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University of Applied Sciences and Arts

From Mind to Motion: EEG-Based Real-Time Car Control in CARLA Simulation

Research Thesis

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Submitted by

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Abstract

This thesis presents the development and evaluation of a non-invasive Brain-Computer Interface (BCI) system utilizing Electroencephalography (EEG) to control a simulated car in the CARLA environment. The primary objective was to enable intuitive "go" and "stop" commands based on distinct user mental states. The methodology involved employing a motor execution paradigm, where participants EEG signals were recorded using the Unicorn Hybrid Black headset while alternating between relaxed and focused states, the latter induced by a stress ball squeeze. This approach was chosen for its robust and reliable neural signatures, offering advantages over motor imagery-based paradigms. The raw EEG data underwent rigorous preprocessing, including re-referencing, bandpass filtering, notch filtering, and Independent Component Analysis (ICA), to ensure signal quality and remove artifacts. The processed signals were then used for binary classification to differentiate between the "relaxed" and "focused" states, which were mapped to "stop" and "go" commands, respectively. The successful implementation of this system demonstrates the feasibility of employing EEG for real-time control in complex simulated environments. The findings highlight the potential of EEG-based BCIs not only for advancing assistive technologies, such as brain-controlled vehicles, but also for innovative applications in neurorehabilitation, offering engaging platforms for patients recovering from neurological conditions like stroke. This work contributes to the ongoing evolution of BCI technology, paving the way for more seamless and effective brain-computer interaction.

Keywords: - Brain-Computer-Interface, Signal Processing, Paradigms, Classification, Carla Simulation

Declaration

I hereby confirm that I have written the Research Thesis at hand independently. I have not used any sources or materials other than those stated, and I have highlighted any citations properly.

16.07.2025, Mohammed Rizwan

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List of Abbreviations

BCI	Brain-Computer-Interface
CNN	Convolutional Neural Network
CSP	Common Spatial Patterns
DL	Deep Learning
ECoG	Electrocorticography
EEG	Electroencephalography
EOG	Electrooculography
EP	Evoked Potential
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
LSL	Lab Streaming Layer
MI	Motor Imagery
PCA	Principal Component Analysis
RNN	Recurrent Neural Network

Chapter 1

Introduction

The human brain, an organ of unparalleled complexity, holds the key to unlocking new frontiers in human-computer interaction. Brain-Computer Interfaces (BCIs) stand at the forefront of this revolution, offering a direct communication pathway between the brain and external devices, bypassing traditional motor pathways. This technology is particularly transformative for individuals with severe physical disabilities, enabling them to interact with their environment and regain a degree of independence. While various BCI paradigms exist, including motor imagery (MI), P300, and Steady-State Visual Evoked Potentials (SSVEP), the challenge lies in developing robust, intuitive, and reliable systems for real-world applications.

This thesis delves into the exciting potential of non-invasive EEG-based BCIs to enable direct control over simulated environments. Specifically, this project demonstrates the application of EEG signals to control a car within the CARLA simulation environment, allowing for fundamental "go" and "stop" commands through distinct mental states. This work is particularly compelling because it addresses the critical need for more accessible and intuitive control mechanisms for virtual and, eventually, physical systems. Beyond direct vehicle control, the principles explored here have significant implications for gaming by BCI for rehabilitation, particularly for stroke patients, offering engaging and effective avenues for neurorehabilitation by promoting brain plasticity through active engagement.

The goal of this project is to develop and validate an EEG-based BCI system capable of accurately classifying user intent ("go" or "stop") and translating these commands into actions within a realistic simulation. This research contributes to the state-of-the-art by focusing on a motor execution paradigm, leveraging its robust neural signatures for more reliable signal acquisition compared to motor imagery, which often suffers from high individual variability and extensive training requirements. By achieving precise control in a simulated driving scenario, this thesis lays foundational groundwork for advanced assistive technologies and innovative rehabilitation tools, underscoring the vital role of BCIs in shaping future human-machine interaction.

Chapter 2

Background on BCI

A Brain-Computer Interface (BCI) is a system that allows direct communication between the human brain and external devices without the need for movement, speech, or any muscular activity. It enables users to control computers, robots, or other machines using only their brain signals. This technology has become especially important for individuals with physical disabilities, offering new ways to interact with the world around them. This section will explain the different types of BCIs, methods of signal acquisition, and various paradigms used to interpret brain activity.

