazardous methods.



Figure 1.15 The sensors are placed on the scalp to measure the electrical potentials produced by the brain (EEG) or the magnetic field (MEG).

1.6.3.1 Functional near-infrared spectroscopy

In 2014 and 2017, a BCI using functional near-infrared spectroscopy for "locked-in" patients with amyotrophic lateral sclerosis (ALS) was able to restore some basic ability of the patients to communicate with other people.

Functional Near-Infrared Spectroscopy (fNIR or fNIRS), is the use of NIRS (near-infrared spectroscopy) for the purpose of functional neuroimaging. Using fNIR, brain activity is measured through hemodynamic responses associated with neuron behaviour. An optical technique to measure localized cortical brain activity.

How does it work?

fNIRS measures the changes in blood flow as fMRI, but using a different technique, infrared light vs magnetic field.

When a task begins there is consumption of oxygen, as the complexity increases, also the request for oxygen increases. fMRI measures how much oxygen is consumed. fNIRS measures also how much oxygen is available in the area (overshot).

Still, the temporal quality of fNIRS is not as good as EEG. fNIRS takes 10 samples per second, which is trumped by EEG's 500 to 1000 samples per second. And the spatial resolution is not as good as fMRI. For example, fMRI can image subcortical brain regions, while fNIRS cannot analyse past the cortex, unable to capture any subcortical activation. Indeed, many researchers who presented their fNIRS at SfN are using the instrument as a supplement to their EEG or fMRI data.

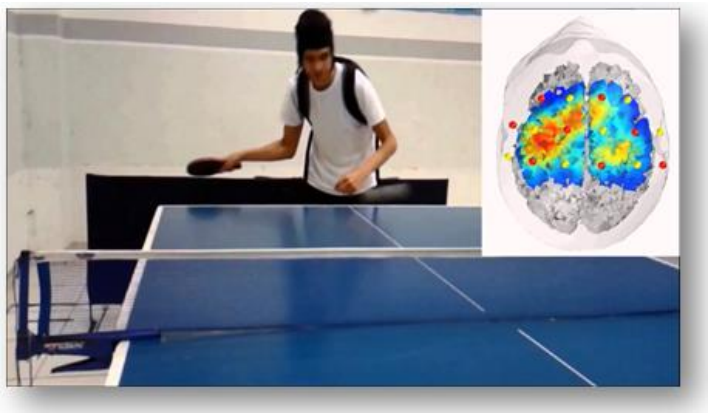


Figure 1.16 NIRS during table-tennis experiment

Benefits:

- Non-invasive
- Portable
- Accessible
- Less sensible to artifacts compared to fMRI and EEG

Has a temporal resolution more similar to EEG fMRI may record one sample per 2 seconds, fNIRS can record 10 samples per 1 second. fNIRS better spatial resolution than EEG and better temporal resolution than fMRI.

1.6.3.2 Electroencephalography (EEG)-based brain-computer interfaces

After the BCI challenge was stated by Vidal in 1973, the initial reports on non-invasive approach included control of a cursor in 2D using VEP (Vidal 1977), control of a buzzer using CNV (Bozinovska et al. 1988, 1990), control of a physical object, a robot, using a brain rhythm (alpha) (Bozinovski et al. 1988), control of a text written on a screen using P300 (Farwell and Donchin, 1988).

EEG provides the recording of electrical activity of the brain from the surface of the scalp.

How does it work?

Electrodes are placed on the scalp to pick-up the electrical current generated by the brain.

When firing, a neuron forms a dipole, with a lower voltage at synapses and higher voltage at the axon. If it's an inhibitory neuron, the dipole is flipped, with lower voltage at axon and higher voltage at the synapses. What causes this voltage shift inside a neuron? Na+ channels open on along the dendrite, causing a flood of positive electrons, this positive charge moves

down the axon, opening more sodium channels, and causing an electric charge to carry down the axon, discharging at the synapse, releasing neurotransmitters along with it. When groups of neurons fire together, they provide enough signal for us to measure from the scalp. We *only* able to measure clusters of neurons using EEG (about the size of a quarter in diameter).

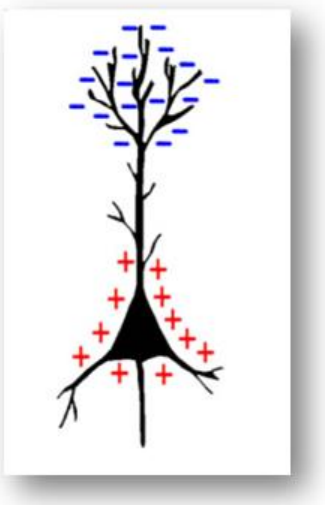


Figure 1.17 Neuron

Advantages: It is portable, it can fit into a small suitcase (vs MEG which requires special built rooms). Lab grade EEG systems may be expensive, but they are cheaper than other BCI methods. In recent years an increasing number of commercial EEG systems have been released.

EEG data contains rhythmic activity, which reflects neural oscillations. Oscillations are described by frequency, power and phase. Oscillations occur at specific frequencies (i.e., at a certain rate). These include delta, theta, alpha, meta, and gamma. Research has found associations between these rhythms and different brain states. For example, commercial EEG headsets - often used for purposes such as meditation - typically measure the amount of brain activity that occurs in the alpha frequency.

- **Spatial resolution**

The spatial resolution of EEG is determined by the number of electrodes used. In research, when higher spatial resolution is desired, typically at least 32 electrodes are used, up to 256. In general, spatial resolution for EEG is low (e.g., compared to ECoG and fMRI) because the signal needs to travel through different layers up to the skull. The resolution, however, can be improved using certain types of filters or by combining EEG with other tools (e.g., fMRI). (image of the electrodes placement)

More electrodes cost more in time (e.g., setup), bandwidth (for data collection and analysis), and money (for material). Commercial headsets often use fewer electrodes because high spatial resolution (i.e., localizing the precise brain regions generating a signal) is not necessarily needed.

“The spatial precision of EEG is fairly low but can be improved by spatial filters such as the surface Laplacian or adaptive source-space-imaging techniques”

Also, spatial accuracy is low, because the activity registered by an electrode is the mixture of different signals generated by different brain regions, close and distant from the one placed under the electrode. Microscopic scale (less than a few cubic milli-meters) = invisible to EEG, potentials are not powerful enough to reach the scalp. Mesoscopic scale (patches of cortex of several cubic milli-meters to a few cubic centi-meters) = can be detected with EEG but using more than 64 electrodes and spatial filtering techniques. Macroscopic scale (large region of cortex of many cubic centi-meters) = easily measurable with EEG.

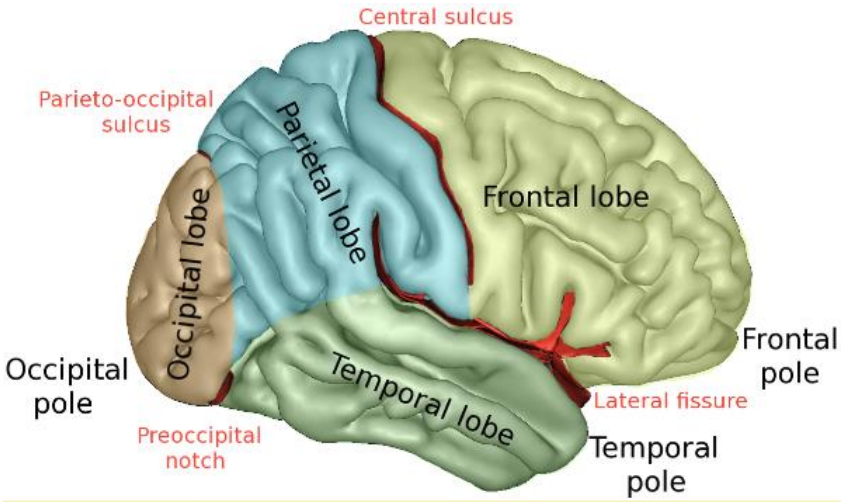


Figure 1.18 Brain lobes

- **Time resolution**

EEG benefit is its excellent time resolution. It is possible to take thousands of snapshots of electrical activity across different sensors in a single second. In EEG is possible to use multiple electrodes, up to 500, based on the experiment. They are used mounted on caps to allow collecting the data from the same scalp region.

- **<u>Comparison</u>**

BCI can use any type of brain imaging. These include fMRI, PET, and NIRS, which rely on changes in blood flow (i.e., hemodynamic response), and MEG and EEG, which measure the

brain's magnetic and electrical activity, respectively. While the spatial resolution of fMRI and NIRS are high, they have poor temporal resolution; MEG and PET have high spatial and temporal resolution; EEG has low spatial but high temporal resolution. Currently, fMRI and MEG rely on expensive, bulky equipment; PET requires the injection of a radioactive substance into the bloodstream. Thus, methods relying on NIRS and, in particular, EEG, are most commonly used.

In the early days of BCI research, another substantial barrier to using electroencephalography (EEG) as a brain–computer interface was the extensive training required before users can work the technology. For example, in experiments beginning in the mid-1990s, Niels Birbaumer at the University of Tübingen in Germany trained severely paralysed people to self-regulate the slow cortical potentials in their EEG to such an extent that these signals could be used as a binary signal to control a computer cursor. (Birbaumer had earlier trained epileptics to prevent impending fits by controlling this low voltage wave.) The experiment saw ten patients trained to move a computer cursor by controlling their brainwaves. The process was slow, requiring more than an hour for patients to write 100 characters with the cursor, while training often took many months. However, the slow cortical potential approach to BCIs has not been used in several years, since other approaches require little or no training, are faster and more accurate, and work for a greater proportion of users.

Another research parameter is the type of oscillatory activity that is measured. Gert Pfurtscheller founded the BCI Lab 1991 and fed his research results on motor imagery in the first online BCI based on oscillatory features and classifiers. Together with Birbaumer and Jonathan Wolpaw at New York State University they focused on developing technology that would allow users to choose the brain signals they found easiest to operate a BCI, including mu and beta rhythms.

A further parameter is the method of feedback used and this is shown in studies of P300 signals. Patterns of P300 waves are generated involuntarily (stimulus-feedback) when people see something they recognize and may allow BCIs to decode categories of thoughts without training patients first. By contrast, the biofeedback methods described above require learning to control brainwaves so the resulting brain activity can be detected.

In 2005 it was reported research on EEG emulation of digital control circuits for BCI, with example of a CNV flip-flop. In 2009 it was reported non-invasive EEG control of a robotic arm using a CNV flip-flop. In 2011 it was reported control of two robotic arms solving Tower

of Hanoi task with three disks using a CNV flip-flop. In 2015 it was described EEG-emulation of a Schmitt trigger, flip-flop, demultiplexer, and modem.

While an EEG based brain-computer interface has been pursued extensively by a number of research labs, recent advancements made by Bin He and his team at the University of Minnesota suggest the potential of an EEG based brain-computer interface to accomplish tasks close to invasive brain-computer interface. Using advanced functional neuroimaging including BOLD functional MRI and EEG source imaging, Bin He and co-workers identified the co-variation and co-localization of electrophysiological and hemodynamic signals induced by motor imagination. Refined by a neuroimaging approach and by a training protocol, Bin He and co-workers demonstrated the ability of a non-invasive EEG based brain-computer interface to control the flight of a virtual helicopter in 3-dimensional space, based upon motor imagination. In June 2013 it was announced that Bin He had developed the technique to enable a remote-control helicopter to be guided through an obstacle course.

In addition to a brain-computer interface based on brain waves, as recorded from scalp EEG electrodes, Bin He and co-workers explored a virtual EEG signal-based brain-computer interface by first solving the EEG inverse problem and then used the resulting virtual EEG for brain-computer interface tasks. Well-controlled studies suggested the merits of such a source analysis-based brain-computer interface.

A 2014 study found that severely motor-impaired patients could communicate faster and more reliably with non-invasive EEG BCI, than with any muscle-based communication channel.

A 2016 study found that the Emotiv EPOC device may be more suitable for control tasks using the attention/meditation level or eye blinking than the Neurosky MindWave device.

A 2019 study found that the application of evolutionary algorithms could improve EEG mental state classification with a non-invasive Muse device, enabling high quality classification of data acquired by a cheap consumer-grade EEG sensing device.

In a 2021 systematic review of randomized controlled trials using BCI for upper-limb rehabilitation after stroke, EEG-based BCI was found to have significant efficacy in improving upper-limb motor function compared to control therapies. More specifically, BCI studies that utilized band power features, motor imagery, and functional electrical stimulation in their design were found to be more efficacious than alternatives. Another 2021 systematic review focused on robotic-assisted EEG-based BCI for hand rehabilitation after stroke. Improvement

in motor assessment scores was observed in three of eleven studies included in the systematic review.



Figure 1.19 Recordings of brainwaves produced by an electroencephalogram

➢ Signal acquisition

In the case of EEG-BCI, the electric potential of the brain activity is measured through electrodes placed on the scalp. Electrodes are metal discs placed on the scalp in positions measured using the International 10/20 system.

There are two main types of electrodes:

Wet - using saline solution of gel. Conductivity is increased because the electrical distance is minimized. The majority are made of stainless steel, tin, gold or silver and which are covered with a silver chloride coating.



Figure 1.20 In the image, gold coated EEG electrodes

Dry - more convenient and easier to use, but can lose higher frequencies

EEG is reliable for real-time applications as it can take measurements every thousandth of a second. EEG problem is noise. Being the electrodes placed on the scalp, there are layers in between, plus background noise and muscles.

HOW EEG ACQUISITION WORKS?

EEG measures the electric activity happening in the brain. What is recorded is the voltage difference between minimum 2 electrodes. The EEG needs to be recorded simultaneously from multiple electrodes, in order to interpret ERP. During synaptic excitation of the dendrites in the neurons, electric currents are generated and picked up by the EEG. Because the signal detected is poor, being the electrodes far from the neurons and having the signal to travel through bones and skull, to record the electric flow is then required an amplifier.

What is needed?

- Electrodes - usually made of silver chloride
- Amplifiers
- A/D converters
- Recording Device

The electrodes acquire the signal from the scalp, the amplifiers process the analog signal to enlarge the amplitude of the EEG signals so that the A/D converter can digitalize the signal in a more accurate way. Finally, the recording device, which may be a personal computer or similar, stores, and displays the data.

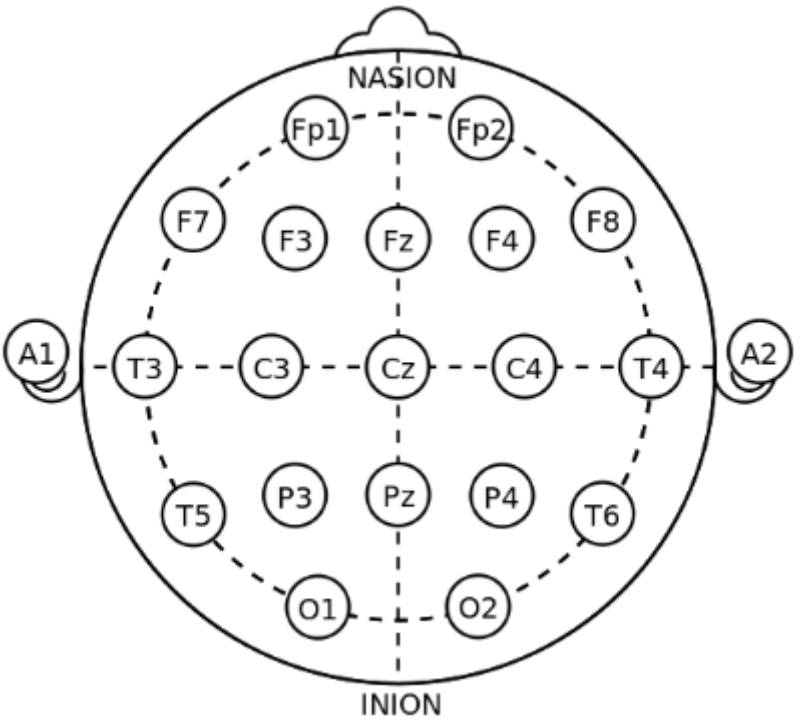


Figure 1.21 electrode locations of International 10-20 system for EEG (electroencephalography) recording

- **Amplifier**

The signal picked up by the electrodes is far away and attenuated by the different layers it has to travel. For this reason, an amplifier is needed to bring the microvolts to a range that can be digitized. The signal is sent to an amplifier through a cable measuring 1-2 metres. Unfortunately, the cables can act as antenna and pickup signals, which would interfere with the EEG signal and cause noise to be amplified. Some active electrodes include a small pre-amplifier within the electrode, to avoid this noise interference. Unfortunately, they are quite large and expensive and might not be appropriate in some situations.

- **A/D converters**

The A/D converter will convert the amplified signal from analog to digital form. The bandwidth for EEG signals is limited to approximately 100Hz, making 200Hz enough for sampling EEG signals.

- **Recording device**

It can be a computer or similar device, which will record, store and display the converted signal.

- **Pre-processing**

The raw EEG data is often not clean because affected by noise and artifacts. There are four main sources of noise and artifacts, which are:

1. EEG equipment
2. Electrical interference external to the subject and recording system
3. The leads and electrodes
4. The subject: electrical activity from the heart, eye blinking, eyeball movements, muscles movements in general.

Eye blinking are very clear in frontal and occipital recordings, while ECGs (from the heart electrical activity) on the occipital electrodes. "A movement of the eyeball and the eyelids causes a change in the potential field because of the existing potential difference of about 100mV between the cornea and the retina"

The pre-processing step helps to clean the data from the noise and artifacts. There are different methods and different steps in pre-processing. Often for example, filters are applied to the data. To remove the DC components of the signal and the drifts are employed high-pass filters, where usually a frequency cut-off of 1Hz is enough. Often also low pass filters can be applied to remove the high frequencies of the signal, because in EEG usually frequencies over 90Hz are not studied. Other methods are used to remove artefacts as the eyeball movements or eye blinking.

After different steps of pre-processing, when the signal is clean from most of the artifacts and noise, the recording is cut in epoch of few seconds: this allows us to have a large number of features from a single EEG recording, and to use them for statistics or to apply classifiers, as we will see in the next sections.

- **Feature Extraction**

The next step is feature extraction: the analysis of the signal and extraction of information. As the EEG signal is very complex, it is impossible to find meaningful information just looking at it. It is needed then to apply processing algorithms which allows to find content (such as a person's intent, for example) which would be hidden at a naked eye. There are many methods for feature extraction, some of them are: Band powers (BP) Cross-correlation between EEG band powers frequency representation (FR) time-frequency representation (TFR) Hjorth parameters, parametric modelling inverse model and specific techniques used for P300 and VEP such as Peak picking (PP) and Slow cortical potentials calculation (SCPs)

- **Classification**

Another step which can be applied to the signal, now mostly clean from artifacts, is to apply classification algorithms. Using machine learning techniques, it is possible to train a classifier to recognize which features, for example, belongs to one or another class mathematical Again, the classification helps to find out which kind of mental task the subject is performing (Ochoa, 2002)

- **Translation**

After the signal has been classified, the result is passed to the feature translation algorithm. At this point the features need to be translated in the corresponding action required. “For example, a P3 potential could be translated into the selection of the letter that evoked it” So, in this case, the algorithm will send a command to the feedback device, to select the letter.

- **Feedback device**

The feedback device receives the command from the translation step. For example, it can be the computer, where the signal will be used to move a cursor, or it could be a robotic arm where the data are used to allow movement.

1.6.3.3 PET (Positron emission tomography)

PET is a nuclear imaging technique used in medicine to observe different processes, such as blood flow, metabolism, neurotransmitters, happening in the body.

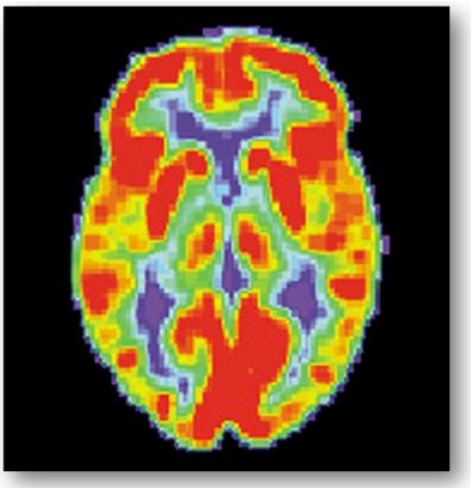


Figure 1.22 PET scan of a normal human brain

How does it work?

A small amount of radioactive material, called radiotracer, is injected in the bloodstream to reach the brain. In the case of the brain, the radiotracer get attached to the glucose and creates a radionuclide called fluorodeoxyglucose (FDG). The brain uses glucose and it will show different levels based on the level activity of the different regions. The images of the PET scan are multicoloured, where areas with more activities are in warmer colours as yellow and red. PET scans of the brain are used often to detect illnesses as cancer or others.



Figure 1.23 This image shows a picture taken from a typical PET facility equipped with an ECAT Exact HR+ PET scanner. PET scanners such as this are steadily being replaced by systems that combine both PET and CT scanners into a single PET/CT imaging device.

1.6.3.4 Dry active electrode arrays

In the early 1990s Babak Taheri, at University of California, Davis demonstrated the first single and also multichannel dry active electrode arrays using micro-machining. The single channel dry EEG electrode construction and results were published in 1994. The arrayed electrode was also demonstrated to perform well compared to silver/silver chloride electrodes. The device consisted of four sites of sensors with integrated electronics to reduce noise by impedance matching.

The advantages of such electrodes are:

(1) no electrolyte used,

(2) no skin preparation,

(3) significantly reduced sensor size, and

(4) compatibility with EEG monitoring systems.

The active electrode array is an integrated system made of an array of capacitive sensors with local integrated circuitry housed in a package with batteries to power the circuitry. This level of integration was required to achieve the functional performance obtained by the electrode.

The electrode was tested on an electrical test bench and on human subjects in four modalities of EEG activity, namely:

(1) spontaneous EEG,

(2) sensory event-related potentials,

(3) brain stem potentials, and

(4) cognitive event-related potentials.

The performance of the dry electrode compared favourably with that of the standard wet electrodes in terms of skin preparation, no gel requirements (dry), and higher signal-to-noise ratio.

In 1999 researchers at Case Western Reserve University, in Cleveland, Ohio, led by Hunter Peckham, used 64-electrode EEG skullcap to return limited hand movements to quadriplegic Jim Jatich. As Jatich concentrated on simple but opposite concepts like up and down, his beta-rhythm EEG output was analysed using software to identify patterns in the noise. A basic pattern was identified and used to control a switch: Above average activity was set to on, below average off. As well as enabling Jatich to control a computer cursor the signals were also used to drive the nerve controllers embedded in his hands, restoring some movement

1.6.3.5 SSVEP mobile EEG BCIs

In 2009, the NCTU Brain-Computer-Interface-headband was reported. The researchers who developed this BCI-headband also engineered silicon-based micro electro-mechanical system (MEMS) dry electrodes designed for application in non-hairy sites of the body. These electrodes were secured to the DAQ board in the headband with snap-on electrode holders. The signal processing module measured alpha activity and the Bluetooth enabled phone assessed the patients' alertness and capacity for cognitive performance. When the subject became drowsy, the phone sent arousing feedback to the operator to rouse them. This research

was supported by the National Science Council, Taiwan, R.O.C., NSC, National Chiao-Tung University, Taiwan's Ministry of Education, and the U.S. Army Research Laboratory.

In 2011, researchers reported a cellular based BCI with the capability of taking EEG data and converting it into a command to cause the phone to ring. This research was supported in part by Abraxis Bioscience LLP, the U.S. Army Research Laboratory, and the Army Research Office. The developed technology was a wearable system composed of a four channel bio-signal acquisition/amplification module, a wireless transmission module, and a Bluetooth enabled cell phone. The electrodes were placed so that they pick up steady state visual evoked potentials (SSVEPs). SSVEPs are electrical responses to flickering visual stimuli with repetition rates over 6 Hz that are best found in the parietal and occipital scalp regions of the visual cortex. It was reported that with this BCI setup, all study participants were able to initiate the phone call with minimal practice in natural environments.

The scientists claim that their studies using a single channel fast Fourier transform (FFT) and multiple channel system canonical correlation analysis (CCA) algorithm support the capacity of mobile BCIs. The CCA algorithm has been applied in other experiments investigating BCIs with claimed high performance in accuracy as well as speed. While the cellular based BCI technology was developed to initiate a phone call from SSVEPs, the researchers said that it can be translated for other applications, such as picking up sensorimotor mu/beta rhythms to function as a motor-imagery based BCI.[125]

In 2013, comparative tests were performed on android cell phone, tablet, and computer based BCIs, analysing the power spectrum density of resultant EEG SSVEPs. The stated goals of this study, which involved scientists supported in part by the U.S. Army Research Laboratory, were to "increase the practicability, portability, and ubiquity of an SSVEP-based BCI, for daily use". Citation It was reported that the stimulation frequency on all mediums was accurate, although the cell phone's signal demonstrated some instability. The amplitudes of the SSVEPs for the laptop and tablet were also reported to be larger than those of the cell phone. These two qualitative characterizations were suggested as indicators of the feasibility of using a mobile stimulus BCI.

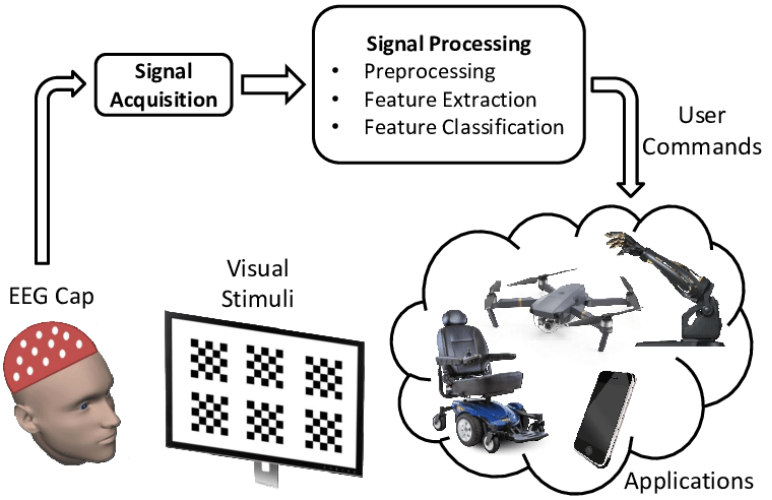


Figure 1.24 SSVEP

➢ Limitations

In 2011, researchers stated that continued work should address ease of use, performance robustness, reducing hardware and software costs.

One of the difficulties with EEG readings is the large susceptibility to motion artifacts. In most of the previously described research projects, the participants were asked to sit still, reducing head and eye movements as much as possible, and measurements were taken in a laboratory setting. However, since the emphasized application of these initiatives had been in creating a mobile device for daily use, the technology had to be tested in motion.

In 2013, researchers tested mobile EEG-based BCI technology, measuring SSVEPs from participants as they walked on a treadmill at varying speeds. This research was supported by the Office of Naval Research, Army Research Office, and the U.S. Army Research Laboratory. Stated results were that as speed increased the SSVEP detectability using CCA decreased. As independent component analysis (ICA) had been shown to be efficient in separating EEG signals from noise, the scientists applied ICA to CCA extracted EEG data. They stated that the CCA data with and without ICA processing were similar. Thus, they concluded that CCA independently demonstrated a robustness to motion artifacts that indicates it may be a beneficial algorithm to apply to BCIs used in real world conditions. One of the major problems in EEG-based BCI applications is the low spatial resolution. Several solutions have been suggested to address this issue since 2019, which include: EEG source connectivity based on graph theory, EEG pattern recognition based on Topomap, EEG-fMRI fusion, and so on.

- **Prosthesis and environment control**

Non-invasive BCIs have also been applied to enable brain-control of prosthetic upper and lower extremity devices in people with paralysis. For example, Gert Pfurtscheller of Graz University of Technology and colleagues demonstrated a BCI-controlled functional electrical stimulation system to restore upper extremity movements in a person with tetraplegia due to spinal cord injury. Between 2012 and 2013, researchers at the University of California, Irvine demonstrated for the first time that it is possible to use BCI technology to restore brain-controlled walking after spinal cord injury. In their spinal cord injury research study, a person with paraplegia was able to operate a BCI-robotic gait orthosis to regain basic brain-controlled ambulation. In 2009 Alex Blainey, an independent researcher based in the UK, successfully used the Emotiv EPOC to control a 5 axis robot arm. He then went on to make several demonstration mind controlled wheelchairs and home automation that could be operated by people with limited or no motor control such as those with paraplegia and cerebral palsy.

Research into military use of BCIs funded by DARPA has been ongoing since the 1970s. The current focus of research is user-to-user communication through analysis of neural signals.

1.6.3.6 MEG and MRI

Magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI) have both been used successfully as non-invasive BCIs. In a widely reported experiment, fMRI allowed two users being scanned to play Pong in real-time by altering their haemodynamic response or brain blood flow through biofeedback techniques.

MRI is a functional neuroimaging technique for mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain, using very sensitive magnetometers.

How does it work?

MEG measures the magnetic field caused by the currents in the brain, and it offers a better spatial resolution compared to EEG. Why? Because magnetic fields suffer far less than electric fields from the spatial blurring effect of the skull and intracerebral fluid. "MEG is maximally sensitive to tangential sources and has low sensitivity to radial sources" "MEG is better than EEG at detecting high-frequency activity (e.g., above 60 Hz). This is because magnetic fields pass through the skull and scalp, whereas the electrical fields are volume conducted through these tissues, which decreases signal-to-noise ratio at higher frequencies."



Figure 1.25 MEG scanner with patient from National Institute of Mental Health

fMRI measurements of haemodynamic responses in real time have also been used to control robot arms with a seven-second delay between thought and movement.

Functional magnetic resonance imaging or functional MRI (fMRI) is a functional neuroimaging procedure using MRI technology that measures brain activity by detecting changes associated with blood flow. This technique relies on the fact that cerebral blood flow and neuronal activation are coupled. When an area of the brain is in use, blood flow to that region also increases.

fMRI has been developed in the 1990s. It is a non-invasive and safe technique, it doesn't use radiation, it's easy to use and it has excellent spatial and good temporal resolution.

How does it work?

In the brain, haemoglobin in capillary red blood cells delivers oxygen to the neurons. Activity causes more demand for oxygen, which leads to an increase of blood flow. The magnetic characteristics of haemoglobin change if it is or not oxygenated. This difference allows the MRI machine, which is a cylindrical tube with a powerful electro-magnet, to detect which areas of the brain are active in a specific moment.



Figure 1.26 In 2008 research developed in the Advanced Telecommunications Research (ATR) Computational Neuroscience Laboratories in Kyoto, Japan, allowed the scientists to reconstruct images directly from the brain and display them on a computer in black and white at a resolution of 10x10 pixels. The article announcing these achievements was the cover story of the journal Neuron of 10 December 2008.

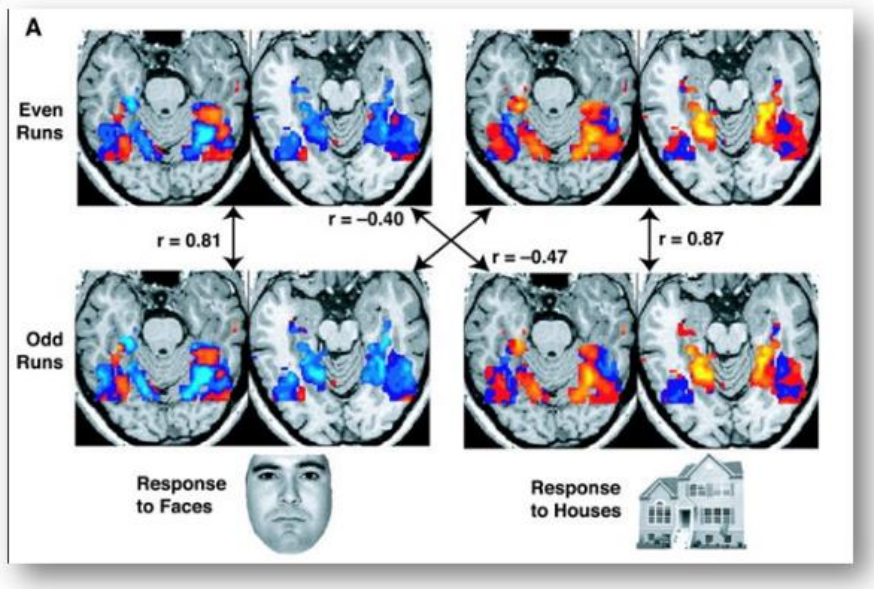


Figure 1.27 fMRI images from a study showing parts of the brain lighting up on seeing houses and other parts on seeing faces. The 'r' values are correlations, with higher positive or negative values indicating a better match.

In 2011 researchers from UC Berkeley published a study reporting second-by-second reconstruction of videos watched by the study's subjects, from fMRI data. This was achieved

by creating a statistical model relating visual patterns in videos shown to the subjects, to the brain activity caused by watching the videos. This model was then used to look up the 100 one-second video segments, in a database of 18 million seconds of random YouTube videos, whose visual patterns most closely matched the brain activity recorded when subjects watched a new video. These 100 one-second video extracts were then combined into a mashed-up image that resembled the video being watched.

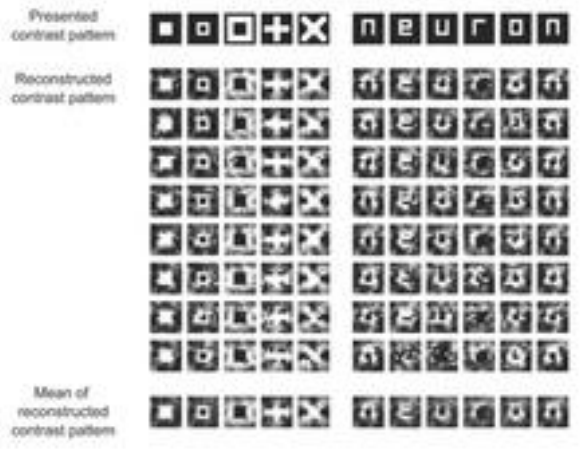


Figure 1.28 ATR Labs' reconstruction of human vision using fMRI (top row: original image; bottom row: reconstruction from mean of combined readings)

1.7 BCI control strategies in neurogaming

- **Motor imagery**

Motor imagery involves the imagination of the movement of various body parts resulting in sensorimotor cortex activation, which modulates sensorimotor oscillations in the EEG. This can be detected by the BCI to infer a user's intent. Motor imagery typically requires a number of sessions of training before acceptable control of the BCI is acquired. These training sessions may take a number of hours over several days before users can consistently employ the technique with acceptable levels of precision. Regardless of the duration of the training session, users are unable to master the control scheme. This results in very slow pace of the gameplay. Advanced machine learning methods were recently developed to compute a subject-specific model for detecting the performance of motor imagery. The top performing algorithm from BCI Competition IV dataset 2 for motor imagery is the Filter Bank Common Spatial Pattern, developed by Ang et al. from A*STAR, Singapore.

- **Bio/neurofeedback for passive BCI designs**

Biofeedback is used to monitor a subject's mental relaxation. In some cases, biofeedback does not monitor electroencephalography (EEG), but instead bodily parameters such as electromyography (EMG), galvanic skin resistance (GSR), and heart rate variability (HRV). Many biofeedback systems are used to treat certain disorders such as attention deficit hyperactivity disorder (ADHD), sleep problems in children, teeth grinding, and chronic pain. EEG biofeedback systems typically monitor four different bands (theta: 4–7 Hz, alpha:8–12 Hz, SMR: 12–15 Hz, beta: 15–18 Hz) and challenge the subject to control them. Passive BCI involves using BCI to enrich human–machine interaction with implicit information on the actual user's state, for example, simulations to detect when users intend to push brakes during an emergency car stopping procedure. Game developers using passive BCIs need to acknowledge that through repetition of game levels the user's cognitive state will change or adapt. Within the first play of a level, the user will react to things differently from during the second play: for example, the user will be less surprised at an event in the game if they are expecting it.

- **Visual evoked potential (VEP)**

A VEP is an electrical potential recorded after a subject is presented with a type of visual stimuli. There are several types of VEPs.

Steady-state visually evoked potentials (SSVEPs) use potentials generated by exciting the retina, using visual stimuli modulated at certain frequencies. SSVEP's stimuli are often formed from alternating checkerboard patterns and at times simply use flashing images. The frequency of the phase reversal of the stimulus used can be clearly distinguished in the spectrum of an EEG; this makes detection of SSVEP stimuli relatively easy. SSVEP has proved to be successful within many BCI systems. This is due to several factors, the signal elicited is measurable in as large a population as the transient VEP and blink movement and electrocardiographic artefacts do not affect the frequencies monitored. In addition, the SSVEP signal is exceptionally robust; the topographic organization of the primary visual cortex is such that a broader area obtains afferents from the central or fovial region of the visual field. SSVEP does have several problems however. As SSVEPs use flashing stimuli to infer a user's intent, the user must gaze at one of the flashing or iterating symbols in order to interact with the system. It is, therefore, likely that the symbols could become irritating and uncomfortable to

use during longer play sessions, which can often last more than an hour which may not be an ideal gameplay.

Another type of VEP used with applications is the P300 potential. The P300 event-related potential is a positive peak in the EEG that occurs at roughly 300 ms after the appearance of a target stimulus (a stimulus for which the user is waiting or seeking) or oddball stimuli. The P300 amplitude decreases as the target stimuli and the ignored stimuli grow more similar. P300 is thought to be related to a higher level attention process or an orienting response using P300 as a control scheme has the advantage of the participant only having to attend limited training sessions. The first application to use the P300 model was the P300 matrix. Within this system, a subject would choose a letter from a grid of 6 by 6 letters and numbers. The rows and columns of the grid flashed sequentially and every time the selected "choice letter" was illuminated the user's P300 was (potentially) elicited. However, the communication process, at approximately 17 characters per minute, was quite slow. The P300 is a BCI that offers a discrete selection rather than a continuous control mechanism. The advantage of P300 use within games is that the player does not have to teach himself/herself how to use a completely new control system and so only has to undertake short training instances, to learn the gameplay mechanics and basic use of the BCI paradigm

Non-brain-based human–computer interface (physiological computing)

Human-computer interaction can benefit from other recording modalities, such as EOG and eye-tracking. However, these modalities do not record brain activity and therefore do not fall within the exact scope of BCIs, but rather can be grouped under the wider field of physiological computing.

- **Electro-oculography (EOG)**

In 1989, a report was given on control of a mobile robot by eye movement using electrooculography (EOG) signals. A mobile robot was driven from a start to a goal point using five EOG commands, interpreted as forward, backward, left, right, and stop.

- **Pupil-size oscillation**

A 2016 article described an entirely new communication device and non-EEG-based human-computer interface, which requires no visual fixation, or ability to move the eyes at all. The interface is based on covert interest; directing one's attention to a chosen letter on a virtual keyboard, without the need to move one's eyes to look directly at the letter. Each letter has its own (background) circle which micro-oscillates in brightness differently from all of the other

letters. The letter selection is based on best fit between unintentional pupil-size oscillation and the background circle's brightness oscillation pattern. Accuracy is additionally improved by the user's mental rehearsing of the words 'bright' and 'dark' in synchrony with the brightness transitions of the letter's circle.

- **Synthetic telepathy**

In a $6.3 million US Army initiative to invent devices for telepathic communication, Gerwin Schalk, underwritten in a $2.2 million grant, found the use of ECoG signals can discriminate the vowels and consonants embedded in spoken and imagined words, shedding light on the distinct mechanisms associated with production of vowels and consonants, and could provide the basis for brain-based communication using imagined speech.

In 2002 Kevin Warwick had an array of 100 electrodes fired into his nervous system in order to link his nervous system into the Internet to investigate enhancement possibilities. With this in place Warwick successfully carried out a series of experiments. With electrodes also implanted into his wife's nervous system, they conducted the first direct electronic communication experiment between the nervous systems of two humans.

Another group of researchers was able to achieve conscious brain-to-brain communication between two people separated by a distance using non-invasive technology that was in contact with the scalp of the participants. The words were encoded by binary streams using the sequences of 0's and 1's by the imaginary motor input of the person "emitting" the information. As the result of this experiment, pseudo-random bits of the information carried encoded words "hola" ("hi" in Spanish) and "ciao" ("goodbye" in Italian) and were transmitted mind-to-mind between humans separated by a distance, with blocked motor and sensory systems, which has low to no probability of this happening by chance.

In the 1960s a researcher was successful after some training in using EEG to create Morse code using their brain alpha waves. Research funded by the US army is being conducted with the goal of allowing users to compose a message in their head, then transfer that message with just the power of thought to a particular individual. On 27 February 2013 the group with Miguel Nicolelis at Duke University and IINN-ELS successfully connected the brains of two rats with electronic interfaces that allowed them to directly share information, in the first-ever direct brain-to-brain interface

1.8 Cell-culture BCIs

Researchers have built devices to interface with neural cells and entire neural networks in cultures outside animals. As well as furthering research on animal implantable devices, experiments on cultured neural tissue have focused on building problem-solving networks, constructing basic computers and manipulating robotic devices. Research into techniques for stimulating and recording from individual neurons grown on semiconductor chips is sometimes referred to as neuroelectronics or neurochips

Development of the first working neurochip was claimed by a Caltech team led by Jerome Pine and Michael Maher in 1997. The Caltech chip had room for 16 neurons.

In 2003 a team led by Theodore Berger, at the University of Southern California, started work on a neurochip designed to function as an artificial or prosthetic hippocampus. The neurochip was designed to function in rat brains and was intended as a prototype for the eventual development of higher-brain prosthesis. The hippocampus was chosen because it is thought to be the most ordered and structured part of the brain and is the most studied area. Its function is to encode experiences for storage as long-term memories elsewhere in the brain.

In 2004 Thomas DeMarse at the University of Florida used a culture of 25,000 neurons taken from a rat's brain to fly a F-22 fighter jet aircraft simulator.[166] After collection, the cortical neurons were cultured in a petri dish and rapidly began to reconnect themselves to form a living neural network. The cells were arranged over a grid of 60 electrodes and used to control the pitch and yaw functions of the simulator. The study's focus was on understanding how the human brain performs and learns computational tasks at a cellular level.

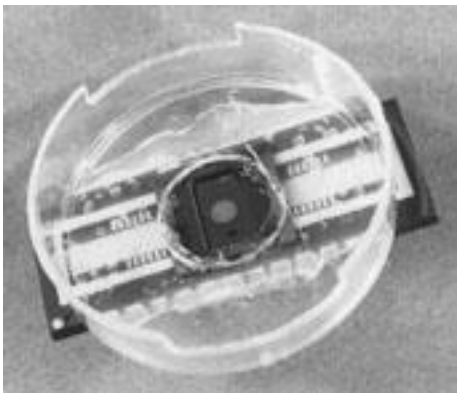


Figure 1.29 The world's first neurochip, developed by Caltech researchers Jerome Pine and Michael Maher

1.9 Collaborative BCIs

The idea of combining/integrating brain signals from multiple individuals was introduced at Humanity+ @Caltech, in December 2010, by a Caltech researcher at JPL, Adrian Stoica, who referred to the concept as multi-brain aggregation. A provisional patent application was filed on January 19, 2011, with the non-provisional patent following one year later. In May 2011, Yijun Wang and Tzyy-Ping Jung published, "A Collaborative Brain-Computer Interface for Improving Human Performance", and in January 2012 Miguel Eckstein published, "Neural decoding of collective wisdom with multi-brain computing". Stoica's first paper on the topic appeared in 2012, after the publication of his patent application.[173] Given the timing of the publications between the patent and papers, Stoica, Wang & Jung, and Eckstein independently pioneered the concept, and are all considered as founders of the field. Later, Stoica would collaborate with University of Essex researchers, Riccardo Poli and Caterina Cinel.[174][175] The work was continued by Poli and Cinel, and their students: Ana Matran-Fernandez, Davide Valeriani, and Saugat Bhattacharyya

- **Ethical considerations**

As technology continually blurs the line between science fiction and reality, the advent of brain-computer interfaces (BCIs) poses a profound ethical quandary. These neural interfaces, heralded as marvels of innovation, facilitate direct communication between the human brain and external devices. However, the ethical landscape surrounding BCIs is intricate and multifaceted, encompassing concerns of privacy invasion, autonomy, consent, and the potential societal implications of merging human cognition with machine interfaces. Delving into the ethical considerations of BCIs illuminates the intricate balance between technological advancement and safeguarding fundamental human rights and values. Many of the concerns raised can be divided into two groups, user centric issues and legal and social issues.

Ethical concerns in the user centric sphere tend to revolve around the safety of the user and the effects that this technology will have on them over a period of time. These can include but are not limited to: long-term effects to the user remain largely unknown, obtaining informed consent from people who have difficulty communicating, the consequences of BCI technology for the quality of life of patients and their families, health-related side-effects (e.g. neurofeedback of sensorimotor rhythm training is reported to affect sleep quality), therapeutic applications and their potential misuse, safety risks, non-convertibility of some of the changes

made to the brain, lack of access to maintenance, repair and spare parts in case of company bankruptcy, etc.

The legal and social aspect of BCIs is a metaphorical minefield for any entity attempting to make BCIs mainstream. Some of these concerns would be issues of accountability and responsibility: claims that the influence of BCIs overrides free will and control over sensory-motor actions, claims that cognitive intention was inaccurately translated due to a BCI malfunction, personality changes involved caused by deep-brain stimulation, concerns regarding the state of becoming a "cyborg" - having parts of the body that are living and parts that are mechanical, questions about personality: what does it mean to be a human, blurring of the division between human and machine and inability to distinguish between human vs. machine-controlled actions, use of the technology in advanced interrogation techniques by governmental authorities, “brain hacking” or the unauthorized access of someone’s BCI, selective enhancement and social stratification, mind reading and privacy, tracking and "tagging system", mind control, movement control, and emotion control. In addition many researchers have theorized that BCIs would only worsen social inequalities seen today.

In their current form, most BCIs are far removed from the ethical issues considered above. They are actually similar to corrective therapies in function. Clausen stated in 2009 that "BCIs pose ethical challenges, but these are conceptually similar to those that bioethicists have addressed for other realms of therapy. Moreover, he suggests that bioethics is well-prepared to deal with the issues that arise with BCI technologies. Haselager and colleagues pointed out that expectations of BCI efficacy and value play a great role in ethical analysis and the way BCI scientists should approach media. Furthermore, standard protocols can be implemented to ensure ethically sound informed-consent procedures with locked-in patients.

The case of BCIs today has parallels in medicine, as will its evolution. Similar to how pharmaceutical science began as a balance for impairments and is now used to increase focus and reduce need for sleep, BCIs will likely transform gradually from therapies to enhancements. Efforts are made inside the BCI community to create consensus on ethical guidelines for BCI research, development and dissemination. As innovation continues, ensuring equitable access to BCIs will be crucial, failing which generational inequalities can arise which can adversely affect the right to human flourishing.

- **Low-cost BCI-based interfaces**

Recently a number of companies have scaled back medical grade EEG technology to create inexpensive BCIs for research as well as entertainment purposes. For example, toys such as the NeuroSky and Mattel MindFlex have seen some commercial success.

- In 2006 Sony patented a neural interface system allowing radio waves to affect signals in the neural cortex.
- In 2007 NeuroSky released the first affordable consumer based EEG along with the game NeuroBoy. This was also the first large scale EEG device to use dry sensor technology.
- In 2008 OCZ Technology developed a device for use in video games relying primarily on electromyography.
- In 2008 Final Fantasy developer Square Enix announced that it was partnering with NeuroSky to create a game, Judecca.
- In 2009 Mattel partnered with NeuroSky to release the Mindflex, a game that used an EEG to steer a ball through an obstacle course. It is by far the best selling consumer based EEG to date.
- In 2009 Uncle Milton Industries partnered with NeuroSky to release the Star Wars Force Trainer, a game designed to create the illusion of possessing the Force.
- In 2009 Emotiv released the EPOC, a 14 channel EEG device that can read 4 mental states, 13 conscious states, facial expressions, and head movements. The EPOC is the first commercial BCI to use dry sensor technology, which can be dampened with a saline solution for a better connection.
- In November 2011 Time magazine selected "necomimi" produced by Neurowear as one of the best inventions of the year. The company announced that it expected to launch a consumer version of the garment, consisting of catlike ears controlled by a brain-wave reader produced by NeuroSky, in spring 2012.
- In February 2014 They Shall Walk (a nonprofit organization fixed on constructing exoskeletons, dubbed LIFESUITs, for paraplegics and quadriplegics) began a partnership with James W. Shakarji on the development of a wireless BCI.
- In 2016, a group of hobbyists developed an open-source BCI board that sends neural signals to the audio jack of a smartphone, dropping the cost of entry-level BCI to £20.

Basic diagnostic software is available for Android devices, as well as a text entry app for Unity.

- In 2020, NextMind released a dev kit including an EEG headset with dry electrodes at $399. The device can be played with some demo applications or developers can create their own use cases using the provided Software Development Kit.

1.10 Future directions

A consortium consisting of 12 European partners has completed a roadmap to support the European Commission in their funding decisions for the new framework program Horizon 2020. The project, which was funded by the European Commission, started in November 2013 and published a roadmap in April 2015. A 2015 publication led by Clemens Brunner describes some of the analyses and achievements of this project, as well as the emerging Brain-Computer Interface Society. For example, this article reviewed work within this project that further defined BCIs and applications, explored recent trends, discussed ethical issues, and evaluated different directions for new BCIs.

- **Disorders of consciousness (DOC)**

Some people have a disorder of consciousness (DOC). This state is defined to include people in a coma and those in a vegetative state (VS) or minimally conscious state (MCS). New BCI research seeks to help people with DOC in different ways. A key initial goal is to identify patients who can perform basic cognitive tasks, which would of course lead to a change in their diagnosis. That is, some people who are diagnosed with DOC may in fact be able to process information and make important life decisions (such as whether to seek therapy, where to live, and their views on end-of-life decisions regarding them). Some who are diagnosed with DOC die as a result of end-of-life decisions, which may be made by family members who sincerely feel this is in the patient's best interests. Given the new prospect of allowing these patients to provide their views on this decision, there would seem to be a strong ethical pressure to develop this research direction to guarantee that DOC patients are given an opportunity to decide whether they want to live.

These and other articles describe new challenges and solutions to use BCI technology to help persons with DOC. One major challenge is that these patients cannot use BCIs based on vision. Hence, new tools rely on auditory and/or vibrotactile stimuli. Patients may wear headphones and/or vibrotactile stimulators placed on the wrists, neck, leg, and/or other locations. Another challenge is that patients may fade in and out of consciousness and can only communicate at

certain times. This may indeed be a cause of mistaken diagnosis. Some patients may only be able to respond to physicians' requests for a few hours per day (which might not be predictable ahead of time) and thus may have been unresponsive during diagnosis. Therefore, new methods rely on tools that are easy to use in field settings, even without expert help, so family members and other people without any medical or technical background can still use them. This reduces the cost, time, need for expertise, and other burdens with DOC assessment. Automated tools can ask simple questions that patients can easily answer, such as "Is your father named George?" or "Were you born in the USA?" Automated instructions inform patients that they may convey yes or no by (for example) focusing their attention on stimuli on the right vs. left wrist. This focused attention produces reliable changes in EEG patterns that can help determine whether the patient is able to communicate. The results could be presented to physicians and therapists, which could lead to a revised diagnosis and therapy. In addition, these patients could then be provided with BCI-based communication tools that could help them convey basic needs, adjust bed position and HVAC (heating, ventilation, and air conditioning), and otherwise empower them to make major life decisions and communicate.

- **Motor recovery**

People may lose some of their ability to move due to many causes, such as stroke or injury. Research in recent years has demonstrated the utility of EEG-based BCI systems in aiding motor recovery and neurorehabilitation in patients who have had a stroke. Several groups have explored systems and methods for motor recovery that include BCIs. In this approach, a BCI measures motor activity while the patient imagines or attempts movements as directed by a therapist. The BCI may provide two benefits: (1) if the BCI indicates that a patient is not imagining a movement correctly (non-compliance), then the BCI could inform the patient and therapist; and (2) rewarding feedback such as functional stimulation or the movement of a virtual avatar also depends on the patient's correct movement imagery.

So far, BCIs for motor recovery have relied on the EEG to measure the patient's motor imagery. However, studies have also used fMRI to study different changes in the brain as persons undergo BCI-based stroke rehab training. Imaging studies combined with EEG-based BCI systems hold promise for investigating neuroplasticity during motor recovery post-stroke. Future systems might include the fMRI and other measures for real-time control, such as functional near-infrared, probably in tandem with EEGs. Non-invasive brain stimulation has also been explored in combination with BCIs for motor recovery. In 2016, scientists out of the University of Melbourne published preclinical proof-of-concept data related to a potential

brain-computer interface technology platform being developed for patients with paralysis to facilitate control of external devices such as robotic limbs, computers and exoskeletons by translating brain activity. Clinical trials are currently underway.

- **Functional brain mapping**

Each year, about 400,000 people undergo brain mapping during neurosurgery. This procedure is often required for people with tumours or epilepsy that do not respond to medication. During this procedure, electrodes are placed on the brain to precisely identify the locations of structures and functional areas. Patients may be awake during neurosurgery and asked to perform certain tasks, such as moving fingers or repeating words. This is necessary so that surgeons can remove only the desired tissue while sparing other regions, such as critical movement or language regions. Removing too much brain tissue can cause permanent damage, while removing too little tissue can leave the underlying condition untreated and require additional neurosurgery.[citation needed] Thus, there is a strong need to improve both methods and systems to map the brain as effectively as possible.

In several recent publications, BCI research experts and medical doctors have collaborated to explore new ways to use BCI technology to improve neurosurgical mapping. This work focuses largely on high gamma activity, which is difficult to detect with non-invasive means. Results have led to improved methods for identifying key areas for movement, language, and other functions. A recent article addressed advances in functional brain mapping and summarizes a workshop.

- **Flexible devices**

Flexible-electronics are polymers or-other-flexible-materials
(e.g. silk, pentacene, PDMS, Parylene, polyimide) that are printed with circuitry; the flexible nature of the organic background materials allowing the electronics created to bend, and the fabrication techniques used to create these devices resembles those used to create integrated circuits and microelectromechanical systems (MEMS). Flexible electronics were first developed in the 1960s and 1970s, but research interest increased in the mid-2000s.

Flexible neural interfaces have been extensively tested in recent years in an effort to minimize brain tissue trauma related to mechanical mismatch between electrode and tissue. Minimizing tissue trauma could, in theory, extend the lifespan of BCIs relying on flexible electrode-tissue interfaces.

- **Neural dust**

Neural dust is a term used to refer to millimeter-sized devices operated as wirelessly powered nerve sensors that were proposed in a 2011 paper from the University of California, Berkeley Wireless Research Center, which described both the challenges and outstanding benefits of creating a long lasting wireless BCI. In one proposed model of the neural dust sensor, the transistor model allowed for a method of separating between local field potentials and action potential "spikes", which would allow for a greatly diversified wealth of data acquirable from the recordings.

1.11 Applications of Brain-Computer Interfaces

- **Robotic Limbs and Wheelchairs:** By supplying a real-time neural feedback loop that rewires the brain, BCIs are capable of restoring movement, mobility and autonomy for paralyzed and disabled patients, heightening their quality of life. In more chronic cases, robotic devices and limbs are integrated.