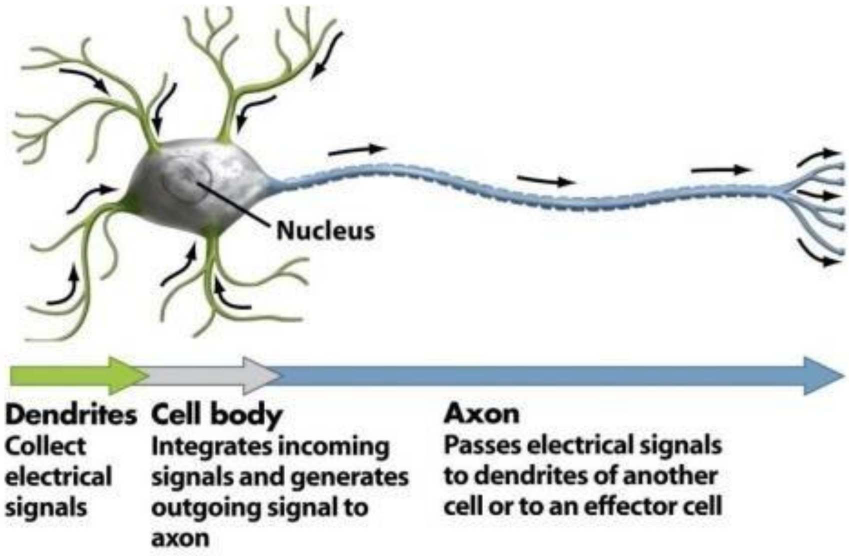


Figure 2.1:Flow of biological neuron (source : https://www.researchgate.net/figure/Flow-of-information-in-biological-neuron_fig4_350036902)

The human brain communicates through electrical signals. When neurons (brain cells) communicate with each other, they transmit tiny electrical impulses. This happens due to a difference in electrical potential across the cell membranes of neurons, which is known as the membrane potential (Rao, 2013). When a neuron is activated, it generates a small electrical spike called an action potential. These combined electrical signals from thousands or millions of neurons create brain waves, which can be detected using special equipment. These brain waves can be recorded non-invasively using devices such as EEG.

The basic operation of a BCI involves three major stages: signal acquisition, signal processing, and command execution. In this work, we focus on a non-invasive BCI using Electroencephalography (EEG) and employ motor execution (ME) rather than motor imagery (MI) to drive command generation. We also use the Unicorn EEG system to collect and process brain data in real time.

The BCI process generally involves three major stages: signal acquisition, signal processing, and command execution. Among the various techniques available for capturing brain activity, Electroencephalography (EEG) is the most widely used due to its non-invasive nature. EEG involves placing sensors (electrodes) on the scalp to detect the brain’s electrical activity. However, EEG signals are typically weak and can be contaminated by noise from eye movements, muscle activity, or external electrical interference. To overcome this, preprocessing techniques such as filtering and artifact removal (e.g., using Independent Component Analysis, ICA) are applied to clean the data and extract relevant features. The methods discussed are widely researched and applied by several industries and research communities. (X. Zhang, 2019) (M. Iftikhar, 2018) (Yao, 2021) (Rao, 2013)

2.1 Brain Signal Acquisition

Understanding how the brain generates electrical signals is just the beginning. We need a mechanism to consistently and in real time record those signals so that they may be converted into meaningful commands for external devices to construct a working Brain-Computer Interface (BCI). The entire BCI system is based on this phase, which is referred to as brain signal acquisition. The system's overall performance will decrease if the input signals are noisy or weak, regardless of how strong the processing algorithms are.

The choice of signal acquisition technique largely depends on the intended application and user requirements. There are various methods to record brain electrical activity, broadly categorized into invasive and non-invasive techniques.