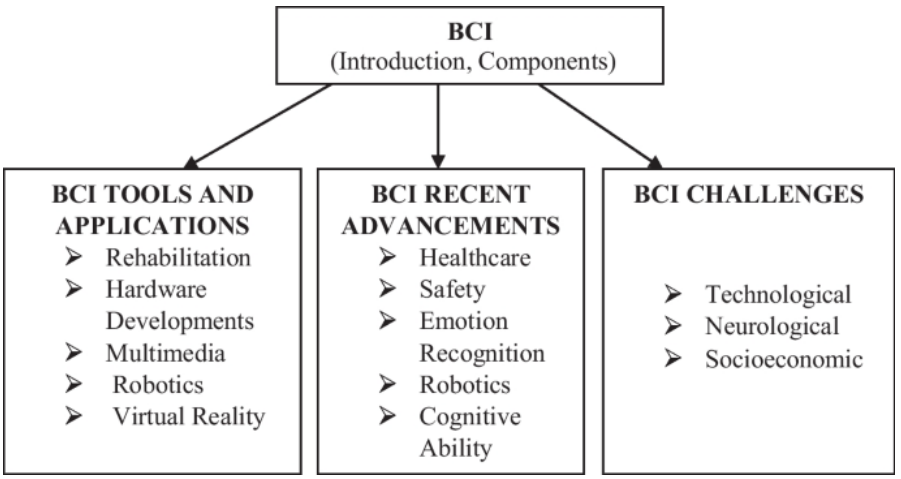


Figure 1.30 Application of BCI

- **Wireless Headsets:** Headsets are a way to deliver a non-invasive approach to brain-computer interfaces. Some boost productivity and enhance focus, as seen with Neurable's Enten, while others restore motor functions to an individual's upper extremities following a stroke, such as the IpsiHand system by Neurolutions Inc.
- **Spellers:** Non-verbal individuals, who may be stuck in a "locked in" state following a stroke or severe injury, can use eye movement for computer-augmented communication.
- **Smartphone and Smart-Home Device Interface:** In several studies, users have exercised control of social networking apps, email administration, virtual assistants and instant message services sans motor skills. Dimming the lights or changing the channel on a TV are examples of how BCIs can be adapted in the home.
- **Drones:** The Department of Defense has funded research to develop hands-free drones for military use. This would allow soldiers to telepathically control swarms of unmanned aerial vehicles.

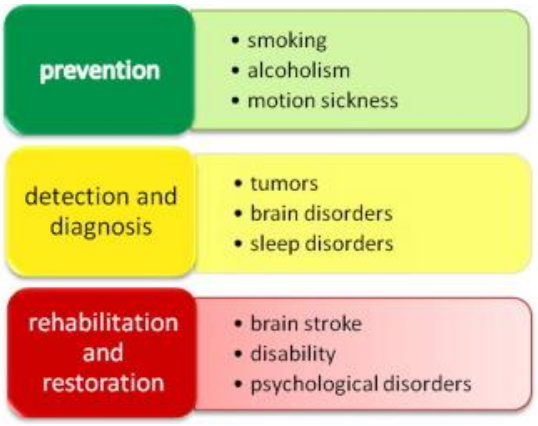


Figure 1.31 Applications of BCI

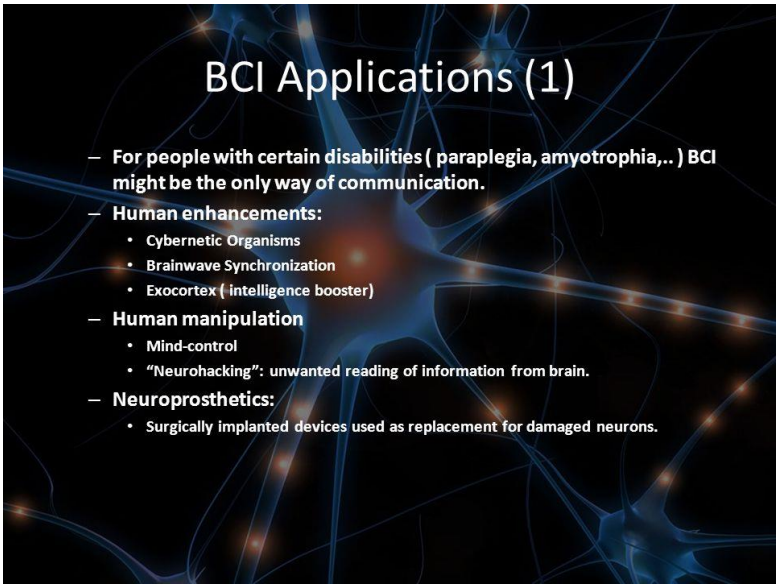


Figure 1.32 BCI Uses and advantages

1.12 Examples of Brain-Computer Interfaces

- **Neuralink's Coin-sized Brainchip**

The neurotechnology company, headed by Elon Musk, is developing a coin-sized surgical implant. In order to monitor brain activity as closely as possible, Neuralink's device, the Link, uses micron-scale wires of electrodes that fan out into the brain. Its primary focus is to treat paralysis. In addition to a "Fitbit for your skull," the start-up is building an eight-foot robot to place the neural threads.

- **Neurable's BCI-enhanced Headphones**

The brain-computer interface start-up is building software and hardware — in the form of headphones — that interpret brain signals to level up productivity. Its first pair, Enten, uses advanced data analysis and signal processing techniques to maximize a users' peak focus periods throughout the day. The wearable, BCI-enhanced device auto mutes notifications, activates noise cancelling and turns on 'Do Not Disturb.' It also tracks how different songs and genres impact a users' focus, then recommends personalized playlists and suggests breaks.

- **Precision Neuroscience's Electrode-packed Film**

The neural platform is approaching brain-computer interface systems with a surgically implanted brain chip that's minimally invasive and fully reversible. The Layer 7 Cortical Interface is a thin film of micro-electrodes, about 1.5 centi-meters in length and a fraction of a hair thick, that conforms to the brain's cortex just under the skull without damaging any tissue.

Precision's tech wants to mainstream BCIs from small-scale research labs to medical facilities as a way to treat neurological diseases. In June 2023, Precision conducted an in-human clinical study of its neural implant.

- **Synchron's Endovascular Alloy Chip**

Backed by Bill Gates and Jeff Bezos, Synchron, a bioelectronics medicine company, is mapping the brain via blood vessels. Inserted through the jugular vein, the Stentrode is a neuroprosthesis placed in the superior sagittal sinus near the motor cortex. The eight-millimeter flexible alloy chip transmits neurological signals to a receiver unit implanted into the patient's chest, which then translates thoughts into clicks and keystrokes on a computer or mobile device in real time. Synchron received approval from the U.S. Food and Drug Administration for human clinical trials in 2021, totalling four patients thus far, according to medical journal JAMA Network.

- **Blackrock Neurotech's Mesh Lace**

The neurotech platform Blackrock Neurotech has been testing its devices in humans since 2004 in its two decades of brain-computer interface development. Blackrock's product portfolio has helped patients regain tactile function, movement of their own limbs and prosthetics as well as the ability to control digital devices solely from thought. Its latest project, Neuralace, is a flexible, hexagonal mesh patch — thinner than an eyelash — designed to conform to the fissures and sulci of the brain. Its large surface area can capture 10,000 neural channels, inching closer to whole-brain data capture.

1.13 Benefits of Brain-Computer Interfaces

- **Restore Mobility and Motor Functions**

Following a course of neurological rehabilitation, brain chips and wearables can give patients direct control over exoskeletons and robotic limbs. This is made possible by reading signals directly from the brain, bypassing the site of injury or disease — such as a severed spinal cord — muscular activity altogether.

- '**Mindwriting' for Non-verbal Individuals**

With brain-computer interfaces, if you can think it, you can speak it. It's just a matter of how fast neural decoding software can catch up.

A team from Stanford University found that its brain chip could hack 62 words per minute, which is on pace with natural conversation. The study featured a non-verbal patient who suffered amyotrophic lateral sclerosis and a pre-programmed vocabulary of 125,000 words, marking "a feasible path forward for using intracortical speech brain-computer interfaces to restore rapid communication to people with paralysis who can no longer speak."

- **Treat Neurological Conditions**

One study noted that individuals with ALS, cerebral palsy, brainstem stroke, spinal cord injuries, muscular dystrophies or chronic peripheral neuropathies may benefit from BCIs. Neural implants may be able to treat conditions or at least improve the quality of life for patients with chronic or terminal diagnoses.

- **Monitor Mental Health**

Brain-computer interfaces may one day be able to ease psychiatric conditions, like bipolar disorder, obsessive-compulsive disorder, depression and anxiety.

Using neurofeedback techniques, they can also help prevent more pedestrian conditions like burnout and fatigue by delivering targeted electrical stimulation to specific areas of the brain.

"It may not look as flashy, because someone in the demo just looks a little bit happier," Norman, whose research at the California Institute of Technology as a postdoctoral fellow focused on this next generation of brain-computer interface tech. "But if you were offered a solution where I said, using a single device, I can treat any form of anxiety that you have, and also offer you sleep on demand and one hundred other applications that could make your life a little better than it was, I do think that quite a few people would adopt that technology."

- **Cognitive Enhancement**

Users can train their brains — memory, executive function and processing speed — to the biofeedback they receive from a neural implant in real time. Similar to wearable tech and apps available today, users would be able to monitor their stats and self-regulate accordingly.

- **Understanding the Brain**

While much of the brain remains a mystery, BCIs are creating a direct channel to our thoughts — complete with a process to decode its language.

"Brain-computer interfaces can be used as a tool to understand how the brain works," said Byron Yu, a professor of electrical and computer engineering and biomedical engineering at Carnegie Mellon University. The focus of his research group is studying how the brain learns.

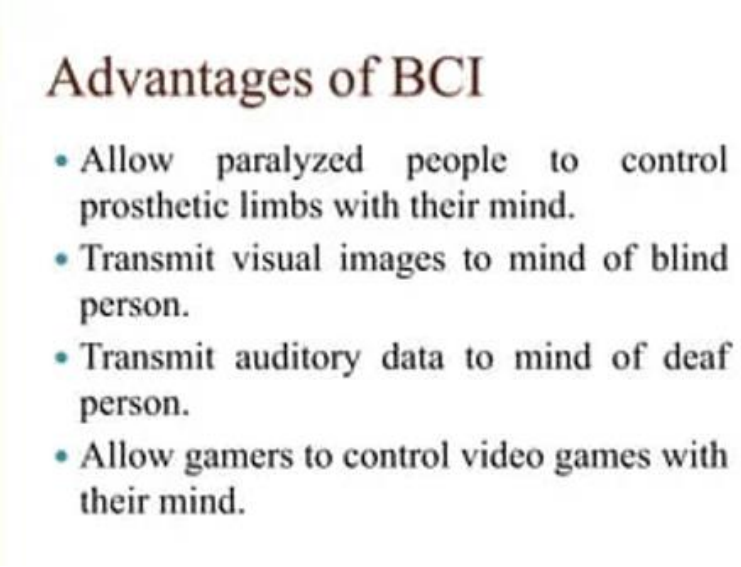


Figure 1.33 Advantages of BCI

1.14 Challenges of Brain-Computer Interfaces

The two largest hurdles keeping BCIs from widespread adoption have to do with regulatory approval and funding.

- **Regulatory Approval**

Given that brain-computer interfaces are registered as a sort of medical device, they lie under the jurisdiction of the FDA. Regardless of the product, the institution's primary concern is patient safety. The challenge is in the fact that BCIs currently exist in a league of their own. The devices themselves bring together a range of fields — implantable materials, safety-critical software, the Internet of Things and wearable medical devices, to name a few — that are not yet standardized. There are no predicate devices. "These are new categories of devices," Precision Neuroscience's Mermel said. "So, until there's a device that gets cleared for market by the FDA, it's an open question of what type of evidence you have to show to demonstrate that the benefit of a device outweighs the risk."

- **Cost and Reimbursement**

If brain-computer interfaces make it to medical practice, who is going to pay for them? Or for the procedures? And what about the health-check follow ups, ongoing maintenance and

upgrades that support the technology over time? Determining whether the tab gets picked up by healthcare and insurance companies, government subsidies or patients out of pocket will greatly determine the devices' level of accessibility to the public and who, based on socioeconomic status, are qualified for a tech-augmented quality of life. "It's important to prioritize the needs and perspectives of end-users, especially the most vulnerable, such as those with disabilities, and consider the potential ethical implications of these technologies," Alcaide said. "We must ensure that these technologies do not perpetuate social biases or further exacerbate existing inequalities."

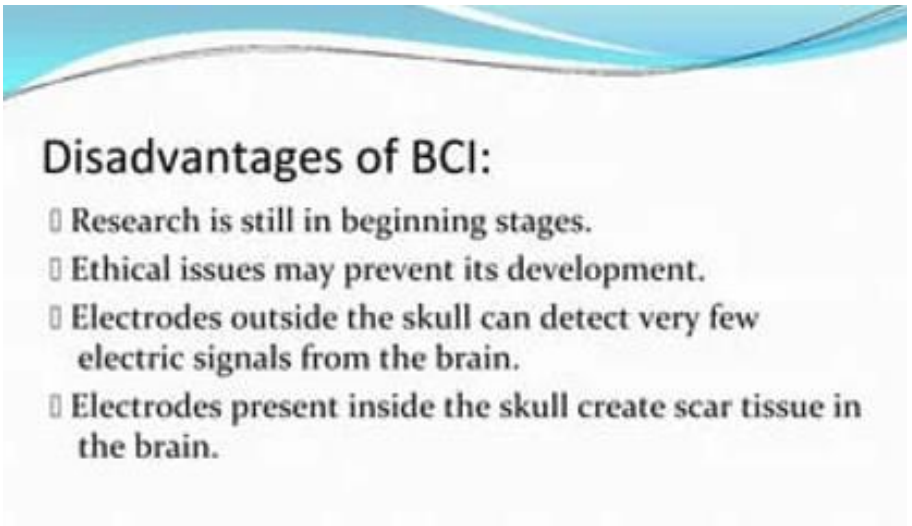


Figure 1.34 Disadvantages of BCI

1.15 LITERATURE SURVEY

Measuring brain signal analysis of Obsessive-Compulsive Disorder

Brain waves are patterns of electrical activity in the brain that can be measured using specialized equipment, such as an electroencephalogram (EEG). Researchers have found detectable differences when looking at the brain wave patterns of people with mental health disorders like OCD and ADHD, compared to brain wave patterns observed in healthy individuals. Given the difficulty of diagnosing OCD in patients, particularly in children, and the limitations of clinical interviews (e.g., patients may choose not to disclose some or all of their symptoms), the potential for brain waves to be used as a biomarker in detecting OCD has attracted a lot of interest from researchers.

1.15. 1 RESEARCH DESIGN OVERVIEW

Previous investigators looking for differences in brain waves compared adults with OCD to adults without OCD, and looked at brain wave patterns that repeat themselves slowly (from

just a few times per second to up to 30 times per second). Their tests were conducted while the adults were awake and had their eyes closed, referred to as the "resting state." These investigators found that the brain wave patterns that repeat themselves slowly were more powerful in individuals with OCD, and that the faster brain wave patterns that they measured were less powerful in individuals with OCD. We decided to focus on even faster (or higher-frequency) patterns called gamma waves, which repeat themselves between 30 and 55 times per second. We did this because gamma waves support the higher cognitive functions that are relevant to the thoughts and obsessions of individuals with OCD. Our theory then, was that based on what we know about how OCD works in the brain, we expected to measure stronger gamma waves in youth with OCD than in typically developing youth. Additionally, we expected to find stronger gamma wave activity in individuals with OCD to be concentrated in the frontal parts of the brain.

Instead of using EEG equipment, we measured brain waves using a technique called magnetoencephalography (MEG). Using MEG had several advantages over EEG: it allowed for us to collect better data about the higher frequency brain waves that we wanted to study, and allowed us to collect data using a helmet instead of many individual electrodes attached to the head – an advantage with any group of patients, but particularly with children. Like researchers who studied adults with OCD, we measured brain waves in youth while they were in the "resting state" — awake with their eyes closed.

Our subjects were between the ages of 11 and 17, and were recruited from 2010 to 2016 from an academic outpatient hospital in the Midwestern United States through clinic referrals and emails sent to hospital employees. Written informed consent and assent were obtained from each parent and subject, respectively, prior to participation. Participants with OCD had a score of at least 15 on the Children's Yale Brown Obsessive Compulsive Scale (CY-BOCS) indicating that they had at least moderate OCD symptoms. In total, we enrolled 10 children with OCD, and 10 typically developing children in the study. Eight of the 10 participants with OCD were in some form of treatment: two were receiving cognitive behavioural therapy with no medication, and six were being treated with a selective serotonin reuptake inhibitor (SSRI).

WHAT WE FOUND

To our knowledge, we are the first to have found differences in resting state gamma wave activity in symptomatic youth with OCD compared with typically developing youth. We found that gamma waves in youth with OCD were stronger in all regions of the brain — not just the

frontal areas like we had hypothesized. Gamma waves in these children were stronger in every way we measured them: their minimum power, or baseline strength, was increased, as was their average power and maximum power.

Although gamma waves were stronger in all areas of the brain that we measured, we found that the most consistent differences between youth with OCD and typically developing youth were in the temporal lobe. Whenever we measured stronger gamma waves in this part of the brain, it was a consistent predictor that the individual being studied belonged to the group of youth with OCD.

At this stage, we aren't sure exactly what is causing the stronger gamma waves we observed in individuals with OCD. Further research studies could examine connections in animal brain slices — a method of analysis that allows researchers to keep brain tissue alive for eight hours after the brain is removed — to better understand the underlying circuitry and its connection to gamma wave activity. Another approach would be to use computer simulations to model various neurotransmitter receptors that may be responsible for differences in gamma activity in children with OCD. This technique was used to identify a receptor that is less active in people with schizophrenia and is linked to increased gamma wave activity. Computer modelling could help answer similar questions about the increased gamma activity we saw in OCD.

1.15.2 CONCLUSION

Our discovery may have revealed a new biomarker in gamma waves that can serve clinicians and patients as an objective measure of illness! Information about a patient's gamma wave activity may give clinicians another layer of information on top of the responses they receive from patients during clinical interviews, and could prove useful as a tool for confirming an OCD diagnosis and predicting the course that the illness will take in that individual.

Unfortunately, magnetoencephalography (MEG) is an expensive tool; clinical charges for a session may run several thousand dollars and it is not yet approved by the FDA for use in OCD. However, progress is being made in the MEG field and costs may decrease as the system changes from being contained in a full room to being worn as a transportable helmet.

Future research should also explore the underlying differences between brain waves at both lower and higher frequencies in children. A better understanding of the brain activity that supports obsessions and compulsions could inform therapies like transcranial stimulation or deep brain stimulation. Further work on gamma waves may show that they can serve as a

marker to predict treatment response to medication or therapy; they may also be measured throughout the course of OCD treatment, and be used to gauge whether a patient is responding.

As interest in the discovery of biomarkers grows, we are excited about what we have found through this study and the potential that it could hold for patients with OCD, particularly children. We are grateful for the funding support that we received from the IOCDF that helped make this study possible.

1.16 Papers:

- **Normal Electrical Activity of the Brain in Obsessive-Compulsive Patients After Anodal Stimulation of the Left Dorsolateral Prefrontal Cortex**

Introduction:

Transcranial Direct Current Stimulation (tDCS) has been used as a non-invasive method to increase the plasticity of brain. Growing evidence has shown several brain disorders such as depression, anxiety disorders, and chronic pain syndrome are improved following tDCS. In patients with Obsessive-Compulsive Disorder (OCD), increased brain rhythm activity particularly in the frontal lobe has been reported in several studies using Electroencephalogram (EEG). To our knowledge, no research has been done on the effects of electrical stimulation on brain signals of patients with OCD. We measured the electrical activity of the brain using EEG in patients with OCD before and after tDCS and compared it to normal participants. Functional neuroimaging during symptom provocation has observed abnormal activity in the orbitofrontal cortex (OFC), left dorsolateral prefrontal cortex (dlPFC), right premotor cortex, left superior temporal gyrus, globus pallidus externus, hippocampus, and right uncus. Weaker foci of abnormal activity were found in the left caudate, posterior cingulate cortex, and superior parietal lobule. However, an older meta-analysis of functional neuroimaging in OCD reported that the only consistent functional neuroimaging finding was increased activity in the orbital gyrus and head of the caudate nucleus, while anterior cingulate cortex (ACC) activation abnormalities were too inconsistent.

Methods:

Eight patients with OCD (3 males) and 8 matched healthy controls were recruited. A 64-channel EEG was used to record a 5-min resting state before and after application of tDCS in both groups. The intervention of tDCS was applied for 15 minutes with 2 mA amplitude where

anode was placed on the left Dorsolateral Prefrontal Cortex (DLPFC) and cathode on the right DLPFC.

Results:

In line with previous studies, the results showed that the power of Delta frequency band in OCD patients are significantly higher than the normal group. Following anodal tDCS, hyperactivity in Delta and Theta bands declined in most channels, particularly in DLPFC (F3, F4) and became similar to normal signals pattern. The reduction in Delta band was significantly more than the other bands.

Conclusion:

Anodal tDCS over the left DLPFC significantly decreased the power of frequency bands of Delta and Theta in Patients with OCD. The pattern of EEG activity after tDCS became particularly similar to normal, so tDCS may have potential clinical application in these patients.

➢ INTRODUCTION

Obsessive-Compulsive Disorder (OCD) is a neuropsychiatric disorder with a lifelong predominance of 2% to 4% which happens at a 1:1 male to female. It is characterized by regressive sudden thoughts (obsessions) and repetitive behaviours. It has been postulated that OCD is largely caused by the dysfunction of Cortico-Striato-Thalamo-Cortical (CSTC) circuitry, including the Orbitofrontal Cortex (OFC), medial prefrontal cortex, basal ganglia, and the Dorsolateral Prefrontal Cortex (DLPFC) (Tortella, 2015). Supporting that, imaging studies in OCD reveal abnormalities in relevant structures like OFC, limbic system, and DLPFC (Velikova et al., 2010). Also based on Liu et al. (2017) study, cognitive dysfunction and compulsive behaviours in patients with OCD are associated with abnormalities within the DLPFC. Their results showed that the resistant OCD subgroup were presented with distractibility and inadequate inhibitory activity. The researchers attributed it to abnormal activity within the fusiform gyrus and DLPFC. Taken together, their findings suggest that dysregulation of these areas plays key roles in the pathophysiology of OCD.

Russell et al. (2003) study on patients with OCD demonstrate that neurobiological abnormalities in the pre-frontal cortex are involved in the pathogenesis of the OCD. These outcomes provide new evidence of localized functional neurochemical marker changes in the left DLPFC in OCD. High levels of N-Acetyl-Aspartate (NAA) in left DLPFC can point to glial hypoplasia, neuronal hypertrophy, and or unusual pruning of neural brain elements in DLPFC (Russell et al., 2003).

Many investigations on the power of Electroencephalogram (EEG) in OCD concluded with conflicting results. Some of them reported an increase in alpha and beta action in the central channels (Prichep et al., 1993), while others reported a decline of both delta and beta (Kuskowski et al., 1993) or increased delta and diminished alpha wave (Ischebeck, Endrass, Simon, & Kathmann, 2014). Another investigation by Desarkar, Sinha, Jagadheesan, & Nizamie, (2007) demonstrates that patients with OCD have fundamentally higher power in contrast with the control group, mostly in theta band and were predominantly left sided in fronto-temporo-parietal districts in delta and alpha bands, and just left sided in the frontal area in beta 2 (12-18 Hz) band. Nevertheless, most studies in this context agree upon that OCD patients at least in one or both band(s) (theta & delta bands) have higher power in contrast with the control group (Karadag et al., 2003; Desarkar et al., 2007; Ischebeck et al., 2014).

Recent functional imaging techniques (low-resolution electromagnetic tomography and variable resolution electromagnetic tomography) based on quantitative EEG have shown expanded beta action in the cingulate gyrus in patients with OCD compared with the control group (Velikova et al., 2010). In addition, increased alpha activity in the corpus striatum, thalamus, temporoparietal and orbitofrontal areas has been reported in OCD responders to selective serotonin reuptake inhibitors (SSRI) whereas a lower frontal beta activity was related to a better treatment response (Fontenelle, Mendlowicz, Ribeiro, Piedade, & Versiani, 2005). On the other hand, non-invasive brain stimulation tools, such as Transcranial Magnetic Stimulation (TMS), Transcranial Direct Current Stimulation (tDCS), and Transcranial Alternating Current Stimulation (tACS) have acquired growing interest as efficient tools to modify cortical excitability and activity.Since OCD is identified with hyperactivity of the orbitofrontal subcortical circuit, tDCS can possibly help these patients by adjusting excitability of the dorsolateral or orbitofrontal prefrontal cortex.

Many investigations have explored the effect of tDCS in OCD. A case report indicates that after ten daily sessions of 2 mA cathodal stimulation for 20 min on the DLPFC, no progressions were seen in OCD symptoms with sham or real stimulation. However, it decreased anxiety and depressive symptoms (Bais, Figee & Denys, 2014).Several studies have recommended that tDCS could be beneficial in reducing symptoms in patients with treatment-resistant OCD

Study participants

Based on DSM-IV (American Psychiatric Association, 1994) criteria, eight patients were diagnosed with OCD by qualified clinical psychologists and eight healthy controls matched for

sex, age, and handedness were recruited, too. Exclusion criteria consisted of having history of any seizures and other neurological disorders, mood disorders, chronic medical disease, severe head injury and any neurosurgical experiences. Moreover, the control group should not have any history of mental problem. For this purpose, we used General Health Questionnaire (GHQ-28) to screen the control group. The statistical sample of the research in the control group included male and female students of the Institute of Cognitive Science, aged 21 to 34 years (with a mean age of 27.5), and the intervention group of male and female patients (OCD group) from the consulting center of the National Iranian Oil Company, aged 22 to 36 years (with a mean age of 29). In this study, a total of 16 people attended, nine men and seven women.

During EEG recording, six patients were drug-free while two of them were under SSRIs medication. Clinical record in the patient group contained OCD's age of onset, duration, and symptom seriousness. Symptom seriousness was evaluated by the Yale–Brown Obsessive Compulsive Scale (Y-BOCS) (Goodman et al., 1989). All patients after full explanation were consented verbally and written to participate in the experiment. This research was performed at the Cognitive Laboratory of Institute for Cognitive Science Studies (ICSS), Tehran, Iran.

➢ Study methods

In this study, 64-channel amplifier device (ANT Neuro Netherlands, 64 ES-410) were used to record brain signals. The brain signals of the participants were recorded for 5 minutes before electrical stimulation (the baseline). Then electrical stimulation (2 mA current intensity) was applied for 15 minutes. The anodal electrode was placed over the DLPFC on the left hemisphere. Cathode electrode was placed in the right area of DLPFC. At the end, we recorded brain signals of the subjects for 5 minutes to observe the effects of electrical stimulation and compare it with the baseline.

- **EEG data acquisition**

Ten-twenty International System for electrode placement has been used in which the impedance was kept down below 5 kΩ. The rate of sampling was 512 Hz. High and low frequency filters, with a notch filter of 50 Hz, were adjusted at 0.5 Hz and 30 Hz, respectively. All people were requested not to smoke or take caffeine 3 hours before the recording. The whole experiment took about 25 minutes in a semi-dark room with the subject's eyes closed.

- **EEG data processing**

We used EEGLAB toolbox in Matlab for data analysis (Delorme & Makeig, 2004). Four channels had to be excluded from the original arrangement of 64 channels because it was impossible to get two minutes of artifact-free data out of them; these channels were F4, FC5, FC4, CP4. Ultimately, 60 electrodes were selected to analyze power spectrum and calculated by using the Fast Fourier Transform (FFT) function implemented in EEGLAB study.

1.16.1 Results

- **Comparison of baseline EEG between OCD and normal subjects**

The power of delta (0.5–3.5 Hz) frequency band in patients with OCD was much higher than the control group in most channels (P<0.05). This difference is more widespread in the delta band and particularly in the left side (Figure 1, A and B). Figure 2 shows the comparison of the power of frontal channels in the delta band between the control and OCD group. For the theta band, although most of the channels had higher power than the normal group, no significant difference was observed in any of the channels. Figure 3 shows comparison of power of frontal channels in the theta band between the control and OCD group. In the alpha band (8–12 Hz), a similar pattern was visible. With regard to beta 1(12.5–18Hz), beta 2(18.5–24), and beta 3(24.5–30) no significant difference was observed (except for one channel in beta 2 and 3). Furthermore, the results of statistical comparisons in delta and theta power (μV2/Hz) in these groups (Only frontal channels) has shown in Table 3 and 4.

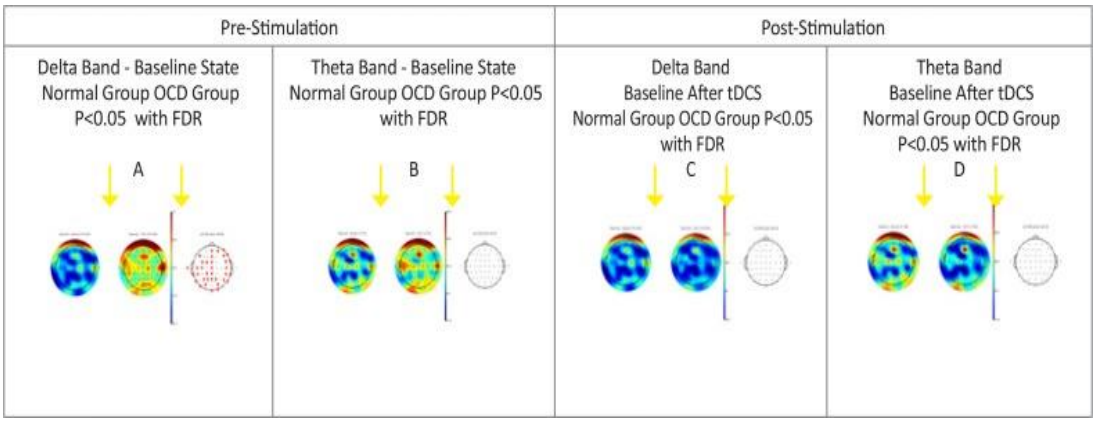


Figure 1. 35 Brain maps showing differences between pre-stimulation in both group and post-stimulation in OCD patients

Comparison of power spectrum of normal subjects with OCD patients before (A, B) and after stimulation (C, D). A: Delta band power; B: Theta band power (both pre-stimulation); C: Delta band power; D: Theta Band power (both post-stimulation). No significant difference was

observed between C and D. Black dots show EEG channel locations and the power of the EEG channels color-coded and plotted at the corresponding location on the scalp. The third top plot related to P value that red dots specify the significant channels. Also, the colour bar on the corner of the brain maps shows the signal strength spectrum in each position**.**

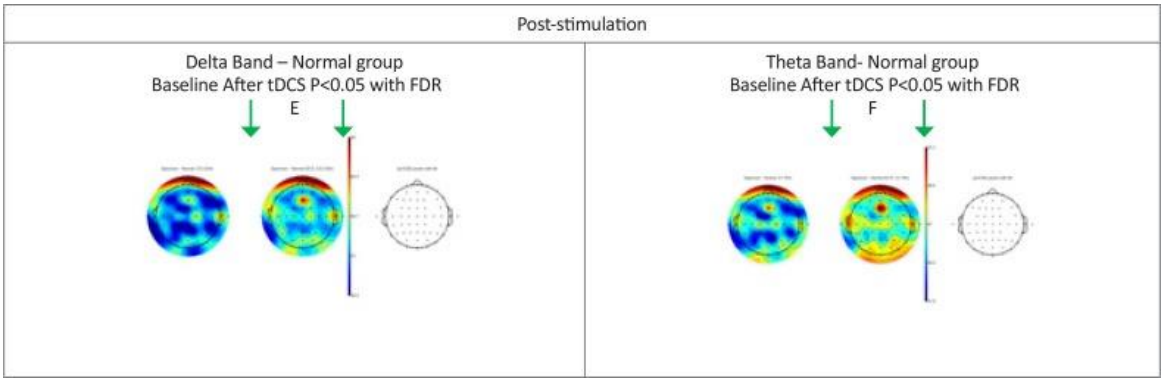


Figure 1.36 Brain maps showing differences between pre and post-stimulation in normal subjects

E: Delta band power; F: Theta band power (both post-stimulation). Black dots show EEG channel locations and the power of the EEG channels color-coded and plotted at the corresponding location on the scalp. The third top plot related to P value that red dots specify the significant channels. Also, the colour bar on the corner of the brain maps shows the signal strength spectrum in each position.

- **Comparing before and after tDCS in patients with OCD and control subjects**

The power spectrum in patients with OCD reduced significantly compared to the baseline status after tDCS. The power spectrum showed a significant reduction after tDCS in the delta and theta bands in most channels. Furthermore, the power of beta bands also decreased. Whereas in normal subjects no significant difference was observed in the baseline status after tDCS (Figure 2, E and F). In addition, the results of statistical comparisons in delta and theta power (μV2/Hz) before and after tDCS in both groups (Only frontal channels) has shown in Table 5 and and 66.

Table 5.

Group comparison in delta power (μV2 /Hz) in pre-stimulation in the control group & post-stimulation in OCD group

Channel	OCD (n=8)		Normal (n=8)		t	P
	Mean	SD	Mean	SD		
F5	49.10	1.72	50.58	3.19	1.11	0.28
F3	49.45	2.83	50.42	3.34	0.58	0.56
F2	54.98	3.25	56.54	3.90	0.81	0.43
F6	49.86	2.63	49.25	3.44	0.37	0.71
FC3	54.94	2.78	53.18	3.19	1.09	0.29
FC1	49.76	0.75	49.56	4.08	0.13	0.89
FC2	54.34	1.68	53.97	2.01	0.37	0.71
FC6	51.45	2.10	51.11	3.66	0.21	0.83

Table 1.1

Table 6.

Group comparison in theta power (μV2 /Hz) in pre-stimulation in the control group and post-stimulation in OCD patients

Channel	OCD (n=8)		Normal (n=8)		t	P
	Mean	SD	Mean	SD		
F5	41.91	0.87	43.50	3.13	1.36	2.07
F3	42.26	1.49	43.52	3.49	0.91	0.38
F2	46.05	2.18	47.37	3.09	0.92	0.37
F6	41.57	3.39	42.25	2.92	0.39	0.70
FC3	45.37	2.16	45.66	2.30	0.24	0.81
FC1	41.61	1.58	41.78	2.79	0.14	0.88
FC2	45.89	2.37	45.80	2.67	0.06	0.94
FC6	43.49	2.79	44.35	4.55	0.43	0.66

Table 1.2

- **Comparing patients with OCD after tDCS with normal subjects' baseline**

Interestingly, the power frequency bands of patients with OCD became similar to the normal group's baseline with respect to the delta and theta bands. No significant difference was observed in the delta band. Comparison of power of frontal channels in the delta and theta bands between normal (pre-stimulation) and OCD (post-stimulation) group

Discussion

Our results show that frequency power of delta and theta bands in patients with OCD is higher than the control group. Our baseline EEG finding is consistent with results of Desarkar et al. (2007) study. Moreover, the results of our study show that the power spectrum in OCD patients reduced appreciably compared to the baseline status after tDCS. Interestingly, after stimulation, the power frequency bands of patients with OCD became similar to the normal group's baseline with respect to the delta and theta bands. To our knowledge, no research has been done to investigate the effects of electrical stimulation on brain signals of OCD patients

- **Brain activation of patients with obsessive-compulsive disorder during neuropsychological and symptom provocation tasks before and after symptom improvement**

Background: Functional neuroimaging studies have implicated hyperactivity of the frontal cortex in obsessive-compulsive disorder (OCD); however, relationships between abnormal brain activity, clinical improvement, and neuropsychological function have not been clarified in OCD. To clarify the pathophysiology of this disorder, regional changes in brain function were examined during administration of cognitive and symptom provocation tasks in patients with OCD before and after treatment.

Methods: Ten outpatients with OCD participated in the study. Functional magnetic resonance imaging (fMRI) was performed before and after treatment. Stroop and symptom provocation tasks were administered during fMRI. Each patient was randomly allocated to receive either pharmacotherapy with fluvoxamine 200 mg/day (n = 4) or behaviour therapy (n = 6) for 12 weeks.

Results: After 12-week treatment, mean (+/- SD) total score on the Yale-Brown Obsessive-Compulsive Scale decreased from 29.00 +/- 3.59 to 14.60 +/- 9.22, representing symptomatic improvement from moderate to mild. After symptom improvement, symptom provocation-related activation in the orbitofrontal, dorsolateral-prefrontal, and anterior cingulate cortices decreased. Conversely, Stroop task-related activation in the parietal cortex and cerebellum increased.

Conclusions: After improvement of OCD with either fluvoxamine or behavioural therapy, hyperactivation of the frontal lobe related to a symptom-provocative state decreases, and posterior brain activity related to action-monitoring function increases.

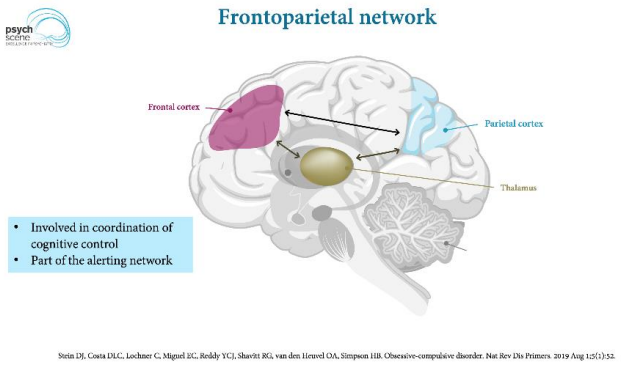


Figure 1.37 Frontoparietal lobe

- **Early visual perceptual processing is altered in obsessive–compulsive disorder**

Objective

Existing studies have shown changes in attention and emotion processing of disorder-relevant visual stimuli in those with obsessive_compulsive_disorder (OCD). However, early visual processing in OCD has not been assessed, as previous studies did not examine the entire time course of visual processing but instead assessed potential differences in pre-determined visual evoked potentials (VEPs). This study investigates the entire visual processing stream in OCD compared to healthy age-matched controls (HC) using emotionally-neutral visual stimuli and a data-driven rather than hypothesis-driven approach.

Methods

35 HC and 26 participants with OCD underwent EEG recording while completing a modified Eriksen flanker task. Permutation-controlled t-tests were used to identify group differences in the data's full-time course of visual evoked potentials. Baseline-corrected amplitudes at time points where the groups were significantly different were analysed using ANCOVAs with BDI, BAI, and SNAP-inattentiveness scores included as covariates.

Results

This analysis identified enhanced P1 amplitudes to two visual stimuli (the initial flanker and the stimulus), corresponding to time windows of 65–93 ms and 157–187 ms post-flanker presentation in the OCD group compared to controls. Group (OCD vs. HC) was the strongest predictor of VEP amplitude during both time windows, with no significant influences of any covariates.

Conclusions

This study showed an enhanced P1 component in people with OCD to neutral visual stimuli, potentially reflecting either inefficient or excessive early visual processing in this population. Additional inquiry is necessary to determine whether altered visual processing is associated with the sensory hypervigilance observed in those with OCD.

Significance

This work identifies early visual processing alterations in OCD using neutral stimuli and a data-driven approach.

1.17 SCOPE OF THE THESIS

Obsessive Compulsive Disorder has been detected using Eriksen Flanker Task. Generally, in the literature survey, we get to see OCD detection using EEG or fMRI data. fNIRS is not used as widely as the other two. But here, instead of EEG or fMRI, fNIRS signal is being used to detect OCD data. The main objective of the thesis is to classify whether a patient is healthy or suffering from OCD using Convolutional Neural Network (CNN) architecture.

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CHAPTER 2

Obsessive Compulsive Disorder

2. WHAT IS OBSESSIVE COMPULSIVE DISORDER(OCD)?

Obsessive-compulsive disorder (OCD) is a long-lasting disorder in which a person experiences uncontrollable and recurring thoughts (obsessions), engages in repetitive behaviours (compulsions), or both. People with OCD have time-consuming symptoms that can cause significant distress or interfere with daily life.

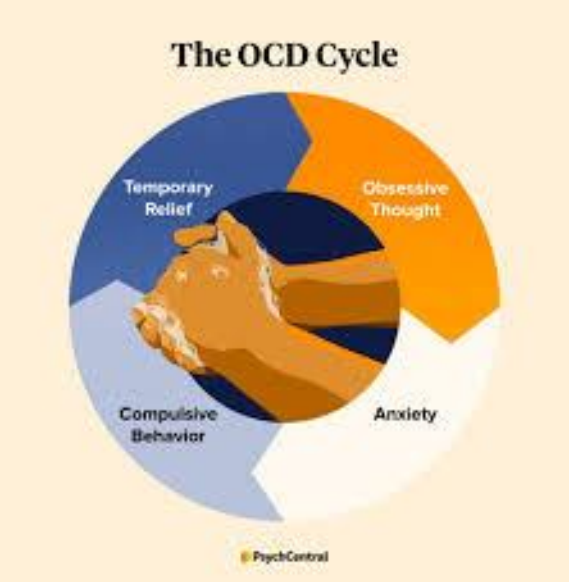


Figure 2.1 OCD Cycle

Obsessive–compulsive disorder (OCD) is a mental and behavioural disorder in which an individual has intrusive thoughts (an *obsession*) and feels the need to perform certain routines (*compulsions*) repeatedly to relieve the distress caused by the obsession, to the extent where it impairs general function.

2.1. What are the signs and symptoms of OCD?

People with OCD may have obsessions, compulsions, or both.

2.1.1 OBSESSIONS

Obsessions are repeated thoughts, urges, or mental images that are intrusive, unwanted, and make most people anxious. Obsessions are persistent unwanted thoughts, mental images, or urges that generate feelings of anxiety, disgust, or discomfort. Some common obsessions include fear of contamination, obsession with symmetry, the fear of acting blasphemously, the sufferer's sexual orientation, and the fear of possibly harming others or themselves.

Common obsessions include:

- Fear of germs or contamination
- Fear of forgetting, losing, or misplacing something
- Fear of losing control over one's behaviour
- Aggressive thoughts toward others or oneself
- Unwanted, forbidden, or taboo thoughts involving sex, religion, or harm
- Desire to have things symmetrical or in perfect order

Obsessions are stress-inducing thoughts that recur and persist, despite efforts to ignore or confront them. People with OCD frequently perform tasks, or compulsions, to seek relief from obsession-related anxiety. Within and among individuals, initial obsessions vary in clarity and vividness. A relatively vague obsession could involve a general sense of disarray or tension, accompanied by a belief that life cannot proceed as normal while the imbalance remains. A more intense obsession could be a preoccupation with the thought or image of a close family member or friend dying, or intrusive thoughts related to relationship rightness. Other obsessions concern the possibility that someone or something other than oneself—such as God, the devil, or disease—will harm either the patient or the people or things the patient cares about. Others with OCD may experience the sensation of invisible protrusions emanating from their bodies, or feel that inanimate objects are ensouled. Another common obsession is scrupulosity, the pathological guilt/anxiety about moral or religious issues. In scrupulosity, a person's obsessions focus on moral or religious fears, such as the fear of being an evil person or the fear of divine retribution for sin. Mysophobia, a pathological fear of contamination and germs, is another common obsession theme.

Some people with OCD experience sexual obsessions that may involve intrusive thoughts or images of "kissing, touching, fondling, oral sex, anal sex, intercourse, incest, and rape" with "strangers, acquaintances, parents, children, family members, friends, co-workers, animals, and religious figures", and can include heterosexual or homosexual contact with people of any age. Similar to other intrusive thoughts or images, some disquieting sexual thoughts are normal at times, but people with OCD may attach extraordinary significance to such thoughts. For example, obsessive fears about sexual orientation can appear to the affected individual, and even to those around them, as a crisis of sexual identity. Furthermore, the doubt that

accompanies OCD leads to uncertainty regarding whether one might act on the troubling thoughts, resulting in self-criticism or self-loathing.



Figure 2.2 Intrusive thoughts

People with OCD may face intrusive thoughts, such as thoughts about the devil (shown is a painted interpretation of Hell).

2.1.2 COMPULSIONS

Compulsions are repetitive behaviours a person feels the urge to do, often in response to an obsession. Common compulsions include:

- Excessive cleaning or handwashing
- Ordering or arranging items in a particular, precise way
- Repeatedly checking things, such as that the door is locked or the oven is off
- Compulsive counting
- Praying or repeating words silently

Compulsions are repeated actions or routines that occur in response to obsessions to achieve a relief from anxiety. Common compulsions include excessive hand washing, cleaning, counting, ordering, repeating, avoiding triggers, hoarding, neutralizing, seeking assurance, praying, and checking things. People with OCD may only perform mental compulsions such as needing to know or remember things. While this is sometimes referred to as primarily obsessional obsessive–compulsive disorder (Pure O), it is also considered a

misnomer due to associated mental compulsions and reassurance seeking behaviours that are consistent with OCD.

Compulsions occur often and typically take up at least one hour per day, impairing one's quality of life. Compulsions cause relief in the moment, but cause obsessions to grow over time due to the repeated reward-seeking behaviour of completing the ritual for relief. Many adults with OCD are aware that their compulsions do not make sense, but they still perform them to relieve the distress caused by obsessions.

Some people with OCD performs compulsive rituals because they inexplicably feel that they must do so, while others act compulsively to mitigate the anxiety that stems from obsessive thoughts. The affected individual might feel that these actions will either prevent a dreaded event from occurring, or push the event from their thoughts. Excessive skin picking, hair pulling, nail biting, and other body-focused repetitive behaviour disorders are all on the obsessive–compulsive spectrum. Some individuals with OCD are aware that their behaviours are not rational, but they feel compelled to follow through with them to fend off feelings of panic or dread.[56] Furthermore, compulsions often stem from memory distrust, a symptom of OCD characterized by insecurity in one's skills in perception, attention, and memory, even in cases where there is no clear evidence of a deficit.

People with OCD rely on compulsions as an escape from their obsessive thoughts; however, they are aware that relief is only temporary, and that intrusive thoughts will return. Some affected individuals use compulsions to avoid situations that may trigger obsessions. Compulsions may be actions directly related to the obsession, such as someone obsessed with contamination compulsively washing their hands, but they can be unrelated as well. In addition to experiencing the anxiety and fear that typically accompanies OCD, affected individuals may spend hours performing compulsions every day. In such situations, it can become difficult for the person to fulfil their work, familial, or social roles. These behaviours can also cause adverse physical symptoms; for example, people who obsessively wash their hands with antibacterial soap and hot water can make their skin red and raw with dermatitis.

In cognitive behavioural therapy (CBT), OCD patients are asked to overcome intrusive thoughts by not indulging in any compulsions. They are taught that rituals keep OCD strong, while not performing them causes OCD to become weaker. This position is supported by the pattern of memory distrust; the more often compulsions are repeated, the more weakened

memory trust becomes, and this cycle continues as memory distrust increases compulsion frequency

Some people with OCD also has a tic disorder involving repetitive movements or sounds. Motor tics are sudden, brief, repetitive movements, such as eye blinking and other eye movements, facial grimacing, shoulder shrugging, and head or shoulder jerking. Vocal tics include things like repetitive throat-clearing, sniffing, or grunting sounds. It is common for people with OCD to also have a diagnosed mood disorder or anxiety disorder.

OCD symptoms may begin anytime but usually start between late childhood and young adulthood. Most people with OCD are diagnosed as young adults.

The symptoms of OCD may start slowly and can go away for a while or worsen as time passes. During times of stress, the symptoms often get worse. A person's obsessions and compulsions also may change over time.

People with OCD might avoid situations that trigger their symptoms or use drugs or alcohol to cope. Many adults with OCD recognize that their compulsive behaviours do not make sense. However, children may not realize that their behaviour is out of the ordinary and often fear that something terrible will happen if they do not perform certain compulsive rituals. Parents or teachers typically recognize OCD symptoms in children.



Figure 2.3 Frequent and excessive hand washing occurs in some people with OCD.

2.2 CAUSES AND RISK FACTORS

- **Genetics:** Studies have shown that having a first-degree relative (parent or sibling) with OCD is associated with an increased chance of developing the disorder. Scientists have not

identified any one gene or set of genes that definitively leads to OCD, but studies exploring the connection between genetics and OCD are ongoing.

- **Biology:** Brain imaging studies have shown that people with OCD often have differences in the frontal cortex and subcortical structures of the brain, areas of the brain that impact the ability to control behaviour and emotional responses. Researchers also have found that several brain areas, brain networks, and biological processes play a key role in obsessive thoughts, compulsive behaviour, and associated fear and anxiety. Research is underway to better understand the connection between OCD symptoms and parts of the brain. This knowledge can help researchers develop and adapt treatments targeted to specific brain locations.
- **Temperament:** Some research has found that people who exhibit more reserved behaviours, experience negative emotions, and show symptoms of anxiety and depression as children are more likely to develop OCD.
- **Childhood trauma:** Some studies have reported an association between childhood trauma and obsessive-compulsive symptoms. More research is needed to understand this relationship.
- **Drug-induced OCD**

  Some medications, toxin exposures, and drugs, such as methamphetamine or cocaine, can induce obsessive-compulsive disorder (OCD) in people without previous symptoms. Some atypical antipsychotics (second-generation antipsychotics) such as olanzapine (Zyprexa) and clozapine (Clozaril) can induce OCD in people, particularly individuals with schizophrenia.
- **Environmen**t

  OCD may be more common in people who have been bullied, abused, or neglected, and it sometimes starts after a significant life event, such as childbirth or bereavement.



Figure 2.4 Symptoms of OCD

2.3 DIAGNOSIS

Formal diagnosis may be performed by a psychologist, psychiatrist, clinical social worker, or other licensed mental health professional.

Psychotherapy

Psychotherapy can be an effective treatment for adults and children with OCD. Research shows that certain types of psychotherapy, including cognitive behavioural therapy and other related therapies, can be as effective as medication for many people. For others, psychotherapy may be most effective when combined with medication.

- **Cognitive behavioural therapy (CBT):** CBT is a type of talk therapy that helps people recognize harmful or untrue ways of thinking so they can more clearly view and respond to challenging situations. CBT helps people learn to question these negative thoughts, determine how they impact their feelings and actions, and change self-defeating behaviour patterns. CBT has been well studied and is considered the "gold standard" of psychotherapy for many people. CBT works best when customized to treat the unique characteristics of specific mental disorders, including OCD.
- **Exposure and response prevention therapy (ERP):** Research shows that ERP, a specific type of CBT, effectively reduces compulsive behaviours, even for people who do not respond well to medication. With ERP, people spend time in a safe environment that

gradually exposes them to situations that trigger their obsession (such as touching dirty objects) and prevent them from engaging in their typical compulsive behaviour (such as handwashing). Although this approach may initially cause anxiety, creating a risk of dropping out of treatment prematurely, compulsions decrease for most people as they continue treatment. It involves teaching the person to deliberately come into contact with situations that trigger obsessive thoughts and fears (exposure), without carrying out the usual compulsive acts associated with the obsession (response prevention). This technique causes patients to gradually learn to tolerate the discomfort and anxiety associated with not performing their compulsions. For many patients, ERP is the add-on treatment of choice when selective serotonin reuptake inhibitors (SSRIs) or serotonin-norepinephrine reuptake inhibitors (SNRIs) medication does not effectively treat OCD symptoms, or vice versa, for individuals who begin treatment with psychotherapy.



Figure 2.5 One exposure and ritual prevention activity would be to check the lock only once and then leave.

Medication

Health care providers may prescribe medication to help treat OCD. The most common medications prescribed for OCD are antidepressants that target serotonin, a chemical transmitter in the brain involved in depression and OCD. The largest category of antidepressants is called selective serotonin reuptake inhibitors.

Antidepressant treatment can take 8–12 weeks before symptoms begin to improve, and treatment for OCD may require higher doses than are typically used to treat depression. For some people, these medications may cause side effects such as headaches, nausea, or difficulty sleeping. Most people with OCD find that medication, often in combination with psychotherapy, can help them manage their symptoms.

Other treatments

In 2018, the FDA approved using a deep form of repetitive transcranial magnetic stimulation (rTMS)—along with medication, psychotherapy, or a combination of both—to treat people with severe OCD who did not respond to other treatments.

Electroconvulsive therapy (ECT) has been found to have effectiveness in some severe and refractory cases. Transcranial magnetic stimulation has shown to provide therapeutic benefits in alleviating symptoms.

Surgery may be used as a last resort in people who do not improve with other treatments. In this procedure, a surgical lesion is made in an area of the brain



Figure 2.6 Treatments for OCD

2.4 ERIKSON FLANKER TASK

n cognitive psychology, the Eriksen flanker task is a set of response inhibition tests used to assess the ability to suppress responses that are inappropriate in a particular context. The target is flanked by non-target stimuli which correspond either to the same directional response as the target (congruent flankers), to the opposite response (incongruent flankers), or to neither (neutral flankers). Eriksen flanker task, published in 1974, is a set of tests to assess selective attention and inhibitory function.

PROCEDURE AND METHOD

In an Eriksen Flanker Task there are three types of stimuli used:

1. **Congruent stimulus**- Flankers call for the same response as the target, and may appear identical. Also referred to as the compatible condition. In this mode, the direction of the nontarget stimuli is the same as the target.
2. **Incongruent stimulus**- Flanker items call for the opposite response of the target and are represented by different symbols. Also referred to as the incompatible condition. In this mode, the direction of the nontarget stimuli is the opposite of the target. Therefore, choosing a correct response is more challenging than the compatible mode.
3. **Neutral stimulus**- Flanker items neither call for the same response nor evoke response conflict.

In the original test described by Eriksen and Eriksen in 1974, letter stimuli were used. Subjects were instructed to make directional responses to certain letters, for example a right response could be associated to the letters **H** and **K**, and a left response to **S** and **C**. Each stimulus consisted of a set of seven letters, with the target stimulus placed in the central position. Examples of congruent stimuli would be **HHHKHHH** and **CCCSCCC**, where both the target stimulus and the flankers correspond to the same directional response. Examples of incongruent stimuli could be **HHHSHHH** and **CCCHCCC** , where the central target letter and the flankers correspond to opposite directional responses

Other variants of the Eriksen Flanker Task have used numbers, colour patches, or arrows as stimuli. Also, although most Eriksen Flanker Tasks show the flankers on the left and right of the target, they can also be placed above or below the target, or in other spatial orientations. These examples all use an arbitrary mapping between the stimulus and the response.

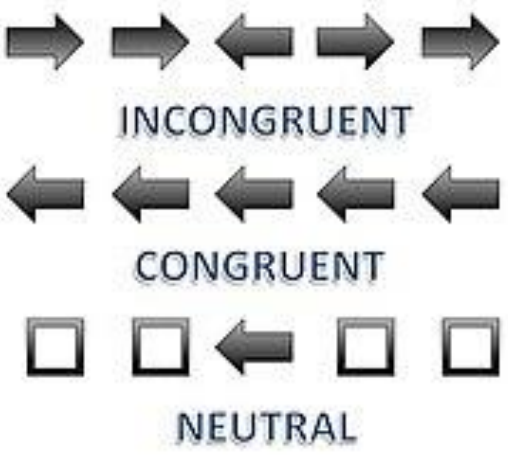


Figure 2.7 Visual stimuli used in Eriksen Flanker Task

Incongruent, congruent, and neutral stimuli represented by arrows. This is what a participant may see in a standard Eriksen Flanker Task.