This work focuses exclusively on Electroencephalography (EEG), a widely used non-invasive signal acquisition technique. For completeness, a brief overview of invasive and other non-invasive methods is also provided

2.1.1 Invasive Method

Invasive brain signal acquisition involves surgical procedures where an electrode is placed in direct contact with required region in the brain are invasive methods of recording brain signals. These techniques are considered the most accurate (Zhao ZP, 2023) in terms of signal quality because the electrodes are in close contact with the neurons, which allows for precise detection of electrical activity. As a result, invasive methods provide signals with high spatial resolution (the ability to pinpoint exactly where in the brain the signal is coming from), high temporal resolution (accurate tracking of the timing of brain activity), and a high signal-to-noise ratio (SNR), meaning the signals are clearer and less affected by interference. Strict clinical settings are used to implement these methods.

Invasive methods can be divided into two categories:

Intracortical recording electrodes are inserted into the brain tissue to identify individual or small-group neuron activity. In these types of applications, devices such as the Utah Array and the Floating Microelectrode Array (FMA) are frequently utilized.

Surface-level invasive recording, such as Electrocorticography (ECoG), This technique places electrodes on the surface of the brain, just beneath the skull but not deep into the brain tissue. It is less invasive than intracortical recording but still requires surgery.

Figure 2.2: Invasive (source : https://www.sciencedirect.com/science/article/abs/pii/B9780128053539000279)

These approaches are commonly used in animal research, especially in studies involving monkeys, where precise understanding of brain function is required. In humans, invasive procedures are performed only in highly controlled clinical environments and are typically limited to individuals with serious medical conditions, such as those with severe paralysis, spinal cord injury, or advanced neurological disorders. In such cases, the potential benefits of restoring movement or communication outweigh the surgical risks.

2.1.1.1 Electrocorticography (ECoG):

ECoG is an extracortical invasive electrophysiological monitoring method (Yao, 2021) (Parvizi J, 2018). It doesn’t require electrodes to be inserted deep into the brain which lowers the risks but still gives detailed, reliable brain signals. It’s less affected by outside noise, like blinking or muscle movement, and the signals it records are cleaner and more accurate than those from surface-level methods (Nathan E. Crone, 2006) (Parvizi J, 2018). ECoG involves placing a thin electrode strip or grid directly on the brain's surface, just beneath the skull.

Mostly performed in a clinical setting, a strip of electrodes are placed on the surface of interest on the brain. Before surgery, doctors use ECoG to monitor brain activity and pinpoint exactly which areas are involved in things like speech or movement. This helps them avoid damaging important regions during operations. Because of these benefits, ECoG has become one of the most widely used approaches for both medical diagnostics and research into brain-computer interfaces. It provides a valuable middle ground between safety and performance.