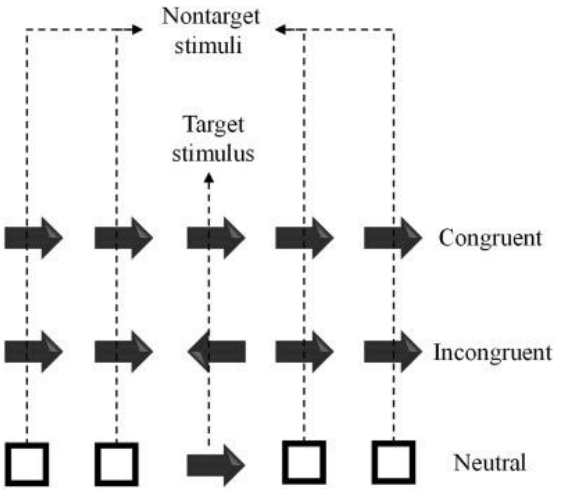


Figure 2.8 Stimuli in OCD

In the original version of the test, letters were used instead of arrow shapes (Eriksen & Eriksen, 1974). For example, individuals were asked to press the right arrow key to respond to the letters "H" and "K," and press the left arrow key for the letters "C" and "S." Therefore, both "HHHKHHH" and "CCCSCCC" are congruent modes. Because in the first case, both letters "K" and "H" associated with the right arrow key, and in the second one, both letters "C" and "S" are associated with the left arrow key. "HHHSHHH" and "CCCHCCC" are examples of incongruent mode because the response associated with the central target is the opposite of what is defined for the nontarget stimuli.

2.5 Neurological basis

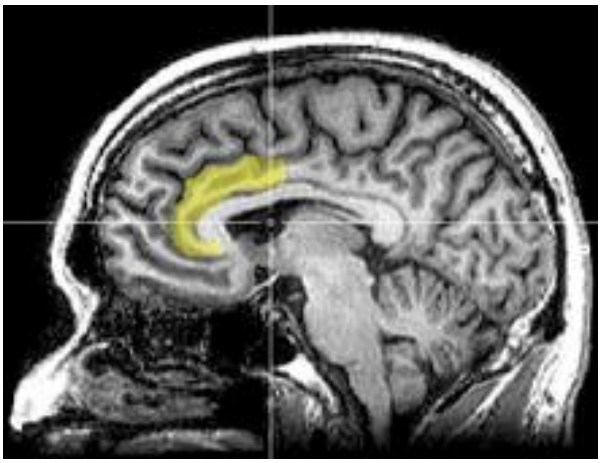


Figure 2.9 The Anterior Cingulate Cortex (ACC) is highlighted in yellow

When subjects participate in the Eriksen Flanker Task, the anterior cingulate cortex, or the ACC, is activated. The ACC is a frontal brain structure responsible for a wide variety of autonomic functions. It is observed to be more active in response to processing incongruent stimuli than congruent stimuli. It is believed that the ACC may monitor the amount of conflict in an Eriksen Flanker trial. Then, that measured conflict is used to enhance the amount of control the participant has on the next trial thus indicating that the more conflict presented on trial *n*, the more control expressed on trial *n* + 1.

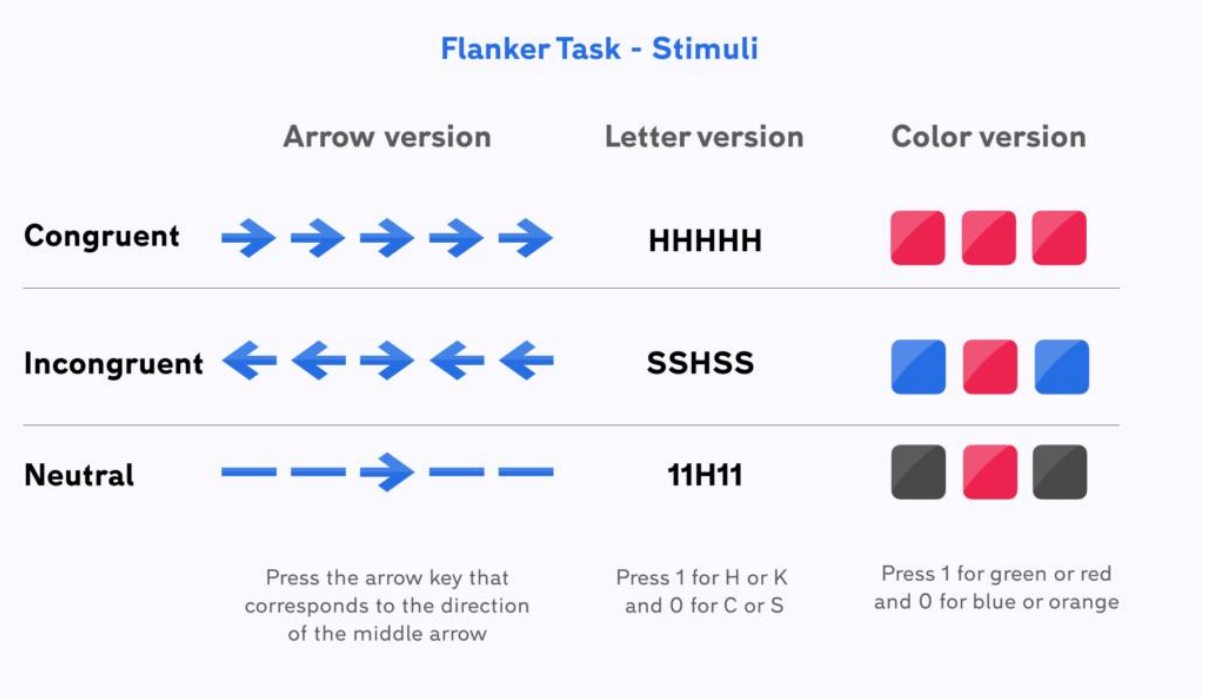


Figure 2.10 Flanker stimuli versions

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CHAPTER 3

Classifiers

3. CLASSIFIERS

3.1 MACHINE LEARNING

Machine learning (**ML**) is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions. Recently, artificial neural networks have been able to surpass many previous approaches in performance. Machine learning (ML) is a branch of artificial intelligence (AI) and computer science that focuses on the using data and algorithms to enable AI to imitate the way that humans learn, gradually improving its accuracy.

ML finds application in many fields, including natural language processing, computer vision, speech recognition, email filtering, agriculture, and medicine.

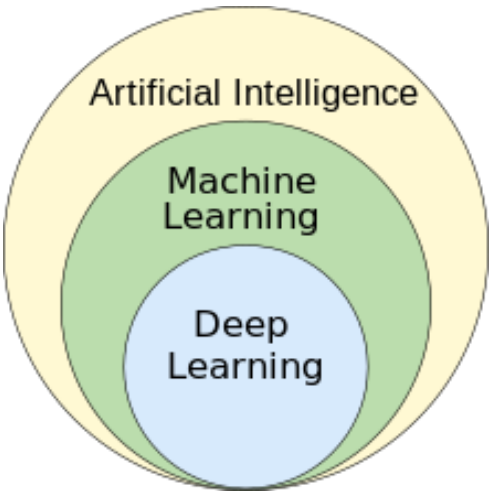


Figure 3.1 Machine learning as subfield of AI

Machine learning approaches are traditionally divided into three broad categories, which correspond to learning paradigms, depending on the nature of the "signal" or "feedback" available to the learning system:

- **Supervised learning**: Supervised learning, also known as supervised machine learning, is defined by its use of labelled datasets to train algorithms to classify data or predict outcomes accurately. The computer is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs. Some methods used in supervised learning include neural networks, naïve bayes, linear regression, logistic regression, random forest, and support vector machine (SVM).

- **Unsupervised learning**: Unsupervised learning, also known as unsupervised machine learning, uses machine learning algorithms to analyse and cluster unlabelled datasets (subsets called clusters). These algorithms discover hidden patterns or data groupings without the need for human intervention. This method's ability to discover similarities and differences in information make it ideal for exploratory data analysis, cross-selling strategies, customer segmentation, and image and pattern recognition. No labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning).
- **Reinforcement learning**: Reinforcement machine learning is a machine learning model that is similar to supervised learning, but the algorithm isn't trained using sample data. This model learns as it goes by using trial and error. A computer program interacts with a dynamic environment in which it must perform a certain goal (such as driving a vehicle or playing a game against an opponent). As it navigates its problem space, the program is provided feedback that's analogous to rewards, which it tries to maximize.
    - **Semi-supervised learning**: Semi-supervised learning offers a happy medium between supervised and unsupervised learning. During training, it uses a smaller labelled data set to guide classification and feature extraction from a larger, unlabelled data set.

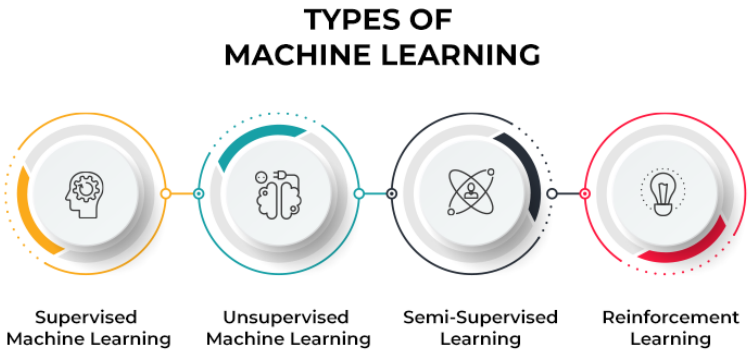


Figure 3.2 Types of Machine Learning

3.1.1 SUPPORT VECTOR MACHINE (SVM)

A support vector machine (SVM) is a supervised machine learning algorithm that classifies data by finding an optimal line or hyperplane that maximizes the distance between each class in an N-dimensional space. Support Vector Machine (SVM) is a powerful machine learning algorithm used for linear or nonlinear classification, regression, and even outlier detection

tasks. SVMs can be used for a variety of tasks, such as text classification, image classification, spam detection, handwriting identification, gene expression analysis, face detection, and anomaly detection. SVMs are adaptable and efficient in a variety of applications because they can manage high-dimensional data and nonlinear relationships. SVM algorithms are very effective as we try to find the maximum separating hyperplane between the different classes available in the target feature.

The main objective of the SVM algorithm is to find the optimal hyperplane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin between the closest points of different classes should be as maximum as possible. The dimension of the hyperplane depends upon the number of features. If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three.

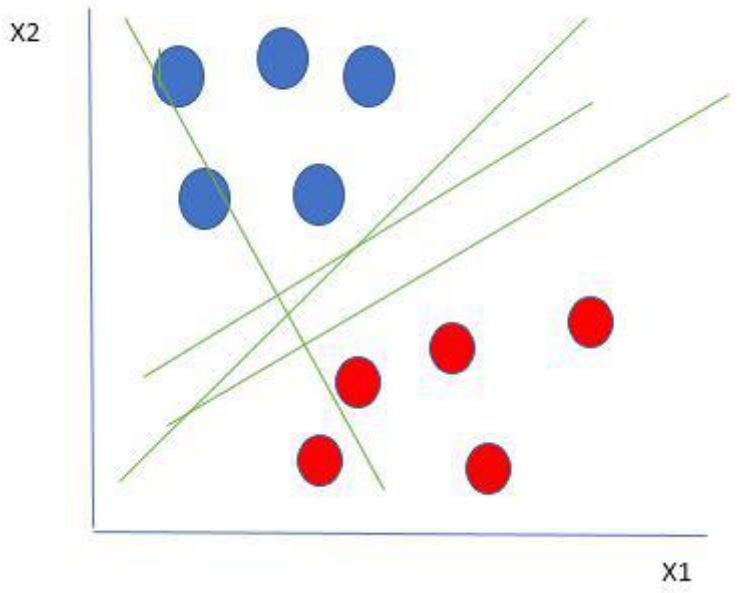


Figure 3.3 Linearly Separable Data points

They distinguish between two classes by finding the optimal hyperplane that maximizes the margin between the closest data points of opposite classes. The number of features in the input data determine if the hyperplane is a line in a 2-D space or a plane in a n-dimensional space. Since multiple hyperplanes can be found to differentiate classes, maximizing the margin between points enables the algorithm to find the best decision boundary between classes. The SVM algorithm is widely used in machine learning as it can handle both linear and nonlinear

classification tasks. However, when the data is not linearly separable, kernel functions are used to transform the data higher-dimensional space to enable linear separation. This application of kernel functions can be known as the "kernel trick", and the choice of kernel function, such as linear kernels, polynomial kernels, radial basis function (RBF) kernels, or sigmoid kernels, depends on data characteristics and the specific use case.

Example: SVM can be understood with the example that we have used in the KNN classifier. Suppose we see a strange cat that also has some features of dogs, so if we want a model that can accurately identify whether it is a cat or dog, so such a model can be created by using the SVM algorithm. We will first train our model with lots of images of cats and dogs so that it can learn about different features of cats and dogs, and then we test it with this strange creature. So as support vector creates a decision boundary between these two data (cat and dog) and choose extreme cases (support vectors), it will see the extreme case of cat and dog. On the basis of the support vectors, it will classify it as a cat. Consider the below diagram:

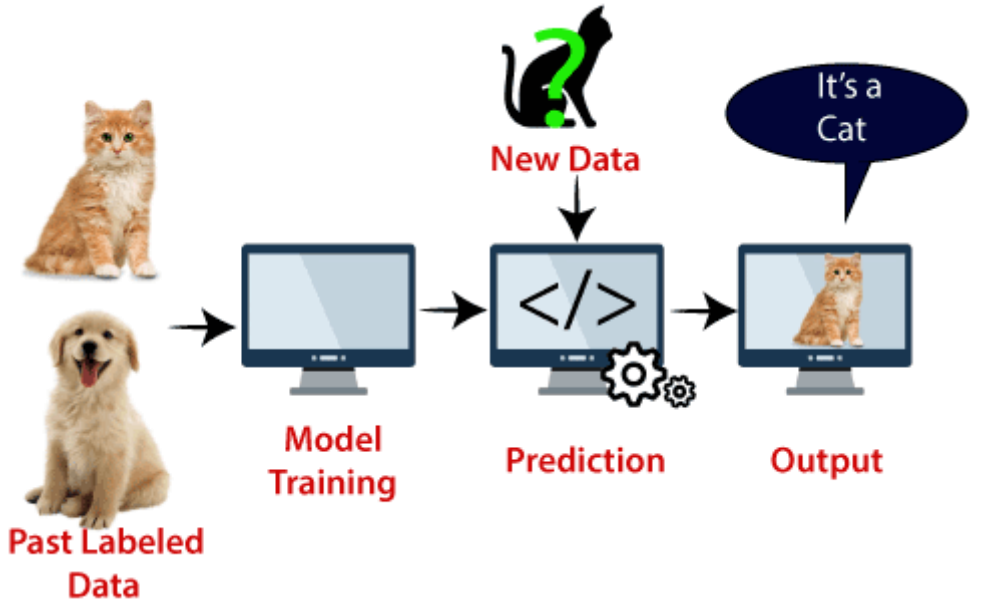


Figure 3.4 SVM algorithm can be used for Face detection, image classification, text categorization, **etc.**

3.1.1.1 Support Vector Machine Terminology

1. **Hyperplane:** Hyperplane is the decision boundary that is used to separate the data points of different classes in a feature space. In the case of linear classifications, it will be a linear equation i.e. wx+b = 0.
2. **Support Vectors:** Support vectors are the closest data points to the hyperplane, which makes a critical role in deciding the hyperplane and margin.

3. **Margin**: Margin is the distance between the support vector and hyperplane. The main objective of the support vector machine algorithm is to maximize the margin. The wider margin indicates better classification performance.
4. **Kernel**: Kernel is the mathematical function, which is used in SVM to map the original input data points into high-dimensional feature spaces, so, that the hyperplane can be easily found out even if the data points are not linearly separable in the original input space. Some of the common kernel functions are linear, polynomial, radial basis function (RBF), and sigmoid.
5. **Hard Margin:** The maximum-margin hyperplane or the hard margin hyperplane is a hyperplane that properly separates the data points of different categories without any misclassifications.
6. **Soft Margin:** When the data is not perfectly separable or contains outliers, SVM permits a soft margin technique. Each data point has a slack variable introduced by the soft-margin SVM formulation, which softens the strict margin requirement and permits certain misclassifications or violations. It discovers a compromise between increasing the margin and reducing violations.
7. **C:** Margin maximisation and misclassification fines are balanced by the regularisation parameter C in SVM. The penalty for going over the margin or misclassifying data items is decided by it. A stricter penalty is imposed with a greater value of C, which results in a smaller margin and perhaps fewer misclassifications.
8. **Hinge Loss:** A typical loss function in SVMs is hinge loss. It punishes incorrect classifications or margin violations. The objective function in SVM is frequently formed by combining it with the regularisation term.
9. **Dual Problem:** A dual Problem of the optimisation problem that requires locating the Lagrange multipliers related to the support vectors can be used to solve SVM. The dual formulation enables the use of kernel tricks and more effective computing.

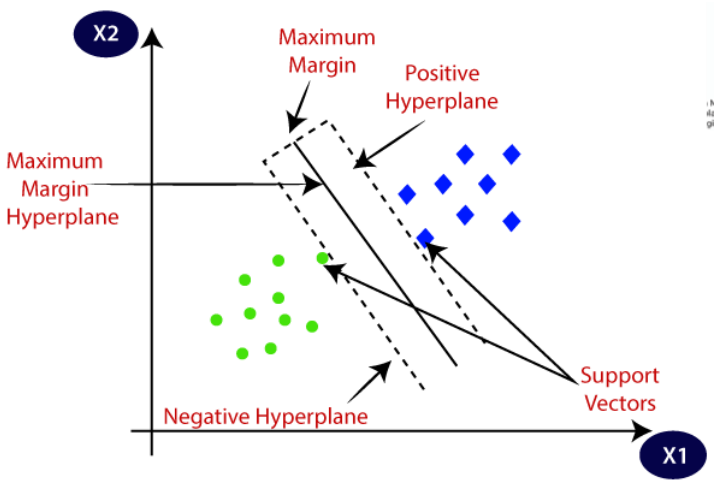


Figure 3.5 SVM

3.1.1.2 Types of SVM classifiers

- **Linear SVMs**

Linear SVMs are used with linearly separable data; this means that the data do not need to undergo any transformations to separate the data into different classes. The decision boundary and support vectors form the appearance of a street, and Professor Patrick Winston from MIT uses the analogy of "fitting the widest possible street" to describe this quadratic optimization problem. Linear SVMs use a linear decision boundary to separate the data points of different classes. When the data can be precisely linearly separated, linear SVMs are very suitable. This means that a single straight line (in 2D) or a hyperplane (in higher dimensions) can entirely divide the data points into their respective classes. A hyperplane that maximizes the margin between the classes is the decision boundary. Mathematically, this separating hyperplane can be represented as:

$wx + b = 0$

where w is the weight vector, x is the input vector, and b is the bias term.

There are two approaches to calculating the margin, or the maximum distance between classes, which are hard-margin classification and soft-margin classification. If we use a hard-margin SVMs, the data points will be perfectly separated outside of the support vectors, or "off the street" to continue with Professor Hinton's analogy. This is represented with the formula,

$(wx_j + b)\, y_j \geq a,$

and then the margin is maximized, which is represented as: max $\gamma = a / \|w\|$, where a is the margin projected onto w.

Soft-margin classification is more flexible, allowing for some misclassification through the use of slack variables (`ξ`). The hyperparameter, C, adjusts the margin; a larger C value narrows the margin for minimal misclassification while a smaller C value widens it, allowing for more misclassified data.

- **Nonlinear SVMs**

Much of the data in real-world scenarios are not linearly separable, and that's where nonlinear SVMs come into play. In order to make the data linearly separable, pre-processing methods are applied to the training data to transform it into a higher-dimensional feature space. That said, higher dimensional spaces can create more complexity by increasing the risk of overfitting the data and by becoming computationally taxing. The "kernel trick" helps to reduce some of that complexity, making the computation more efficient, and it does this by replacing dot product calculations with an equivalent kernel function. Non-Linear SVM can be used to classify data when it cannot be separated into two classes by a straight line (in the case of 2D). By using kernel functions, nonlinear SVMs can handle nonlinearly separable data. The original input data is transformed by these kernel functions into a higher-dimensional feature space, where the data points can be linearly separated. A linear SVM is used to locate a nonlinear decision boundary in this modified space.

There are a number of different kernel types that can be applied to classify data. Some popular kernel functions include:

- Polynomial kernel
- Radial basis function kernel (also known as a Gaussian or RBF kernel)
- Sigmoid kernel

How does SVM works?

Linear SVM:

The working of the SVM algorithm can be understood by using an example. Suppose we have a dataset that has two tags (green and blue), and the dataset has two features x1 and x2. We want a classifier that can classify the pair (x1, x2) of coordinates in either green or blue. Consider the below image:

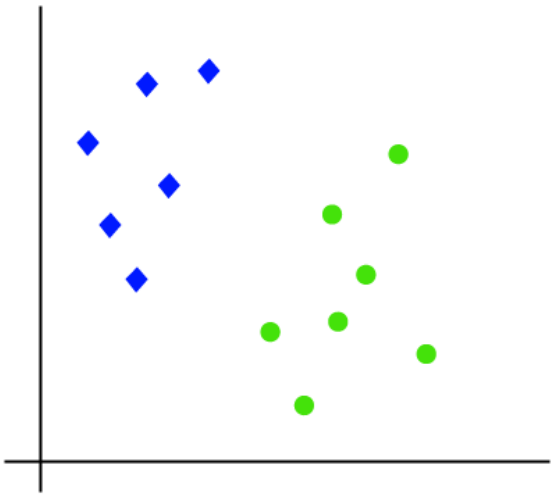


Figure 3.6 Working of Linear SVM 1

So, as it is 2-d space so by just using a straight line, we can easily separate these two classes. But there can be multiple lines that can separate these classes. Consider the below image:

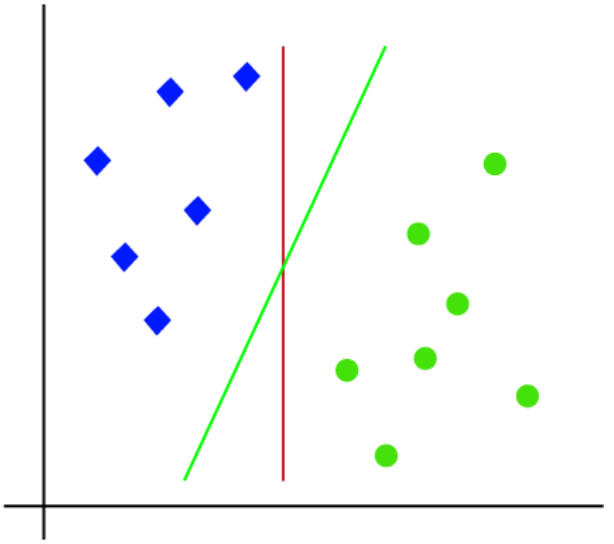


Figure 3.7 Working of Linear SVM 2

Hence, the SVM algorithm helps to find the best line or decision boundary; this best boundary or region is called as a **hyperplane**. SVM algorithm finds the closest point of the lines from both the classes. These points are called support vectors. The distance between the vectors and the hyperplane is called as **margin**. And the goal of SVM is to maximize this margin. The **hyperplane** with maximum margin is called the **optimal hyperplane**.

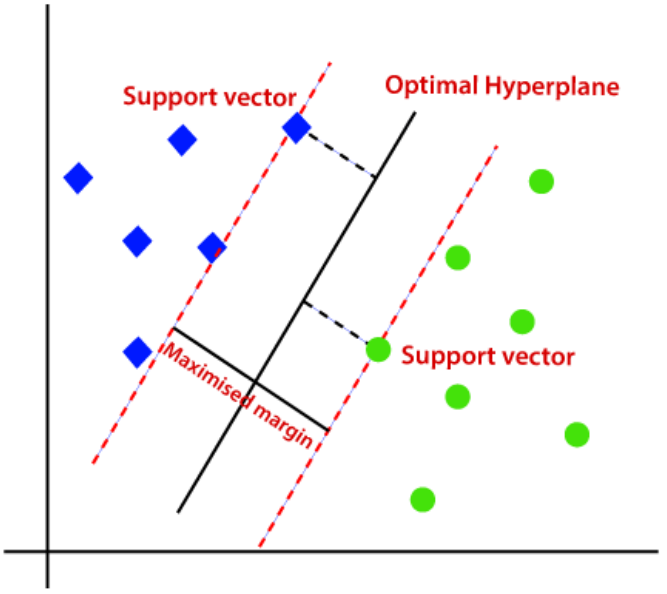


Figure 3.8 SVM in detail

Non-Linear SVM:

If data is linearly arranged, then we can separate it by using a straight line, but for non-linear data, we cannot draw a single straight line. Consider the below image:

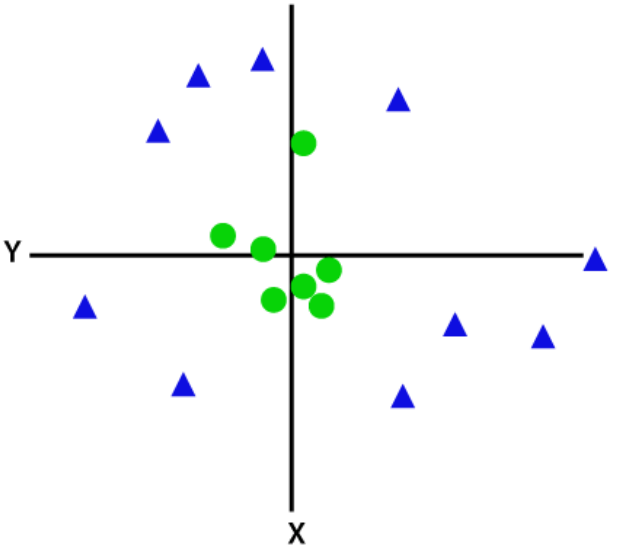


Figure 3.9 Working of Non- linear SVM 1

So, to separate these data points, we need to add one more dimension. For linear data, we have used two dimensions x and y, so for non-linear data, we will add a third-dimension z. It can be calculated as:

$z=x^2 +y^2$

By adding the third dimension, the sample space will become as below image:

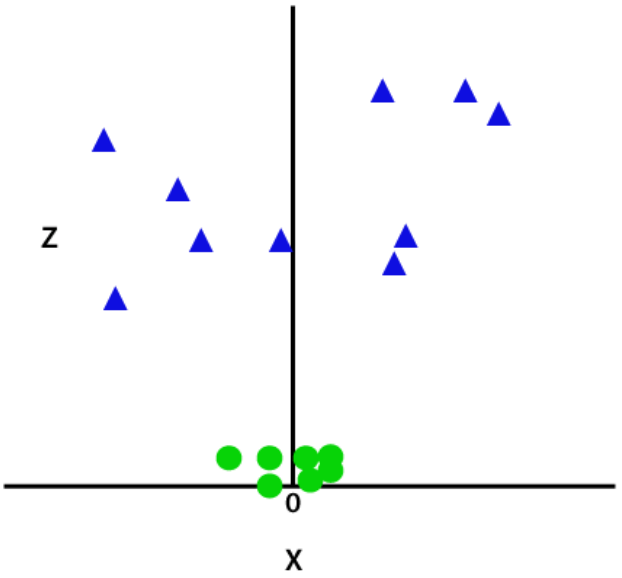


Figure 3.10 Working of non- linear SVM 2

So now, SVM will divide the datasets into classes in the following way. Consider the below image:

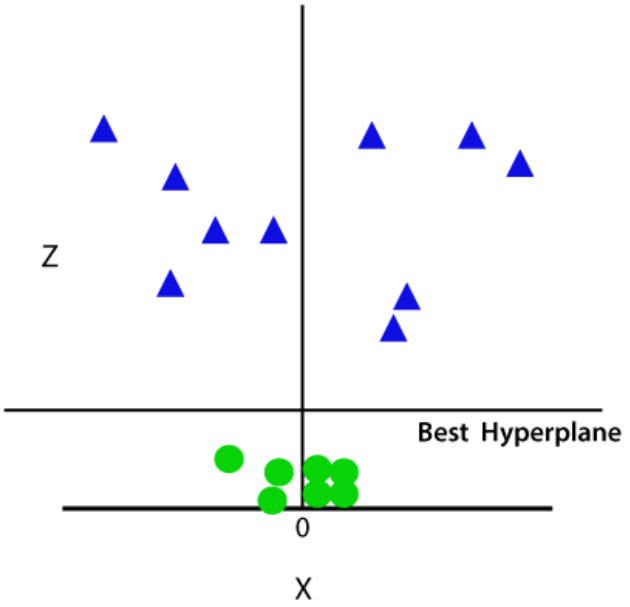


Figure 3.11 SVM 3

Since we are in 3-d Space, hence it is looking like a plane parallel to the x-axis. If we convert it in 2d space with z=1, then it will become as:

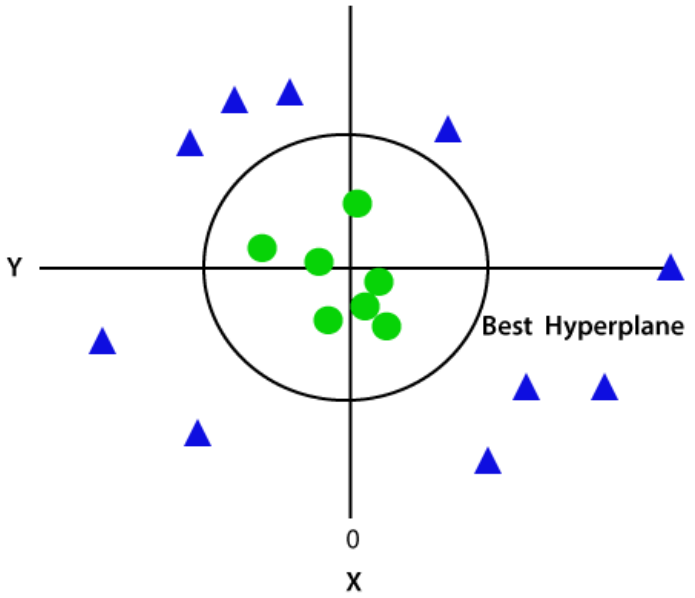


Figure 3.12 SVM 4

Hence, we get a circumference of radius 1 in case of non-linear data.