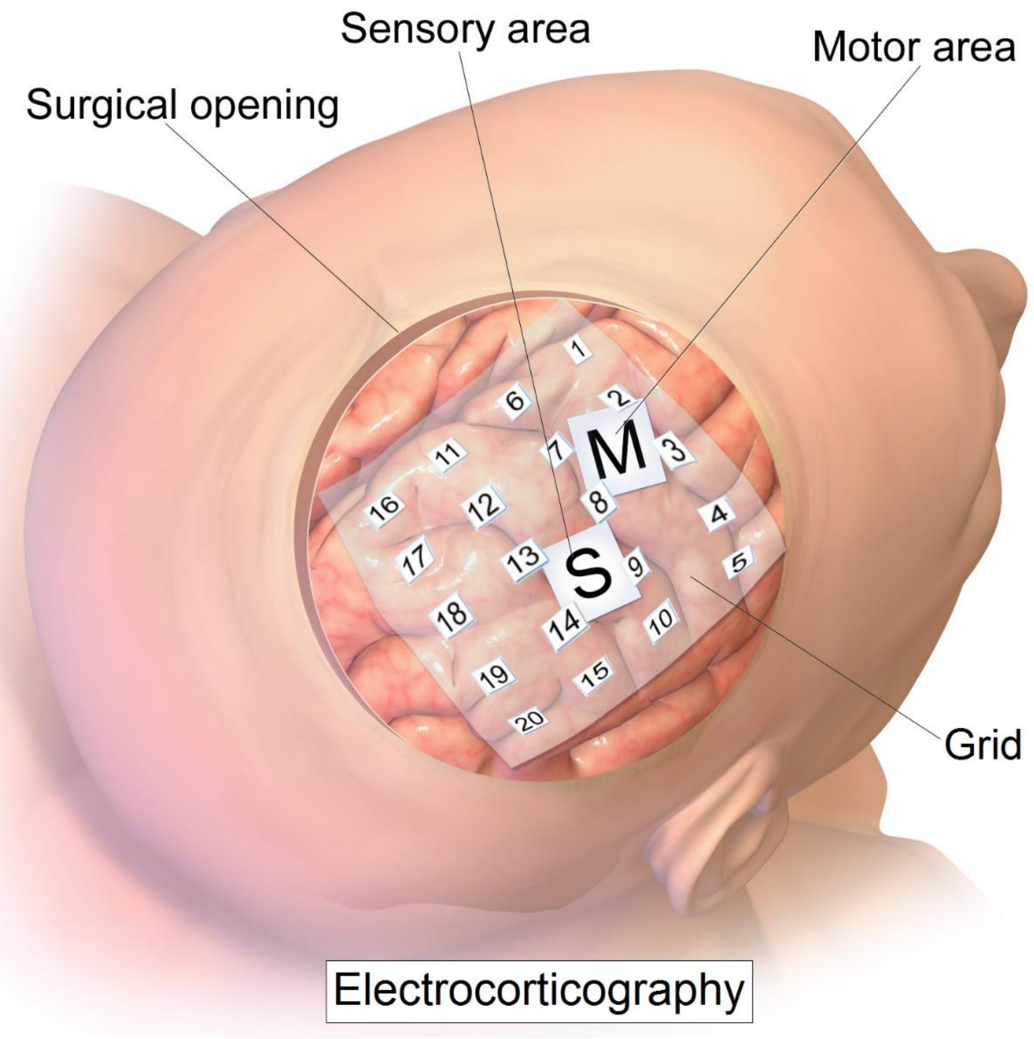


Figure 2.3: Intracranial electrode gird for ECoG (Source : https://en.wikipedia.org/wiki/Electrocorticography)

2.1.2 Non- Invasive Method

These brain signal acquisition methods measure brain activity without surgery or putting electrodes inside the skull. These methods track electrical or magnetic activity on the surface of the scalp, making them safer and easier to use than invasive techniques. Some common non-invasive methods include.

Electroencephalography (EEG): EEG measures electrical activity in the brain using tiny sensors on the scalp.

Functional Magnetic Resonance Imaging (fMRI): fMRI reveals which parts of the brain are active during specific tasks by measuring changes in blood flow.

Functional Near-Infrared Spectroscopy (fNIRS): fNIRS measures variations in blood oxygen levels in the brain using light, which allows researchers to better understand brain activity, particularly in cognitive regions.

Magnetoencephalography (MEG): MEG provides comprehensive information about brain processes by detecting the magnetic fields produced by brain activity.

Electrooculography (EOG): Often employed in visual processing research, EOG measures electrical activity surrounding the eyes to follow eye movements. (Bulling A, 2011)

In this research paper, we are using EEG to measure brain activity and study brain patterns without needing surgery using the Unicorn Hybrid Black

2.1.2.1 Electroencephalography (EEG)

Electroencephalography (EEG) is the most used non-invasive technique for measuring electrical activity in the brain, making it a popular choice for Brain-Computer Interface (BCI) applications. In EEG-based BCIs, electrodes are placed on the scalp to record brain electrical signals generated by neural activity. These signals are then analysed and translated into commands to control external devices, such as prosthetics, computers, or communication aids.

EEG is widely favoured in BCIs due to its safety, ease of setup, and ability to provide real-time data without requiring invasive procedures. Electrodes are typically placed according to the internationally recognized 10-20 system (Herwig U, 2003), though slight adjustments may be made depending on the application. The spatial resolution of EEG signals is influenced by the number of electrodes used, while the temporal resolution is determined by the system's sampling rate.

EEG generally offers better temporal resolution than spatial resolution. However, EEG systems typically have lower spatial and temporal resolution and poor signal-to-noise ratio (SNR) compared to invasive methods (Rao, 2013). The skull and other tissues between the cortex and scalp contribute to signal distortion, leading to spatial smearing.

Despite these limitations, EEG stands out among non-invasive methods for its high temporal resolution, tolerance to noise and artifacts, low cost, and lack of exposure to high-intensity magnetic fields. EEG-based BCIs have been successfully applied in various fields, such as assisting individuals with disabilities. For instance, individuals with paralysis can use EEG-based systems to control robotic arms, move cursors on a screen, or communicate, improving their ability to interact with their environment.