3.1.1.3 Popular kernel functions in SVM

The SVM kernel is a function that takes low-dimensional input space and transforms it into higher-dimensional space, that is, it converts non-separable problems to separable problems. It is mostly useful in non-linear separation problems. Simply put the kernel, does some extremely complex data transformations and then finds out the process to separate the data based on the labels or outputs defined.

$$\begin{aligned}
\text{Linear}: \; & K(w,b) = w^T x + b \\
\text{Polynomial}: \; & K(w,x) = (\gamma w^T x + b)^N \\
\text{Gaussian RBF}: \; & K(w,x) = \exp(-\gamma ||x_i - x_j||^n \\
\text{Sigmoid}: \; & K(x_i, x_j) = \tanh(\alpha x_i^T x_j + b)
\end{aligned}$$

3.1.1.4 Advantages of SVM

- Effective in high-dimensional cases.
- Its memory is efficient as it uses a subset of training points in the decision function called support vectors.
- Different kernel functions can be specified for the decision functions and its possible to specify custom kernels.

3.1.1.5 Applications of SVMs

While SVMs can be applied for a number of tasks, these are some of the most popular applications of SVMs across industries.

- **Text classification**

SVMs are commonly used in natural language processing (NLP) for tasks such as sentiment analysis, spam detection, and topic modelling. They lend themselves to these data as they perform well with high-dimensional data.

- **Image classification**

SVMs are applied in image classification tasks such as object detection and image retrieval. It can also be useful in security domains, classifying an image as one that has been tampered with.

- **Bioinformatics**

SVMs are also used for protein classification, gene expression analysis, and disease diagnosis. SVMs are often applied in cancer research (link resides outside ibm.com) because they can detect subtle trends in complex datasets.

- **Geographic information system (GIS)**

SVMs can analyse layered geophysical structures underground, filtering out the 'noise' from electromagnetic data. They have also helped to predict the seismic liquefaction potential of soil, which is relevant to field of civil engineering.

- SVMs are helpful in text and hypertext categorization, as their application can significantly reduce the need for labelled training instances in both the standard inductive and transductive settings. Some methods for shallow semantic parsing are based on support vector machines.
- Classification of images can also be performed using SVMs. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes after just three to four rounds of relevance feedback. This is also true for image segmentation systems, including those using a modified version SVM that uses the privileged approach as suggested by Vapnik.
- Classification of satellite data like SAR data using supervised SVM.

- Hand-written characters can be recognized using SVM.

3.1.1.6 Issues

Potential drawbacks of the SVM include the following aspects:

- Requires full labelling of input data
- Uncalibrated class membership probabilities—SVM stems from Vapnik's theory which avoids estimating probabilities on finite data
- The SVM is only directly applicable for two-class tasks. Therefore, algorithms that reduce the multi-class task to several binary problems have to be applied; see the multi-class SVM section.
- Parameters of a solved model are difficult to interpret.

1) 3.2.1 LINEAR DISCRIMINANT ANALYSIS (LDA)

Linear discriminant analysis (LDA) is an approach used in supervised machine learning to solve multi-class classification problems. LDA separates multiple classes with multiple features through data dimensionality reduction. This technique is important in data science as it helps optimize machine learning models.

Linear Discriminant Analysis (LDA), also known as Normal Discriminant Analysis (NDA) or Discriminant Function Analysis (DFA), is a dimensionality reduction technique primarily utilized in supervised classification problems. It facilitates the modelling of distinctions between groups, effectively separating two or more classes. LDA operates by projecting features from a higher-dimensional space into a lower-dimensional one. In machine learning, LDA serves as a supervised learning algorithm specifically designed for classification tasks, aiming to identify a linear combination of features that optimally segregates classes within a dataset**.** LDA algorithms model the data distribution for each class and use Bayes' theorem to classify new data points. Bayes calculates conditional probabilities—the probability of an event given some other event has occurred. LDA algorithms make predictions by using Bayes to calculate the probability of whether an input data set will belong to a particular output.

LDA works by identifying a linear combination of features that separates or characterizes two or more classes of objects or events. LDA does this by projecting data with two or more dimensions into one dimension so that it can be more easily classified. The technique is, therefore, sometimes referred to as dimensionality reduction. This versatility ensures that LDA

can be used for multi-class data classification problems, unlike logistic regression, which is limited to binary classification. LDA is thus often applied to enhance the operation of other learning classification algorithms such as decision tree, random forest, or support vector machines (SVM).

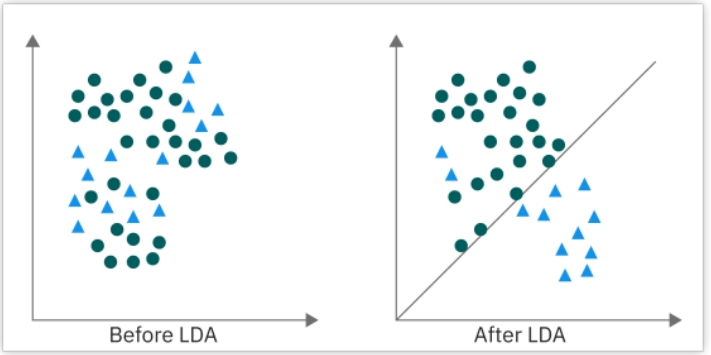


Figure 3.13 Before and After LDA

For example, we have two classes and we need to separate them efficiently. Classes can have multiple features. Using only a single feature to classify them may result in some overlapping as shown in the below figure. So, we will keep on increasing the number of features for proper classification.

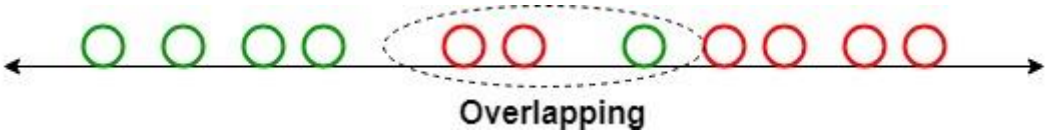


Figure 3.14 Overlapping in LDA

To overcome the overlapping issue in the classification process, we must increase the number of features regularly.

Example:

Let's assume we have to classify two different classes having two sets of data points in a 2-dimensional plane as shown below image:

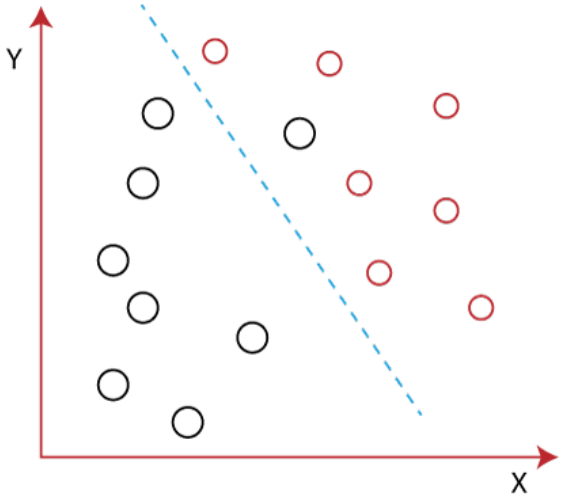


Figure 3.15 Example of LDA

However, it is impossible to draw a straight line in a 2-d plane that can separate these data points efficiently but using linear Discriminant analysis; we can dimensionally reduce the 2-D plane into the 1-D plane. Using this technique, we can also maximize the separability between multiple classes.

A practical application of LDA

Suppose that a bank is deciding whether to approve or reject loan applications. The bank uses two features to make this decision: the applicant's credit score and annual income.

Here, the two features or classes are plotted on a 2-dimensional (2D) plane with an X-Y axis. If we tried to classify approvals using just one feature, we might observe overlap. By applying LDA, we can draw a straight line that completely separates these two class data points. LDA achieves this by using the X–Y axis to create a new axis, separating the different classes with a straight line and projecting data onto the new axis.

To create this new axis and reduce dimensionality, LDA follows these criteria:

- Maximize the distance between the means of two classes.
- Minimize the variance within individual classes.

3.2.1.1 Assumptions of LDA

LDA assumes that the

1) data has a Gaussian distribution and that the

2) covariance matrices of the different classes are equal. It also assumes that the

3) data is linearly separable, meaning that a linear decision boundary can accurately classify the different classes.

LDAs operate by projecting a feature space, that is, a dataset with n-dimensions, onto a smaller space "k", where k is less than or equal to n – 1, without losing class information. An LDA model comprises the statistical properties that are calculated for the data in each class. Where there are multiple features or variables, these properties are calculated over the multivariate Gaussian distribution.

The multivariates are:

- Means
- Covariance matrix, which measures how each variable or feature relates to others within the class

Suppose we have two sets of data points belonging to two different classes that we want to classify. As shown in the given 2D graph, when the data points are plotted on the 2D plane, there's no straight line that can separate the two classes of data points completely. Hence, in this case, LDA (Linear Discriminant Analysis) is used which reduces the 2D graph into a 1D graph in order to maximize the separability between the two classes.

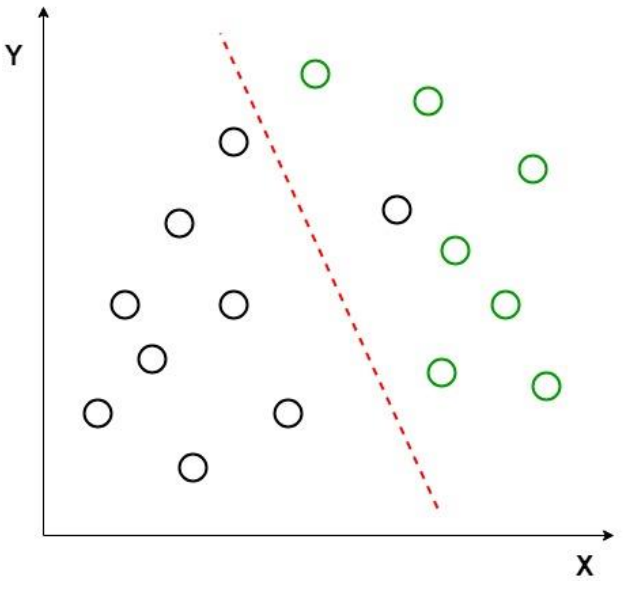


Figure 3.16 Linearly Separable Dataset

Here, Linear Discriminant Analysis uses both axes (X and Y) to create a new axis and projects data onto a new axis in a way to maximize the separation of the two categories and hence, reduces the 2D graph into a 1D graph.

Two criteria are used by LDA to create a new axis:

1. Maximize the distance between the means of the two classes.
2. Minimize the variation within each class.

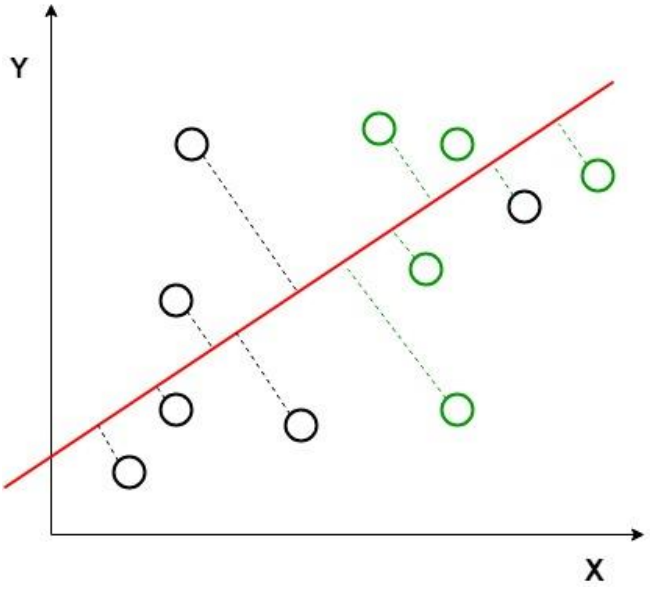


Figure 3.17 The perpendicular distance between the line and points

In the above graph, it can be seen that a new axis (in red) is generated and plotted in the 2D graph such that it maximizes the distance between the means of the two classes and minimizes the variation within each class. In simple terms, this newly generated axis increases the separation between the data points of the two classes. After generating this new axis using the above-mentioned criteria, all the data points of the classes are plotted on this new axis and-are-shown-in-the-figure-given-below.

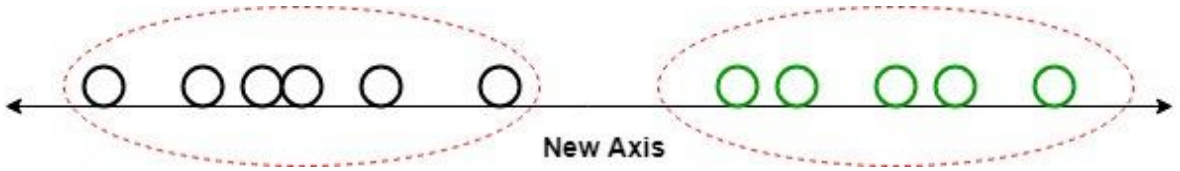


Figure 3.18 New Axis of LDA

But Linear Discriminant Analysis fails when the mean of the distributions are shared, as it becomes impossible for LDA to find a new axis that makes both classes linearly separable. In such cases, we use non-linear discriminant analysis.

3.2.1.2 Preparing to implement linear discriminant analysis

To use LDA effectively, it's essential to prepare the data set beforehand. These are the steps and best practices for implementing LDA:

1. Pre-process the data to ensure that it is normalized and centered

This is achieved by passing the n-component parameter of the LDA, which identifies the number of linear discriminants to retrieve.

2. Choose an appropriate number of dimensions for the lower-dimensional space

This is achieved by passing the n-component parameter of the LDA, which identifies the number of linear discriminants to retrieve.

3. Regularize the model

Regularization aims to prevent overfitting, where the statistical model fits exactly against its training data and undermines its accuracy.

4. Using cross-validation to evaluate model performance

You can evaluate classifiers like LDA by plotting a confusion matrix, with actual class values as rows and predicted class values as columns. A confusion matrix makes it easy to see whether a classifier is confusing two classes—that is, mislabelling one class as another. For example, consider a 10 x 10 confusion matrix predicting images from zero through 9. Actuals are plotted in rows on the y-axis. Predictions are plotted in columns on the x-axis. To see how many times a classifier confused images of 4s and 9s in the 10 x 10 confusion matrix example, you would check the 4th row and the 9th column.

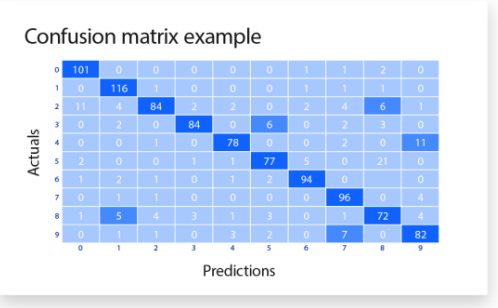


Figure 3.19 Confusion matrix

3.2.1.3 How the linear discriminant function works

- **Calculate the between-class variance**

The between-class variance is the separability between classes—the distance between the class means.

- **Calculate the within-class variance**

The within-class variance is the distance between class means and samples.

- **Project the data into a lower-dimensional space**

This maximizes the between-class variance and minimizes the within-class variance. We can represent the linear discriminant function for two classes mathematically with the following

$$\delta(x) = x * (\sigma^2 * (\mu_0 - \mu_1) - 2 * \sigma^2 * (\mu_0^2 - \mu_1^2) + \ln(P(w_0) / P(w_1)))$$

Where:

- $\delta(x)$ represents the linear discriminant function.
- x represents the input data point.
- μ_0 and μ_1 are the means of the two classes.
- σ^2 is the common within-class variance.
- $P(\omega_0)$ and $P(\omega_1)$ are the prior probabilities of the two classes.

3.2.1.4 Extension to Linear Discriminant Analysis (LDA)

1. **Quadratic Discriminant Analysis (QDA):** For multiple input variables, each class deploys its own estimate of variance.
2. **Flexible Discriminant Analysis (FDA):** it is used when there are non-linear groups of inputs are used, such as splines.
3. **Flexible Discriminant Analysis (FDA):** This uses regularization in the estimate of the variance (actually covariance) and hence moderates the influence of different variables on LDA.

3.2.1.5 Applications of linear discriminant analysis

- ***Credit risk assessment in finance***

To mitigate risk, financial institutions must identify and minimize credit default. LDA can help identify applicants who might be likely to default on loans from those who are creditworthy by sifting through financial factors and behaviour data.

- ***Disease diagnosis in healthcare***

Fast and accurate disease diagnosis is crucial for effective treatment. Hospitals and healthcare providers must interpret an immense amount of medical data. LDA helps simplify complex data sets and improve diagnostic accuracy by identifying patterns and relationships in patient data.

- ***Customer segmentation in e-commerce***

For effective marketing, e-commerce businesses must be able to categorize diverse customer bases. LDA is pivotal in segmenting customers, enabling e-commerce companies to tailor their marketing strategies for different customer groups. The outcome is more personalized shopping experiences, increasing customer loyalty and sales.

- ***Quality control in manufacturing***

Producing high-quality goods while minimizing defects is a fundamental challenge. Sensor data from machinery can be used with LDA to identify patterns associated with defects. By detecting irregularities in real-time, manufacturers can take immediate corrective actions, and they can improve product quality and reduce wastage.

- ***Campaign optimization in marketing***

You can maximize your advertising budget by targeting the right audience with personalized content, but identifying those respective audience segments can be difficult. LDA can simplify this process by classifying customer attributes and behaviours, enhancing the customization of advertising campaigns. This approach can lead to a higher return on investment (ROI) and a better customer experience.

- ***Face Recognition:***

In the field of Computer Vision, face recognition is a very popular application in which each face is represented by a very large number of pixel values. Linear discriminant analysis (LDA) is used here to reduce the number of features to a more manageable number before the process of classification. Each of the new dimensions generated is a linear combination of pixel values, which form a template. The linear combinations obtained using Fisher's linear discriminant are called Fisher's faces.

- ***In-Learning***

Nowadays, robots are being trained for learning and talking to simulate human work, and it can also be considered a classification problem. In this case, LDA builds similar groups on the basis of different parameters, including pitches, frequencies, sound, tunes, etc.

3.2.1.6 Advantages of using LDA

1. **Use simplicity and efficiency of computation:** It is a simple and computationally efficient algorithm. It's relatively easy to understand and implement, making it accessible to those new to machine learning. Also, its efficient computation ensures quick results.
2. **Manage high-dimensional data:** It can work well even when the number of features is much larger than the number of training samples. LDA is valuable in applications like text analysis, image recognition, and genomics, where data is often high-dimensional.
3. **Handle multicollinearity:** It can handle multicollinearity (correlation between features) in the data. It transforms the data into a lower-dimensional space while maintaining information integrity.

3.2.1.7 Disadvantages of LDA

1. It assumes that the data has a Gaussian distribution, which may not always be the case.
2. It assumes that the covariance matrices of the different classes are equal, which may not be true in some datasets.
3. It assumes that the data is linearly separable, which may not be the case for some datasets.
4. It may not perform well in high-dimensional feature spaces.

Shared mean distributions: LDA encounters challenges when class distributions share means. LDA struggles to create a new axis that linearly separates both classes. As a result, LDA might not effectively discriminate between classes with overlapping statistical properties. For example, imagine a scenario in which two species of flowers have highly similar petal length and width. LDA may find it difficult to separate these species based on these features alone. Alternative techniques, such as nonlinear discriminant analysis methods, are preferred here.

Not suitable for unlabelled data: LDA is applied as a supervised learning algorithm–that is, it classifies or separates labelled data. In contrast, principal component analysis (PCA), another dimension reduction technique, ignores class labels and preserves variance.

3.3.1 K-NEAREST NEIGHBOUR (KNN) ALGORITHM

The **K-Nearest Neighbours (KNN) algorithm** is a supervised machine learning method employed to tackle classification and regression problems. The k-nearest neighbours (KNN) algorithm is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. It is one of the popular and simplest classification and regression classifiers used in machine learning today. KNN is one of the most basic yet essential classification algorithms in machine learning. It belongs to the supervised learning domain and finds intense application in pattern recognition, data mining, and intrusion detection.

It is widely disposable in real-life scenarios since it is non-parametric, meaning it does not make any underlying assumptions about the distribution of data (as opposed to other algorithms such as GMM, which assume a Gaussian distribution of the given data). We are given some prior data (also called training data), which classifies coordinates into groups identified by an attribute.

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a **non-parametric algorithm**, which means it does not make any assumption on underlying data.
- It is also called a **lazy learner algorithm** because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

- **Example:** Suppose, we have an image of a creature that looks similar to cat and dog, but we want to know either it is a cat or dog. So for this identification, we can use the KNN algorithm, as it works on a similarity measure. Our KNN model will find the similar features of the new data set to the cats and dogs images and based on the most similar features it will put it in either cat or dog category.

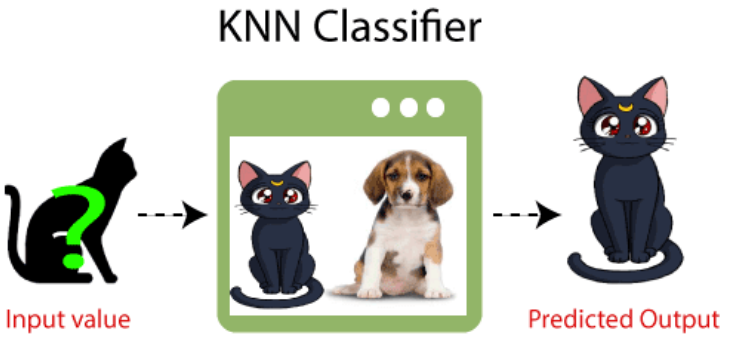


Figure 3.20 KNN Classifier

As an example, consider the following table of data points containing two features:

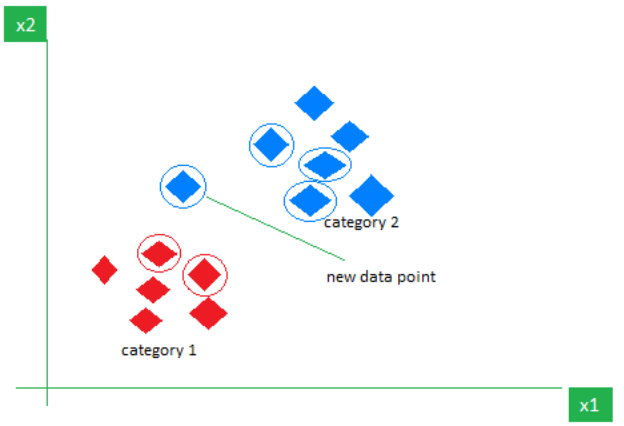


Figure 3.21 Now, given another set of data points (also called testing data), allocate these points to a group by analysing the training set. Note that the unclassified points are marked as 'White'.

3.3.1.1 Why do we need a KNN algorithm?

(K-NN) algorithm is a versatile and widely used machine learning algorithm that is primarily used for its simplicity and ease of implementation. It does not require any assumptions about the underlying data distribution. It can also handle both numerical and categorical data,

making it a flexible choice for various types of datasets in classification and regression tasks. It is a non-parametric method that makes predictions based on the similarity of data points in a given dataset. K-NN is less sensitive to outliers compared to other algorithms.

The K-NN algorithm works by finding the K nearest neighbours to a given data point based on a distance metric, such as Euclidean distance. The class or value of the data point is then determined by the majority vote or average of the K neighbours. This approach allows the algorithm to adapt to different patterns and make predictions based on the local structure of the data.

Suppose there are two categories, i.e., Category A and Category B, and we have a new data point x1, so this data point will lie in which of these categories. To solve this type of problem, we need a K-NN algorithm. With the help of K-NN, we can easily identify the category or class of a particular dataset. Consider the below diagram:

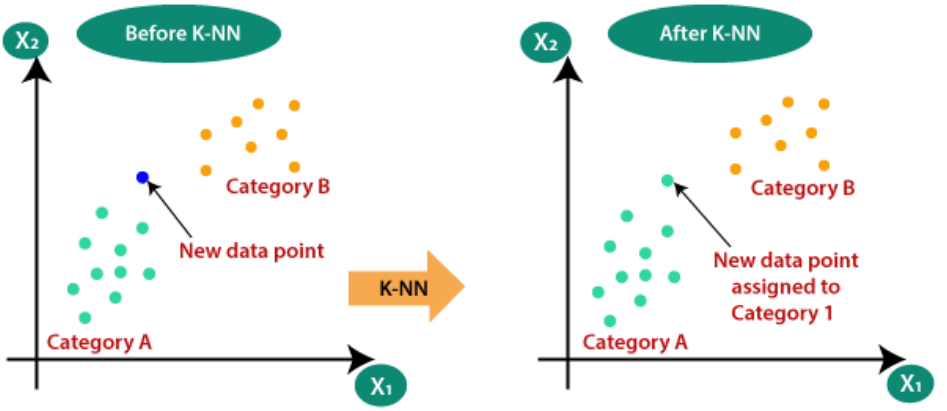
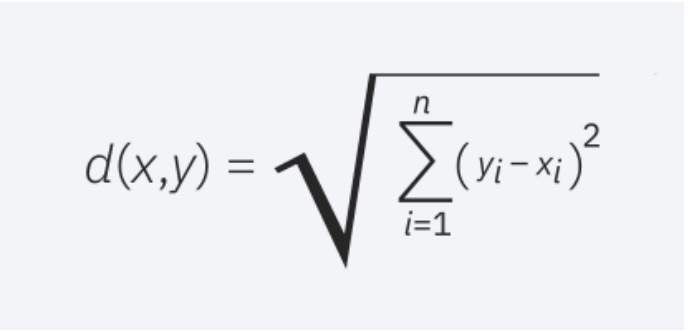


Figure 3.22 Before and after KNN results

3.3.1.2 Distance Metrics Used in KNN Algorithm

Euclidean Distance

This is nothing but the cartesian distance between the two points which are in the plane/hyperplane. Euclidean distance can also be visualized as the length of the straight line that joins the two points which are into consideration. This metric helps us calculate the net displacement done between the two states of an object.

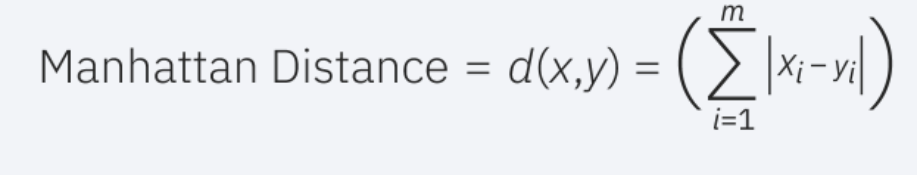


$$d(x,y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2}$$

Figure 3.23 Euclidean distance formula

Manhattan Distance

Manhattan Distance metric is generally used when we are interested in the total distance travelled by the object instead of the displacement. This metric is calculated by summing the absolute difference between the coordinates of the points in n-dimensions.

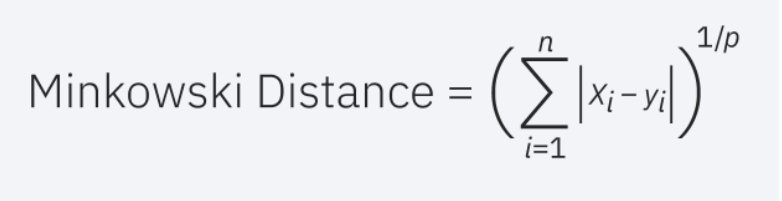


$$\text{Manhattan Distance} = d(x,y) = \left(\sum_{i=1}^{m} |x_i - y_i|\right)$$

Figure 3.24 Manhattan distance formula

Minkowski Distance

We can say that the Euclidean, as well as the Manhattan distance, are special cases of the Minkowski distance.



$$\text{Minkowski Distance} = \left(\sum_{i=1}^{n} |x_i - y_i|\right)^{1/p}$$

Figure 3.25 Minkowski distance formula

Hamming distance: This technique is used typically used with Boolean or string vectors, identifying the points where the vectors do not match. As a result, it has also been referred to as the overlap metric. This can be represented with the following formula:

$$\text{Hamming Distance} = D_H = \left(\sum_{i=1}^{k} |x_i - y_i|\right)$$

$$x = y \quad D = 0$$
$$x \neq y \quad D \neq 1$$

Figure 3.26 Hamming distance formula

3.3.1.3 How does K-NN work?

The K-NN working can be explained on the basis of the below algorithm:

- **Step-1:** Select the number K of the neighbours

K represents the number of nearest neighbours that needs to be considered while making prediction.

- **Step-2:** Calculate the Euclidean distance of **K number of neighbours**

To measure the similarity between target and training data points, Euclidean distance is used. Distance is calculated between each of the data points in the dataset and target point.

- **Step-3:** Take the K nearest neighbours as per the calculated Euclidean distance.

The k data points with the smallest distances to the target point are the nearest neighbours.

- **Step-4:** Among these k neighbours, count the number of the data points in each category.
- **Step-5:** Assign the new data points to that category for which the number of the neighbour is maximum.

In the classification problem, the class labels of are determined by performing majority voting. The class with the most occurrences among the neighbours becomes the predicted class for the target data point.

In the regression problem, the class label is calculated by taking average of the target values of K nearest neighbours. The calculated average value becomes the predicted output for the target data point.

- **Step-6:** Our model is ready.

Suppose we have a new data point and we need to put it in the required category. Consider the below image:

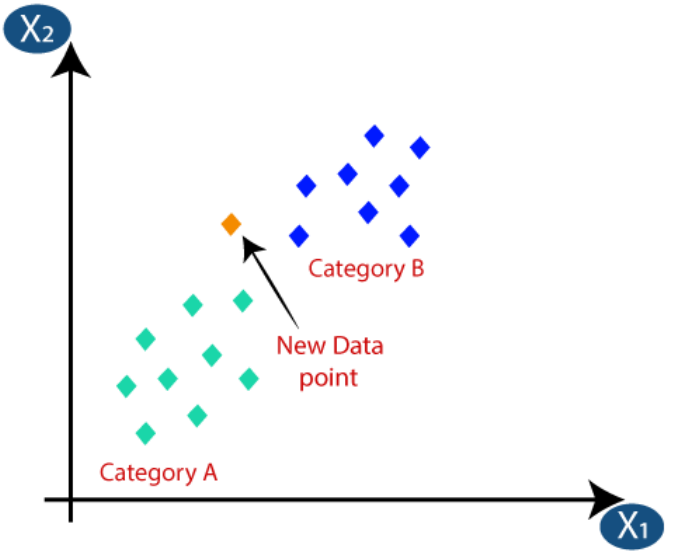


Figure 3.27 Finding the new data point in LDA

- Firstly, we will choose the number of neighbours, so we will choose the k=5.
- Next, we will calculate the **Euclidean distance** between the data points. The Euclidean distance is the distance between two points, which we have already studied in geometry. It can be calculated as:

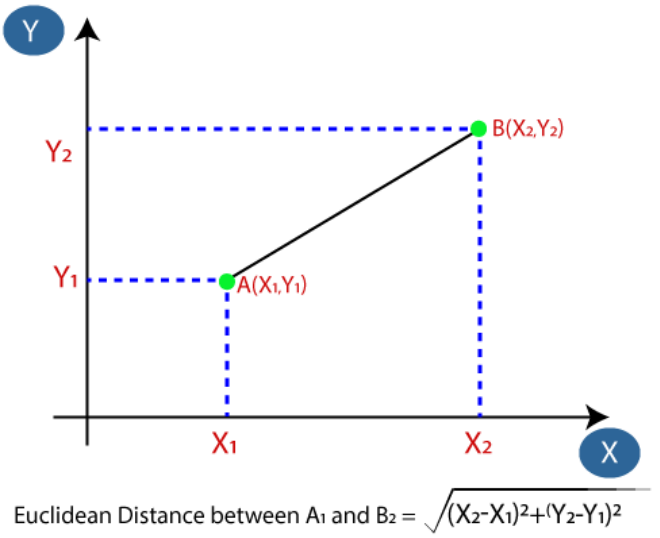


Figure 3.28 Calculating Euclidean distance

- By calculating the Euclidean distance, we got the nearest neighbours, as three nearest neighbours in category A and two nearest neighbours in category B. Consider the below image:

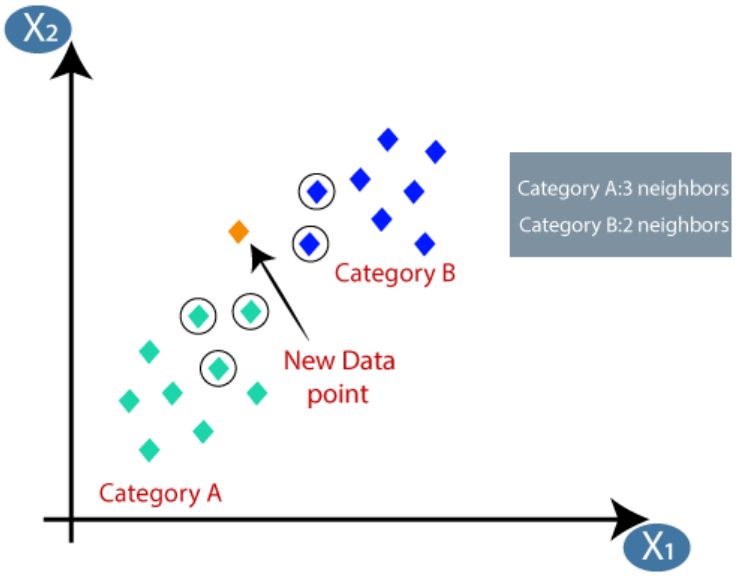


Figure 3.28 KNN 1

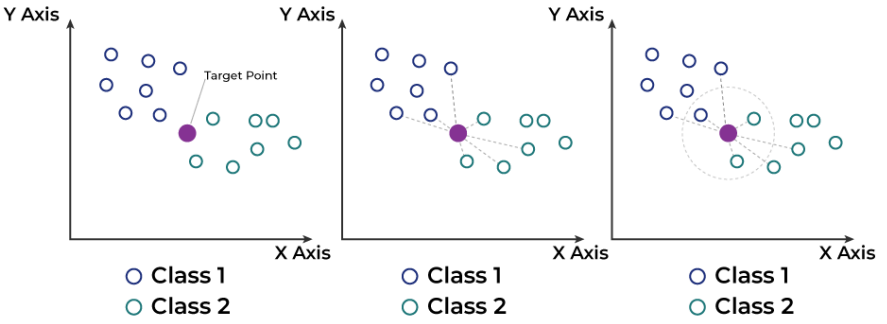


Figure 3.29 Final result of KNN

3.3.1.4 Advantages and disadvantages of the KNN algorithm

Advantages of KNN Algorithm:

- It is simple to implement.
- It is robust to the noisy training data
- It can be more effective if the training data is large.

- **Adapts Easily** – As per the working of the KNN algorithm it stores all the data in memory storage and hence whenever a new example or data point is added then the algorithm adjusts itself as per that new example and has its contribution to the future predictions as well.
- **Few Hyperparameters** – The only parameters which are required in the training of a KNN algorithm are the value of k and the choice of the distance metric which we would like to choose from our evaluation metric.

Disadvantages of KNN Algorithm:

- Always needs to determine the value of K which may be complex some time.
- The computation cost is high because of calculating the distance between the data points for all the training samples. As we have heard about this that the KNN algorithm is also considered a Lazy Algorithm. The main significance of this term is that this takes lots of computing power as well as data storage. This makes this algorithm both time-consuming and resource exhausting.
- **Curse of Dimensionality** – There is a term known as the peaking phenomenon according to this the KNN algorithm is affected by the curse of dimensionality which implies the algorithm faces a hard time classifying the data points properly when the dimensionality is too high.
- **Prone to Overfitting** – As the algorithm is affected due to the curse of dimensionality it is prone to the problem of overfitting as well. Hence generally feature selection as well as dimensionality reduction techniques are applied to deal with this problem.

3.3.1.5 Applications of the KNN Algorithm

- **Data Pre-processing** – While dealing with any Machine Learning problem we first perform the EDA part in which if we find that the data contains missing values then there are multiple imputation methods are available as well. One of such method is KNN Imputer which is quite effective ad generally used for sophisticated imputation methodologies.
- **Pattern Recognition** – KNN algorithms work very well if you have trained a KNN algorithm using the MNIST dataset and then performed the evaluation process then you must have come across the fact that the accuracy is too high.

- **Recommendation Engines** – The main task which is performed by a KNN algorithm is to assign a new query point to a pre-existed group that has been created using a huge corpus of datasets. This is exactly what is required in the recommender systems to assign each user to a particular group and then provide them recommendations based on that group's preferences.
- **Healthcare**: KNN has also had application within the healthcare industry, making predictions on the risk of heart attacks and prostate cancer. The algorithm works by calculating the most likely gene expressions.

3.4.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNNs) are a powerful tool for machine learning, especially in tasks related to computer vision. Convolutional Neural Networks, or CNNs, are a specialized class of neural networks designed to effectively process grid-like data, such as images.

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain, and they are well-suited for capturing hierarchical patterns and spatial dependencies within images.

3.2 DEEP LEARNING

Deep learning is a branch of machine learning which is based on artificial neural networks. It is capable of learning complex patterns and relationships within data. In deep learning, we don't need to explicitly program everything. It has become increasingly popular in recent years due to the advances in processing power and the availability of large datasets. Because it is based on artificial neural networks (ANNs) also known as deep neural networks (DNNs). These neural networks are inspired by the structure and function of the human brain's biological neurons, and they are designed to learn from large amounts of data.

1. Deep Learning is a subfield of Machine Learning that involves the use of neural networks to model and solve complex problems. Neural networks are modelled after the structure and function of the human brain and consist of layers of interconnected nodes that process and transform data.

2. The key characteristic of Deep Learning is the use of deep neural networks, which have multiple layers of interconnected nodes. These networks can learn complex representations of data by discovering hierarchical patterns and features in the data. Deep Learning algorithms can automatically learn and improve from data without the need for manual feature engineering.
3. Deep Learning has achieved significant success in various fields, including image recognition, natural language processing, speech recognition, and recommendation systems. Some of the popular Deep Learning architectures include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Belief Networks (DBNs).
4. Training deep neural networks typically requires a large amount of data and computational resources. However, the availability of cloud computing and the development of specialized hardware, such as Graphics Processing Units (GPUs), has made it easier to train deep neural networks.

In a fully connected Deep neural network, there is an input layer and one or more hidden layers connected one after the other. Each neuron receives input from the previous layer neurons or the input layer. The output of one neuron becomes the input to other neurons in the next layer of the network, and this process continues until the final layer produces the output of the network. The layers of the neural network transform the input data through a series of nonlinear transformations, allowing the network to learn complex representations of the input data.

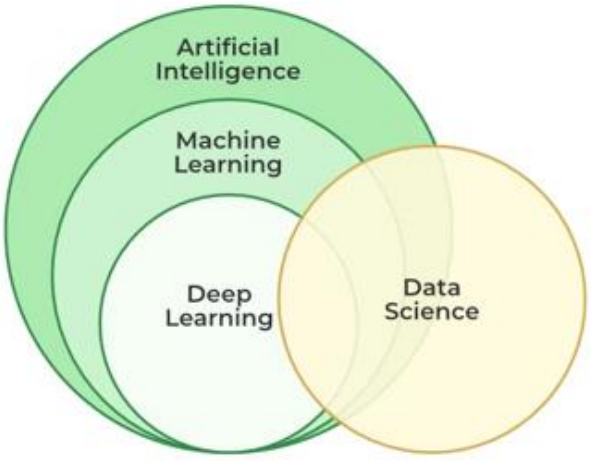


Figure 3.30 Deep learning

Deep learning can be used for supervised, unsupervised as well as reinforcement machine learning. it uses a variety of ways to process these.

- **Supervised Machine Learning:** Supervised machine learning is the machine learning technique in which the neural network learns to make predictions or classify data based on the labelled datasets. Here we input both input features along with the target variables. the neural network learns to make predictions based on the cost or error that comes from the difference between the predicted and the actual target, this process is known as backpropagation. Deep learning algorithms like Convolutional neural networks, Recurrent neural networks are used for many supervised tasks like image classifications and recognition, sentiment analysis, language translations, etc.
- **Unsupervised Machine Learning:** Unsupervised machine learning is the machine learning technique in which the neural network learns to discover the patterns or to cluster the dataset based on unlabelled datasets. Here there are no target variables. while the machine has to self-determined the hidden patterns or relationships within the datasets. Deep learning algorithms like autoencoders and generative models are used for unsupervised tasks like clustering, dimensionality reduction, and anomaly detection.
- **Reinforcement Machine Learning**: Reinforcement Machine Learning is the machine learning technique in which an agent learns to make decisions in an environment to maximize a reward signal. The agent interacts with the environment by taking action and observing the resulting rewards. Deep learning can be used to learn policies, or a set of actions, that maximizes the cumulative reward over time. Deep reinforcement learning algorithms like Deep Q networks and Deep Deterministic Policy Gradient (DDPG) are used to reinforce tasks like robotics and game playing etc.

3.2.1 Applications of Deep Learning:

- **Object detection and recognition:** Deep learning model can be used to identify and locate objects within images and videos, making it possible for machines to perform tasks such as self-driving cars, surveillance, and robotics.
- **Image classification:** Deep learning models can be used to classify images into categories such as animals, plants, and buildings. This is used in applications such as medical imaging, quality control, and image retrieval.

- **Image segmentation:** Deep learning models can be used for image segmentation into different regions, making it possible to identify specific features within images.
    - **Automatic Text Generation** – Deep learning model can learn the corpus of text and new text like summaries, essays can be automatically generated using these trained models.
    - **Language translation:** Deep learning models can translate text from one language to another, making it possible to communicate with people from different linguistic backgrounds.
    - **Sentiment analysis:** Deep learning models can analyse the sentiment of a piece of text, making it possible to determine whether the text is positive, negative, or neutral. This is used in applications such as customer service, social media monitoring, and political analysis.
    - **Speech recognition:** Deep learning models can recognize and transcribe spoken words, making it possible to perform tasks such as speech-to-text conversion, voice search, and voice-controlled devices.
    - **Game playing:** Deep reinforcement learning models have been able to beat human experts at games such as Go, Chess, and Atari.
    - **Robotics:** Deep reinforcement learning models can be used to train robots to perform complex tasks such as grasping objects, navigation, and manipulation.
    - **Control systems:** Deep reinforcement learning models can be used to control complex systems such as power grids, traffic management, and supply chain optimization.

3.2.2 Advantages of Deep Learning:

1. High accuracy: Deep Learning algorithms can achieve state-of-the-art performance in various tasks, such as image recognition and natural language processing.
2. Automated feature engineering: Deep Learning algorithms can automatically discover and learn relevant features from data without the need for manual feature engineering.
3. Scalability: Deep Learning models can scale to handle large and complex datasets, and can learn from massive amounts of data.

4. Flexibility: Deep Learning models can be applied to a wide range of tasks and can handle various types of data, such as images, text, and speech.
5. Continual improvement: Deep Learning models can continually improve their performance as more data becomes available.

3.2.3 Disadvantages of Deep Learning:

1. High computational requirements: Deep Learning models require large amounts of data and computational resources to train and optimize.
2. Requires large amounts of labelled data: Deep Learning models often require a large amount of labelled data for training, which can be expensive and time- consuming to acquire.
3. Interpretability: Deep Learning models can be challenging to interpret, making it difficult to-understand-how-they-make-decisions.
   Overfitting: Deep Learning models can sometimes overfit to the training data, resulting in poor performance on new and unseen data.
4. Black-box nature: Deep Learning models are often treated as black boxes, making it difficult to understand how they work and how they arrived at their predictions. In summary, while Deep Learning offers many advantages, including high accuracy and scalability, it also has some disadvantages, such as high computational requirements, the need for large amounts of labelled data, and interpretability challenges. These limitations need to be carefully considered when deciding whether to use Deep Learning for a specific task.

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CHAPTER 4

Results

4 INTRODUCTION

In this chapter, we are using fNIRS signal to detect whether a person is healthy or suffering from Obsessive Compulsive Disorder and classifying using Convolutional Neural Network (CNN) structure.

4.1 SYSTEM OVERVIEW

Here is a block diagram showing how the fNIRS signal is classifying whether a person is healthy or suffering from OCD.

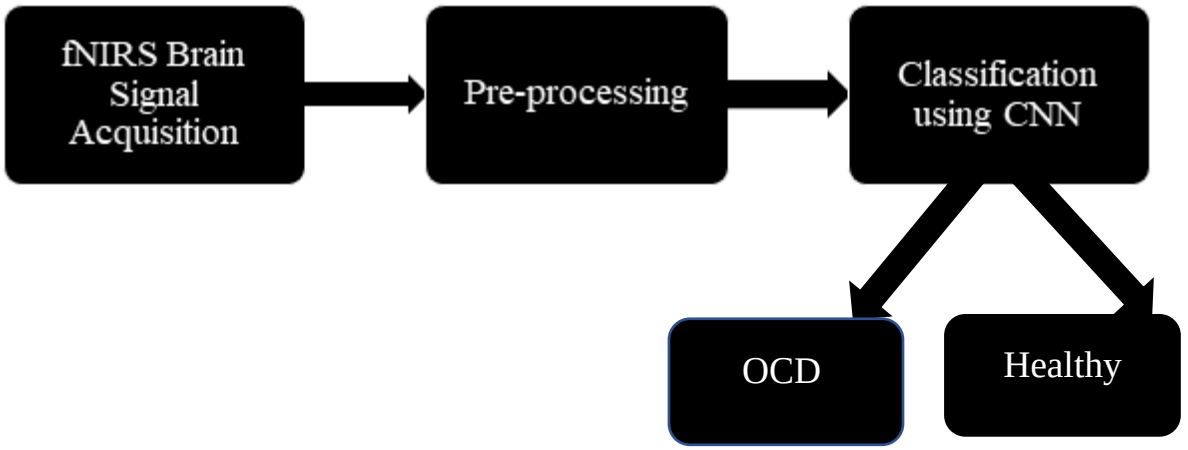


Figure 4.1 Block diagram of signal processing using fNIRS

4.2 CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNNs) are a powerful tool for machine learning, especially in tasks related to computer vision. Convolutional Neural Networks, or CNNs, are a specialized class of neural networks designed to effectively process grid-like data, such as images.

A **Convolutional Neural Network** (CNN) is a type of **deep learning algorithm** that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, **pooling layers**, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain, and they are well-suited for capturing hierarchical patterns and spatial dependencies within images.

In a regular Neural Network there are three types of layers:

1. **Input Layers:** It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).
2. **Hidden Layer:** The input from the Input layer is then fed into the hidden layer. There can be many hidden layers depending on our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of the output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.
3. **Output Layer:** The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts the output of each class into the probability score of each class.

The data is fed into the model and output from each layer is obtained from the above step is called **feedforward**, we then calculate the error using an error function, some common error functions are cross-entropy, square loss error, etc. The error function measures how well the network is performing. After that, we backpropagate into the model by calculating the derivatives. This step is called **Backpropagation** which basically is used to minimize the loss.

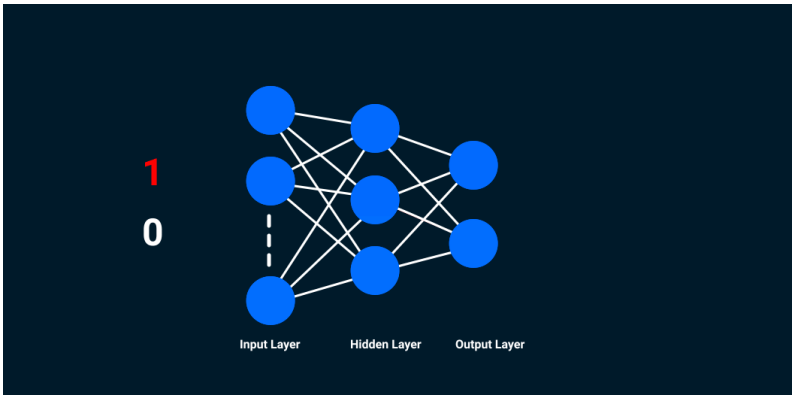


Figure 4.2 Neural network

4.2.1 Key components of a Convolutional Neural Network:

1. **Convolutional Layers:** These layers apply convolutional operations to input images, using filters (also known as kernels) to detect features such as edges, textures, and more

complex patterns. Convolutional operations help preserve the spatial relationships between pixels.

2. **Pooling Layers:** Pooling layers down-sample the spatial dimensions of the input, reducing the computational complexity and the number of parameters in the network. Max pooling is a common pooling operation, selecting the maximum value from a group of neighbouring pixels.
3. **Activation Functions:** Non-linear activation functions, such as Rectified Linear Unit (ReLU), introduce non-linearity to the model, allowing it to learn more complex relationships in the data.
4. **Fully Connected Layers:** These layers are responsible for making predictions based on the high-level features learned by the previous layers. They connect every neuron in one layer to every neuron in the next layer.

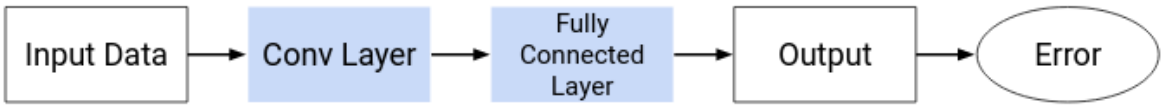


Figure 4.3 Key components of CNN

CNNs are trained using a large dataset of labelled images, where the network learns to recognize patterns and features that are associated with specific objects or classes. Proven to be highly effective in image-related tasks, achieving state-of-the-art performance in various computer vision applications. Their ability to automatically learn hierarchical representations of features makes them well-suited for tasks where the spatial relationships and patterns in the data are crucial for accurate predictions. CNNs are widely used in areas such as image classification, object detection, facial recognition, and medical image analysis.

The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes.

The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

4.2.2 Convolutional Neural Network Design

- The construction of a convolutional neural network is a multi-layered feed-forward neural network, made by assembling many unseen layers on top of each other in a particular order.
- It is the sequential design that give permission to CNN to learn hierarchical attributes.
- In CNN, some of them followed by grouping layers and hidden layers are typically convolutional layers followed by activation layers.
- The pre-processing needed in a ConvNet is kindred to that of the related pattern of neurons in the human brain and was motivated by the organization of the Visual Cortex

4.2.3 Convolutional Neural Network Training

CNNs are trained using a supervised learning approach. This means that the CNN is given a set of labelled training images. The CNN then learns to map the input images to their correct labels.

The training process for a CNN involves the following steps:

1. **Data Preparation:** The training images are pre-processed to ensure that they are all in the same format and size.
2. **Loss Function:** A loss function is used to measure how well the CNN is performing on the training data. The loss function is typically calculated by taking the difference between the predicted labels and the actual labels of the training images.
3. **Optimizer:** An optimizer is used to update the weights of the CNN in order to minimize the loss function.
4. **Backpropagation:** Backpropagation is a technique used to calculate the gradients of the loss function with respect to the weights of the CNN. The gradients are then used to update the weights of the CNN using the optimizer.

4.2.4 CNN architecture

Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

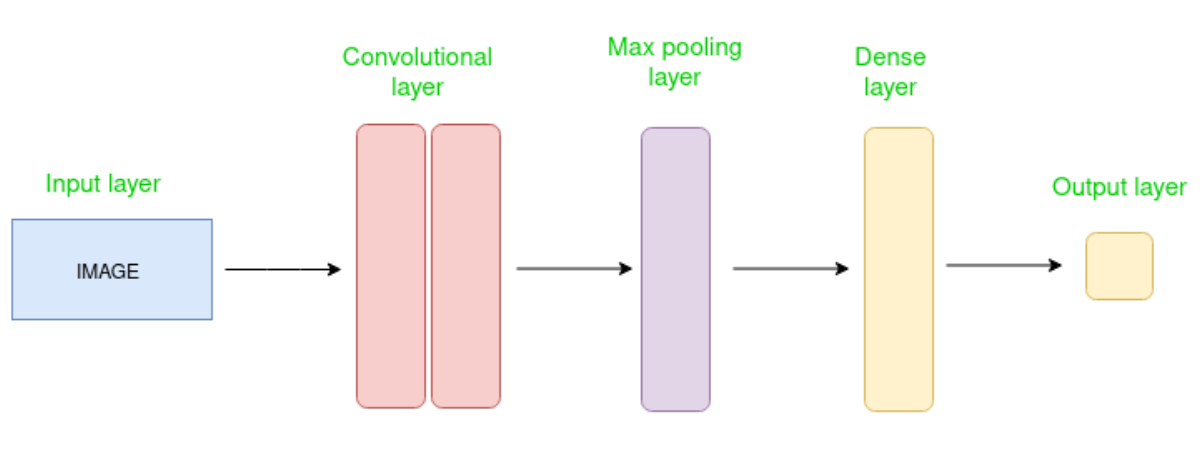


Figure 4.4 Simple CNN architecture

The Convolutional layer applies filters to the input image to extract features, the Pooling layer down samples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

4.2.5 How Convolutional Layers works

Convolution Neural Networks or covnets are neural networks that share their parameters. Imagine you have an image. It can be represented as a cuboid having its length, width (dimension of the image), and height (i.e the channel as images generally have red, green, and blue channels).