While EEG may not offer the same level of signal resolution as invasive methods, its non-invasive nature makes it an attractive option for developing accessible, safe, and cost-effective BCI systems across a range of applications.

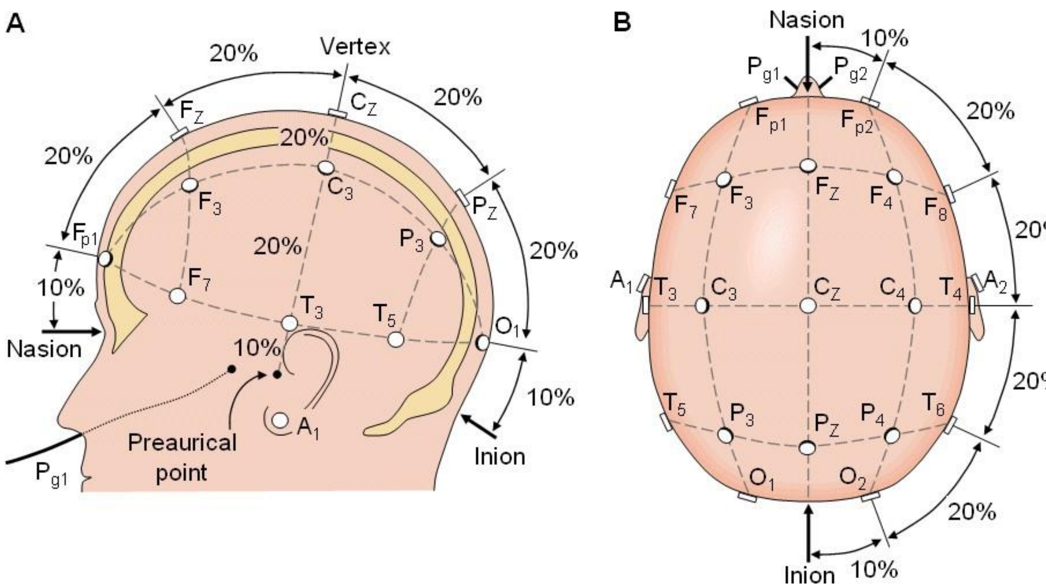


Figure 2.4: 10-20 system of internationally accepted electrode placement.

(Source: https://www.bem.fi/book/13/13x/1302ax.htm)

Chapter 3

EEG Paradigms

To effectively study the brain's response to specific tasks or stimuli, researchers design structured experimental setups known as EEG paradigms. These paradigms provide a systematic way to capture and analyse electrical activity in the brain under controlled conditions. By asking participants to engage tasks such as focusing on visual cues, responding to sounds, or remaining at rest researchers can observe how different mental states or cognitive processes manifest in the EEG signal. The choice of paradigm depends on the objective of the experiment, as well as whether the focus is on spontaneous brain activity or event-related responses. EEG paradigms play a central role in translating raw brainwave data into meaningful insights about attention, perception, memory, and neurological function.

3.1 Motor Imagery (MI)

Motor Imagery (MI) refers to the mental simulation of a movement without any actual physical execution. When a person imagines moving a body part such as the left hand or right foot it activates many of the same brain regions involved in real movement, particularly within the sensorimotor cortex (Padfield, Zabalza, Zhao, & Masero, 2019). Unlike physical actions, MI does not produce visible movement or require any external stimuli. Instead, it relies on internal motor intention, making it a key paradigm for active Brain-Computer Interfaces (BCIs).

From a neurophysiological perspective, MI induces measurable changes in brain activity, specifically in the mu (8–13 Hz) and beta (13–30 Hz) frequency bands. These changes appear as event-related desynchronization (ERD) and event-related synchronization (ERS) over the primary motor cortex (M1), supplementary motor area (SMA), and premotor cortex (C Neuper, 2001). During MI, ERD reflects decreased neural synchrony due to active processing, while ERS reflects a rebound or return to baseline after mental effort ends. These patterns can be detected using non-invasive tools like EEG.