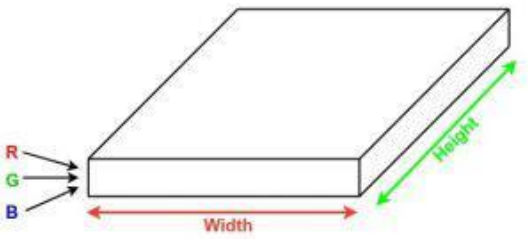


Figure 4.5 Dimension of an image

Now imagine taking a small patch of this image and running a small neural network, called a filter or kernel on it, with say, K outputs and representing them vertically. Now slide that neural network across the whole image, as a result, we will get another image with different widths, heights, and depths. Instead of just R, G, and B channels now we have more channels but lesser width and height. This operation is called **Convolution**. If the patch size is the same as that of the image it will be a regular neural network. Because of this small patch, we have fewer weights.

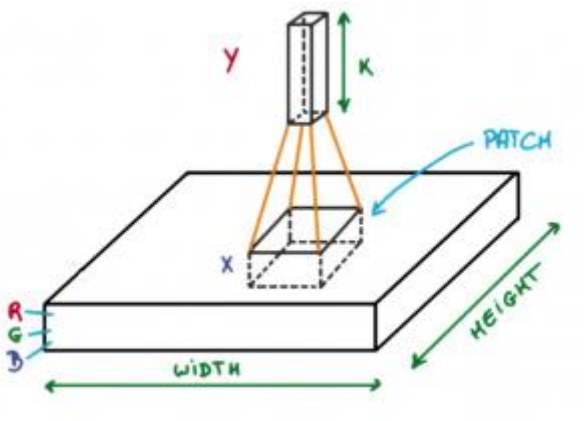


Figure 4.6 Dimension of an image after taking small patch

4.2.6 Deep Learning Udacity

- Convolution layers consist of a set of learnable filters (or kernels) having small widths and heights and the same depth as that of input volume (3 if the input layer is image input).
- For example, if we have to run convolution on an image with dimensions 34x34x3. The possible size of filters can be axax3, where 'a' can be anything like 3, 5, or 7 but smaller as compared to the image dimension.
- During the forward pass, we slide each filter across the whole input volume step by step where each step is called **stride** (which can have a value of 2, 3, or even 4 for high-dimensional images) and compute the dot product between the kernel weights and patch from input volume.
- As we slide our filters we'll get a 2-D output for each filter and we'll stack them together as a result, we'll get output volume having a depth equal to the number of filters. The network will learn all the filters.

4.2.7 Layers used to build ConvNets

A complete Convolution Neural Networks architecture is also known as covnets. A covnets is a sequence of layers, and every layer transforms one volume to another through a differentiable function.

Types of layers: datasets

Let's take an example by running a covnets on of image of dimension 32 x 32 x 3.

- **Input Layers:** It's the layer in which we give input to our model. In CNN, Generally, the input will be an image or a sequence of images. This layer holds the raw input of the image with width 32, height 32, and depth 3.
- **Convolutional Layers:** This is the layer, which is used to extract the feature from the input dataset. It applies a set of learnable filters known as the kernels to the input images. The filters/kernels are smaller matrices usually 2×2, 3×3, or 5×5 shape. it slides over the input image data and computes the dot product between kernel weight and the corresponding input image patch. The output of this layer is referred as feature maps. Suppose we use a total of 12 filters for this layer we'll get an output volume of dimension 32 x 32 x 12.
- **Activation Layer:** By adding an activation function to the output of the preceding layer, activation layers add nonlinearity to the network. it will apply an element-wise activation function to the output of the convolution layer. Some common activation functions are **RELU**: max(0, x), **Tanh**, **Leaky RELU**, etc. The volume remains unchanged hence output volume will have dimensions 32 x 32 x 12.
- **Pooling layer:** This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents overfitting. Two common types of pooling layers are **max pooling** and **average pooling**. If we use a max pool with 2 x 2 filters and stride 2, the resultant volume will be of dimension 16x16x12.

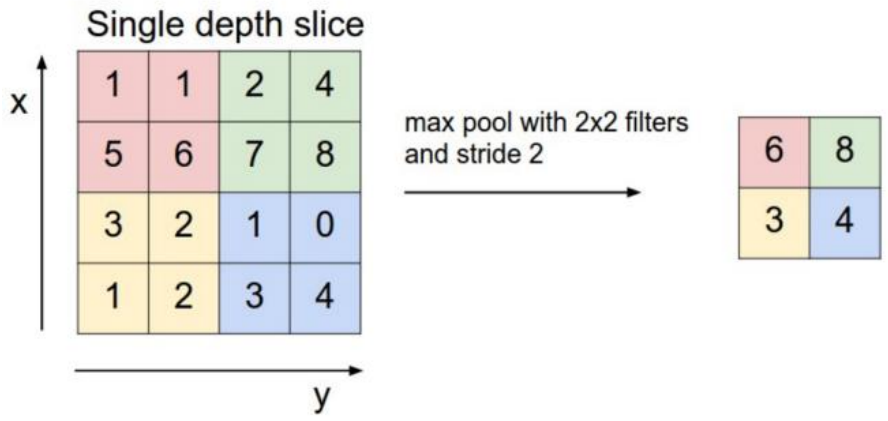


Figure 4.7 CNN image After applying filter

- **Flattening:** The resulting feature maps are flattened into a one-dimensional vector after the convolution and pooling layers so they can be passed into a completely linked layer for categorization or regression.
- **Fully Connected Layers:** It takes the input from the previous layer and computes the final classification or regression task.
    - **Output Layer:** The output from the fully connected layers is then fed into a logistic function for classification tasks like sigmoid or softmax which converts the output of each class into the probability score of each class.

4.2.8 EQUATIONS OF CNN

Convolution is often represented mathematically with an asterisk * sign. If we have an input image represented as X and a filter represented with *f*, then the expression would be:

$$Z = X * f \quad \text{... (1)}$$

Let us understand the process of convolution using a simple example. Consider that we have an image of size 3 x 3 and a filter of size 2 x 2:

1	7	2
11	1	23
2	2	2

1	1
0	1

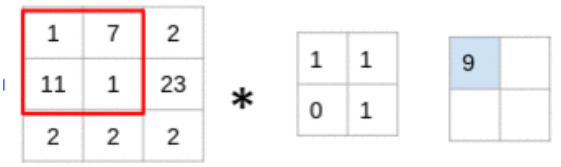
The filter goes through the patches of images, performs an element-wise multiplication, and the values are summed up:

(1x1 + 7x1 + 11x0 + 1x1) = 9

(7x1 + 2x1 + 1x0 + 23x1) = 32

(11x1 + 1x1 + 2x0 + 2x1) = 14

(1x1 + 23x1 + 2x0 + 2x1) = 26



How would we find the shape of an output for more complex inputs or filter dimensions? There is a simple formula to do so:

Dimension of image = (n, n)

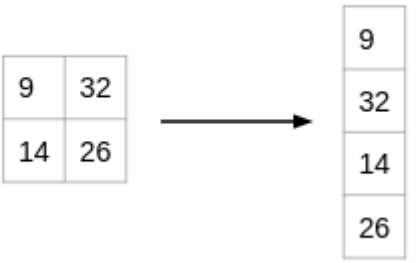
Dimension of filter = (f,f)

Dimension of output will be ((n-f+1), (n-f+1))

Fully Connected Layer

So far, the convolution layer has extracted some valuable features from the data. These features are sent to the fully connected layer that generates the final results. The fully connected layer in a CNN is nothing but the traditional neural network!

The output from the convolution layer was a 2D matrix. Ideally, we would want each row to represent a single input image. In fact, the fully connected layer can only work with 1D data. Hence, the values generated from the previous operation are first converted into a 1D format.

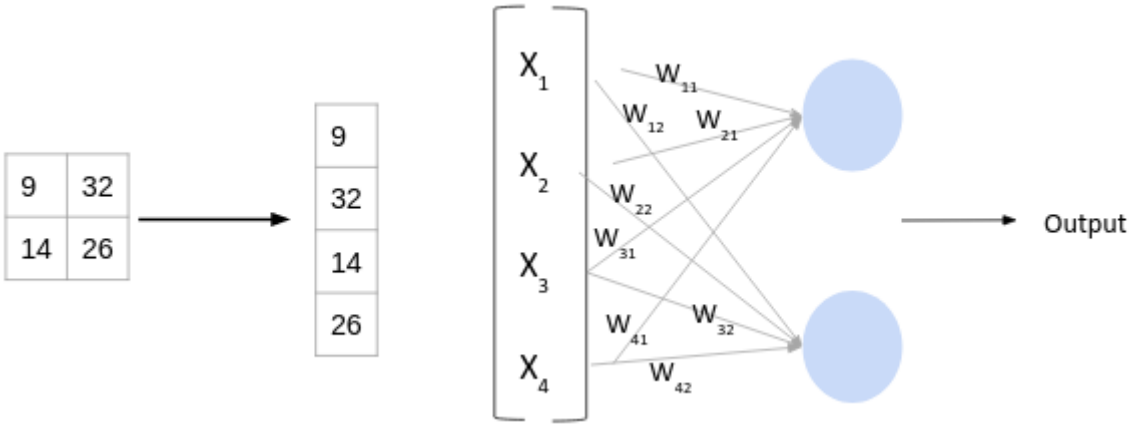


Once the data is converted into a 1D array, it is sent to the fully connected layer. All of these individual values are treated as separate features that represent the image. The fully connected layer performs two operations on the incoming data – **a linear transformation and a non-linear transformation.**

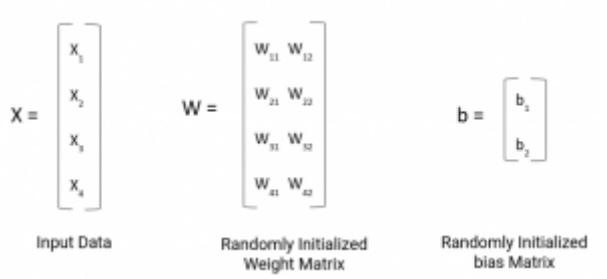
We first perform a linear transformation on this data. The equation for linear transformation is:

$Z = W^T.X + b$ ….. (2)

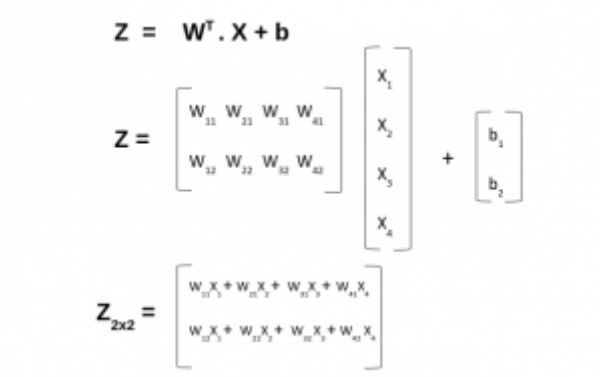
Here, X is the input, W is weight, and b (called bias) is a constant. Note that the W in this case will be a matrix of (randomly initialized) numbers. Can you guess what would be the size of this matrix?



Considering the size of the matrix is (m, n) – m will be equal to the number of features or inputs for this layer. Since we have 4 features from the convolution layer, m here would be 4. The value of n will depend on the number of neurons in the layer. For instance, if we have two neurons, then the shape of weight matrix will be (4, 2):



Having defined the weight and bias matrix, let us put these in the equation for linear transformation:



Now, there is one final step in the forward propagation process – the non-linear transformations. Let us understand the concept of non-linear transformation and it's role in the forward propagation process.

Non-Linear transformation

The linear transformation alone cannot capture complex relationships. Thus, we introduce an additional component in the network which adds non-linearity to the data. This new component in the architecture is called the **activation function**.

These activation functions are added at each layer in the neural network. The activation function to be used will depend on the type of problem you are solving.

We will be working on a binary classification problem and will use the Sigmoid activation function. Let's quickly look at the mathematical expression for this:

$f(x) = 1/(1+e^{-x})$ ….. (3)

The range of a Sigmoid function is between 0 and 1. This means that for any input value, the result would always be in the range (0, 1). A Sigmoid function is majorly used for binary classification problems and we will use this for both convolution and fully-connected layers.

Forward Propagation Summary

Step 1: Load the input images in a variable (say X)

Step 2: Define (randomly initialize) a filter matrix. Images are convolved with the filter

$Z_1 = X * f$ ..... (4)

Step 3: Apply the Sigmoid activation function on the result

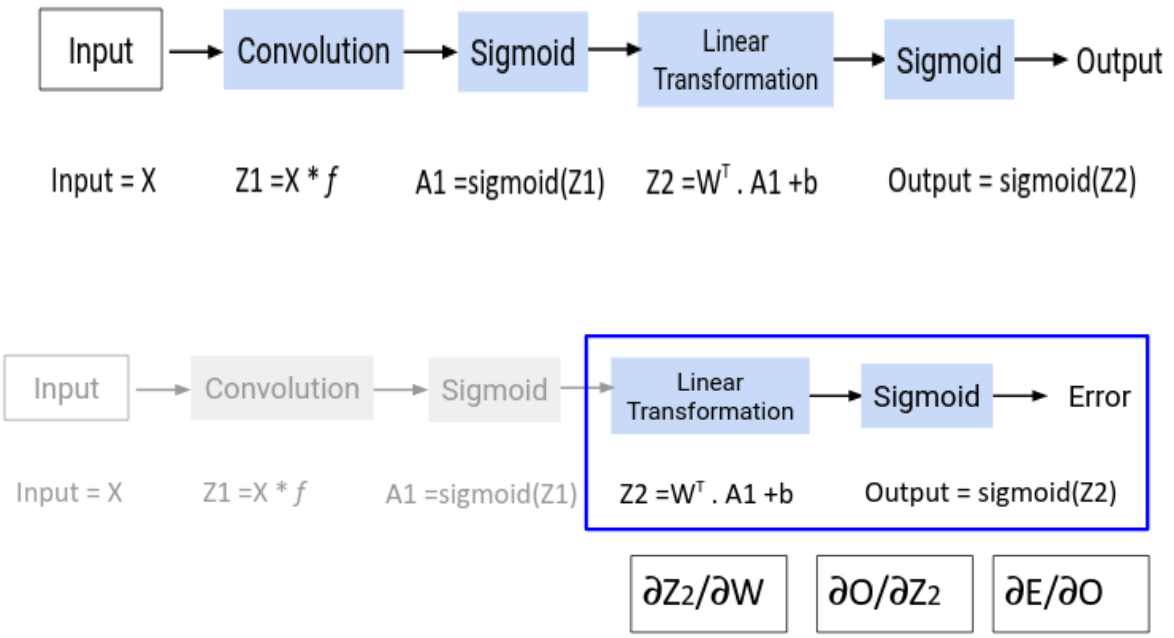
$A = \text{sigmoid}(Z_1)$ …… (5)

Step 4: Define (randomly initialize) weight and bias matrix. Apply linear transformation on the values

$Z_2 = W^T.A + b$ ….. (6)

Step 5: Apply the Sigmoid function on the data. This will be the final output

$O = \text{sigmoid}(Z_2)$ ….. (7)



Backward Propagation (Fully Connected layer)

$\partial E/\partial W = \partial E/\partial O . \partial O/\partial Z_2 . \partial z/\partial W$

1. Change in error with respect to output: Suppose the actual values for the data are denoted as y' and the predicted output is represented as O. Then the error would be given by this equation:

$E = (y' - O)^2/2$ ….. (8)

If we differentiate the error with respect to the output, we will get the following equation:

$\partial E/\partial O = -(y'-O)$ ….. (9)

2. Change in output with respect to Z_2 (linear transformation output)

To find the derivative of output O with respect to Z_2, we must first define O in terms of Z_2. If you look at the computation graph from the forward propagation section above, you would see that the output is simply the sigmoid of Z_2. Thus, $\partial O/\partial Z_2$ is effectively the derivative of Sigmoid. Recall the equation for the Sigmoid function:

f(x) = 1/(1+e^-x) …… (10)

The derivative of this function comes out to be:

$f'(x) = (1+e^{-x})^{-1}[1-(1+e^{-x})^{-1}]$ …… (11)

f'(x) = sigmoid(x)(1-sigmoid(x)) ….. (12)

$\partial O/\partial Z_2 = (O)(1-O)$ ….. (13)

3. Change in Z_2 with respect to W (Weights) : The value Z_2 is the result of the linear transformation process. Here is the equation of Z_2 in terms of weights:

$Z_2 = W^T.A_1 + b$ …… (14)

On differentiating Z_2 with respect to W, we will get the value A_1 itself:

$\partial Z_2/\partial W = A_1$ ……. (15)

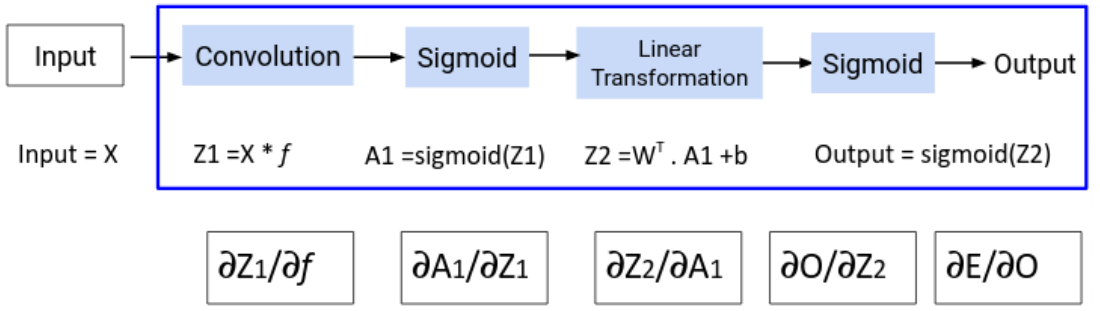
Now that we have the individual derivations, we can use the chain rule to find the change in error with respect to weights:

$\partial E/\partial W = \partial E/\partial O \; . \; \partial O/\partial Z_2 . \; \partial Z_2/\partial W$ …… (16)

$\partial E/\partial W = -(y'-o) \; . \; \text{sigmoid}' . \; A_1$ …… (17)

The shape of $\partial E/\partial W$ will be the same as the weight matrix W. We can update the values in the weight matrix using the following equation:

$W_new = W_old - lr*\partial E/\partial W$ …… (18)



Backward Propagation (Convolution layer)

$\partial E/\partial W = \partial E/\partial O. \; \partial O/\partial Z_2. \; \partial z/\partial W$ …... (19)

We will find the values of these derivatives separately.

1. Change in error with respect to output

Suppose the actual values for the data are denoted as y' and the predicted output is represented as O. Then the error would be given by this equation:

$E = (y' - O)^2/2$ …… (20)

If we differentiate the error with respect to the output, we will get the following equation:

$\partial E/\partial O = -(y'-O)$ …… (21)

2. Change in output with respect to Z_2 (linear transformation output)

To find the derivative of output O with respect to Z_2, we must first define O in terms of Z_2. If you look at the computation graph from the forward propagation section above, you would see that the output is simply the sigmoid of Z_2. Thus, $\partial O/\partial Z_2$ is effectively the derivative of Sigmoid. Recall the equation for the Sigmoid function:

$f(x) = 1/(1+e\text{^}-x)$ …… (22)

The derivative of this function comes out to be:

$f'(x) = (1+e^{-x})^{-1}[1-(1+e^{-x})^{-1}]$ …… (23)

$f'(x) = sigmoid(x)(1-sigmoid(x))$ …… (24)

$\partial O/\partial Z_2 = (O)(1-O)$ …… (25)

3. Change in Z_2 with respect to W (Weights)

The value Z_2 is the result of the linear transformation process. Here is the equation of Z_2 in terms of weights:

$Z_2 = W^T.A_1 + b$ ….. (26)

On differentiating Z_2 with respect to W, we will get the value A_1 itself:

$\partial Z_2/\partial W = A_1$ …… (27)

Now that we have the individual derivations, we can use the chain rule to find the change in error with respect to weights:

$\partial E/\partial W = \partial E/\partial O \; . \; \partial O/\partial Z_2 . \; \partial Z_2/\partial W$ ….. (28)

$\partial E/\partial W = -(y'-o) \; . \; sigmoid' . \; A_1$ …… (29)

The shape of $\partial E/\partial W$ will be the same as the weight matrix W. We can update the values in the weight matrix using the following equation:

$W_new = W_old - lr*\partial E/\partial W$ …… (30)

4.3 EXPERIMENTS AND RESULTS

4.3.1 Experimental setup

Functional near-infrared spectroscopy (**fNIRS**) is an optical brain monitoring technique which uses near-infrared spectroscopy for the purpose of functional neuroimaging. Using fNIRS, brain activity is measured by using near-infrared light to estimate cortical hemodynamic activity which occur in response to neural activity. Alongside EEG, fNIRS is one of the most common non-invasive neuroimaging techniques which can be used in portable contexts. The signal is often compared with the BOLD signal measured by fMRI and is capable of measuring changes both in oxy- and deoxyhaemoglobin concentration, but can only measure from regions near the cortical surface. fNIRS may also be referred to as Optical Topography (OT) and is sometimes referred to simply as NIRS.

fNIRS estimates the concentration of haemoglobin from changes in absorption of near infrared light. As light moves or propagates through the head, it is alternately scattered or absorbed by the tissue through which it travels. Because haemoglobin is a significant absorber of near-infrared light, changes in absorbed light can be used to reliably measure changes in haemoglobin concentration. Different fNIRS techniques can also use the way in which light propagates to estimate blood volume and oxygenation. The technique is safe, non-invasive, and can be used with other imaging modalities.

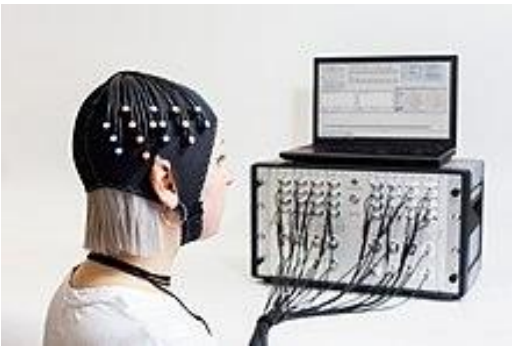


Figure 4.9 fNIRS

It is composed of 4 sources and 10 detectors, which form 16 source/detector pairs separated by 2.5 cm. The sensor pad is positioned on the subject's forehead

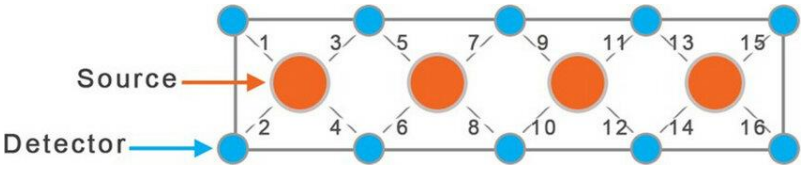


Figure 4.10 What fNIRS consists of

4.3.2 Experiment:

For this experiment, we are considering 12 participants which consists of healthy as well as persons suffering from OCD. The visual stimuli diagram for detection of OCD is as follows:

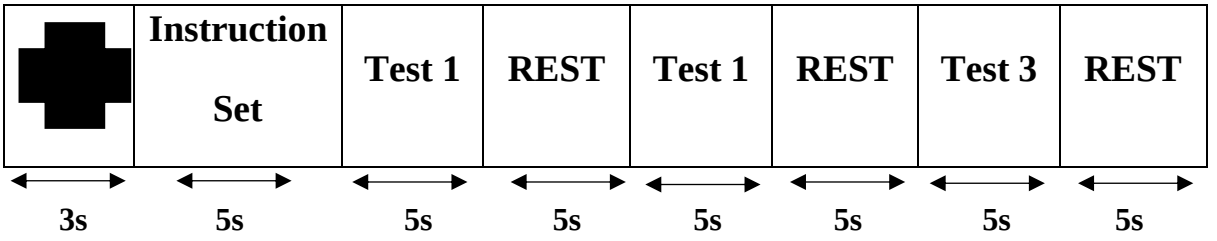


Figure 4.11 Trials of the experiment

The first 3s which is represented by a cross sign is Fixation cross which helps the subject to focus on the cognitive task. The next 5s consists of the Instruction set that contains the 3 different types of visual stimuli used in detecting OCD or healthy patient from Eriksen Flanker Task that is, Congruent, Incongruent and Neutral stimuli.

Congruent stimulus – Also known as compatible condition, here the direction of the non-target stimuli is same as that of the target.

Incongruent stimulus – Also known as incompatible condition, here the direction of the non-target stimuli is opposite to that of the target.

Neutral stimulus –It has neither the same or the opposite direction of the target stimulus.

Different kinds of characters, letters, animations, colour patches, arrow directions, numbers are used to draw the 3 different stimuli.

For example,



This represents a Congruent stimulus



This is an Incongruent Stimulus



This is a Neutral Stimulus

Then the experiment starts from Test 1 which appears for 5s. In these tests, the person (either healthy or OCD) is seated in a chair and active fNIRS electrodes are fitted in the scalp of the person to allow measurement of brain tissue concentration changes of the oxygenation and deoxygenation haemoglobin. The participant is told to look at the external device (computer) and identify whether the stimuli is Congruent, Incongruent or Neutral. The participants do not have any prior knowledge about the results of the stimuli.

After recording the data for each test, a 5s REST time is given before starting of the next test that is Test 2. Again, similarly the participant (healthy or OCD) will be told to look at the screen of the computer to identify the type of stimuli and this keeps on repeating for 20 tests. Each of the 12 participants' data is recorded individually for all the 20 tests and the difference in data between a healthy participant and a participant suffering from OCD is noted.

After the results, we get to see that a participant who has OCD takes longer duration to identify the different stimuli than a healthy participant. When subjects participate in Eriksen Flanker task, the anterior cingulate cortex or the ACC is activated. It is observed to be more active in response to processing incongruent stimuli than congruent stimuli.

4.3.3 RELATIVE PERFORMANCE ANALYSIS

Here, we are finding out the classification accuracy (CA %) of different classifiers in Machine Learning such as SVM, LDA, KNN, CNN.

Classifiers	CA%
1) SVM	65.36 %
2) LDA	70.23 %
3) KNN	78.40 %
4) CNN	88.46 %

Table 4.1 Shows highest Classification Accuracy %

Thus, Convolutional Neural network (CNN) has the highest classification accuracy percentage

4.4 References

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CHAPTER 5

Conclusion

5. CONCLUSION

Thus, we are able to conclude that using fNIRS, we can easily identify whether a person is healthy or suffering from Obsessive Compulsive Disorder using Convolutional Neural Network (CNN) classification. We also found out the Classification Accuracy percentage of all the classifiers and CNN had the maximum or highest CA %.

5.1. Advantages of CNN

- CNNs can achieve state-of-the-art accuracy on a variety of image recognition tasks, such as image classification, object detection, and image segmentation.
- CNNs can be very efficient, especially when implemented on specialized hardware such as GPUs.
- CNNs are relatively robust to noise and variations in the input data.
- CNNs can be adapted to a variety of different tasks by simply changing the architecture of the network.
    - Good at detecting patterns and features in images, videos, and audio signals.
    - Robust to translation, rotation, and scaling invariance.
    - End-to-end training, no need for manual feature extraction.
    - Can handle large amounts of data and achieve high accuracy.

5.2 APPLICATION AND FUTURE SCOPES

From the experiment, we can have various applications that can be helpful in future. Some of them are:

- Using fNIRS, we can detect if a person is suffering from OCD or not and early detection can lead to early treatment which will help people to recover faster and reduce the severity and complexity of the disorder.
- It's an easy process and requires less computational cost.
- It's a safe method to use
- It's a non-invasive method hence does cause any side effects as such to the brain.