One of the most promising aspects of the MI paradigm is its potential for neurorehabilitation. Because imagined movements engage the same neural pathways as actual movements, patients especially those recovering from stroke or spinal cord injuries can use MI-based BCIs to stimulate brain plasticity and support motor recovery (Cervera MA, 2018). For instance, imagining left-foot movement activates the contralateral motor cortex in the right hemisphere, helping retrain brain regions affected by injury.

MI is also widely used to control external devices through BCIs. For example, (Tanaka, 2005) developed an MI-BCI system where users could control the left or right turns of an electric wheelchair by imagining corresponding limb movements. Later, (Choi, 2008) expanded this concept to include forward motion commands, successfully testing it under real-world conditions. Similarly, (Akce, 2010) used MI signals to control a remotely piloted unmanned aerial vehicle, and (Chae, 2012) developed a humanoid robot guided by EEG signals and real-time feedback from a head-mounted camera.

The appeal of MI-based BCIs lies in their intuitive design they harness the brain's natural motor functions, making them relatively easy to learn and use. They also offer flexibility, as they do not depend on visual or tactile stimuli, allowing for a broader range of applications. These systems can be life-changing for individuals with severe physical disabilities, offering them new ways to interact with the environment.

However, a key challenge in MI-based BCI systems is the individual variability in performance. Some users find it difficult to consistently produce clear motor imagery signals a phenomenon sometimes referred to as BCI illiteracy. This can stem from differences in cognitive ability, concentration levels, or MI strategy. To address this, regular training and feedback are essential. Techniques such as neurofeedback, guided imagery, and personalized classifier design can significantly improve user performance over time.

In summary, Motor Imagery is a powerful, non-invasive BCI paradigm that mimics real movement through thought alone. It holds vast potential for both assistive technology and rehabilitation, providing users with an intuitive and flexible means of controlling external devices by tapping directly into their mental motor plans.

These ERD/ERS patterns reflect changes in EEG signal power and frequency during sensory, cognitive, and motor tasks. The different frequency ranges used for brain signal analysis are shown in Table 3.1.

Brainwave	Frequency Range	Associated Mental State	Common Situations	Function	Role in BCI
Alpha	8-13 Hz	Relaxed, Calm, Alert	Resting with eyes closed, meditation	Reflects a calm, idle brain	Used for relaxation, stress management, and neurofeedback in BCI systems
Beta	13-30 Hz	Active Thinking, Focus	Concentration, problem-solving, mental effort	Indicates high mental engagement	Used in motor imagery tasks and controlling external devices like robotic arms or cursors
Gamma	30-100 Hz	Higher Cognitive Function	Problem-solving, learning, sensory processing	Plays a role in memory, perception, and complex processing	Explored for high-level cognitive tasks and precise control in BCI systems

Delta	0.5-4 Hz	Deep Sleep, Unconscious	Deep sleep, coma, unconscious states	Associated with restorative sleep and unconscious brain activity	Less common in BCI; may be relevant for sleep studies or disorders related to recovery

Table 3.1 EEG Frequency bands

3.2 P300 Paradigm

The P300 paradigm is one of the most used methods in EEG-based Brain-Computer Interface (BCI) systems. It is based on a specific brain signal known as the P300 wave, which appears about 300 milliseconds after a person recognizes an important or rare stimulus something they are actively looking for (Li, 2025). This signal is part of a group of brain responses called event-related potentials (ERPs) and is especially linked to attention and decision-making.

The P300 is usually triggered using what's called the "oddball paradigm". In this setup, the user is presented with a stream of frequent, non-target items mixed with occasional target items (the ones the user is focused on) (L.A. Farwell, 1988). For example, in a typical experiment, a grid of letters might flash one by one on a screen, and the user is told to focus on a particular letter they want to select. When that target letter flashes, the brain recognizes it and produces the P300 wave a clear, positive peak in the EEG signal around 300 milliseconds after the flash.

This brain response is strongest over the parietal lobe but can also be detected from the frontal and central regions of the brain. These areas are responsible for processing attention, evaluating the importance of incoming information, and making decisions.

In a P300-based BCI system, this neural response is used to interpret user intentions. A well-known example is the P300 speller, originally proposed by Farwell and Donchin (1988) where a grid of letters or symbols is displayed on a screen, and the user is instructed to focus on the character they want to select. Rows and columns flash in random order, and when the target row or column flashes, the user's brain generates a P300 response. EEG electrodes placed on the scalp capture this signal, which is then processed using machine learning algorithms to determine the user's chosen character. This system allows individuals to communicate or control external devices without any physical movement.

One of the major advantages of the P300 paradigm is that it requires little to no training. Most users can begin using a P300-based BCI system after only a brief introduction, making it highly suitable for clinical and assistive applications. Its non-invasive nature, high accuracy, and broad accessibility make it ideal for people with severe motor disabilities, such as those with amyotrophic lateral sclerosis (ALS), spinal cord injuries, or other conditions that limit physical communication.

In addition to communication systems, the P300 paradigm has been applied in other areas such as rehabilitation, cognitive assessment, and fatigue monitoring. For example, researchers have explored its use in supporting language recovery for stroke patients, as well as measuring mental fatigue in children after playing cognitive games. These applications demonstrate the flexibility and usefulness of the P300 signal beyond traditional typing or control tasks.

Despite its many strengths, the P300 paradigm also has some limitations. Because it depends on external stimuli, such as flashing lights or sounds, users may experience fatigue or reduced performance over long periods. The paradigm also requires a high level of sustained attention, meaning that distractions or a drop in concentration can weaken the P300 signal. Additionally, while it is accurate, the information transfer rate that is, how fast commands can be issued can be slower compared to other BCI paradigms like SSVEP or motor imagery.

To improve the performance and user experience of P300-based BCIs, ongoing research focuses on enhancing signal detection, reducing the number of required stimuli, and incorporating adaptive interfaces. In some systems, the P300 is also combined with other paradigms in hybrid BCIs, which can improve both speed and accuracy by using multiple types of brain signals.

3.3 SSVEP

The Steady-State Visual Evoked Potential (SSVEP) paradigm is a commonly used method in EEG-based Brain-Computer Interface (BCI) systems. It takes advantage of the brain's natural electrical response to visual stimuli that flicker at specific, constant frequencies (Vialatte, 2009).

When a person focuses their gaze on a flickering light or visual object, their brain generates a synchronized electrical signal at the same frequency as the flicker. This response, known as the SSVEP, can be easily detected using EEG, especially from electrodes placed over the occipital region of the scalp, which corresponds to the visual cortex.

These SSVEP responses are highly reliable because they are strong, stable, and have a high signal-to-noise ratio, making them very effective for interpreting a user's intent in real time. For example, if a stimulus flashes at 10 Hz, the EEG signal from a user focusing on that target will show a clear peak at 10 Hz and possibly at harmonics like 20 Hz or 30 Hz. This makes it possible for BCI systems to accurately determine which visual target the user is looking at, and to use that information to trigger a command such as moving a wheelchair, selecting a letter, or controlling a smart device (Blankertz, 2007).

SSVEP-based BCIs usually display multiple flickering targets on a screen, each associated with a unique command or function. The user simply looks at the one they wish to select. Since the response happens automatically when looking at the stimulus, no training is usually needed, making this paradigm very accessible even for beginners or users with limited motor ability.

One of the biggest advantages of the SSVEP approach is its high information transfer rate in other words, it allows fast communication between the user and the system. It's also relatively robust against noise and artifacts, meaning it performs well even in less-than-perfect conditions. Because the response is consistent across users, it works well in both laboratory and real-world scenarios.

Researchers have also explored ways to make SSVEP-based systems more flexible and accurate by combining them with other technologies. For example, some hybrid BCI systems pair SSVEP with signals from eye movements (electrooculography or EOG) or use augmented reality (AR) to create more interactive and engaging interfaces. These approaches can help reduce the reliance on bulky or fixed display screens and open the door to more practical applications like stroke rehabilitation tools, brain-controlled wheelchairs, or assistive robots that respond to users' visual attention (Li Y, 2013).

However, like all paradigms, SSVEP has some limitations. Since it relies on visual stimuli that flicker continuously, users may experience eye strain, visual fatigue, or discomfort during long sessions. Some individuals may also be sensitive to flickering lights, which can limit the usability of SSVEP systems for them. Additionally, maintaining steady visual focus is crucial so users with vision impairments or difficulty focusing may face challenges.

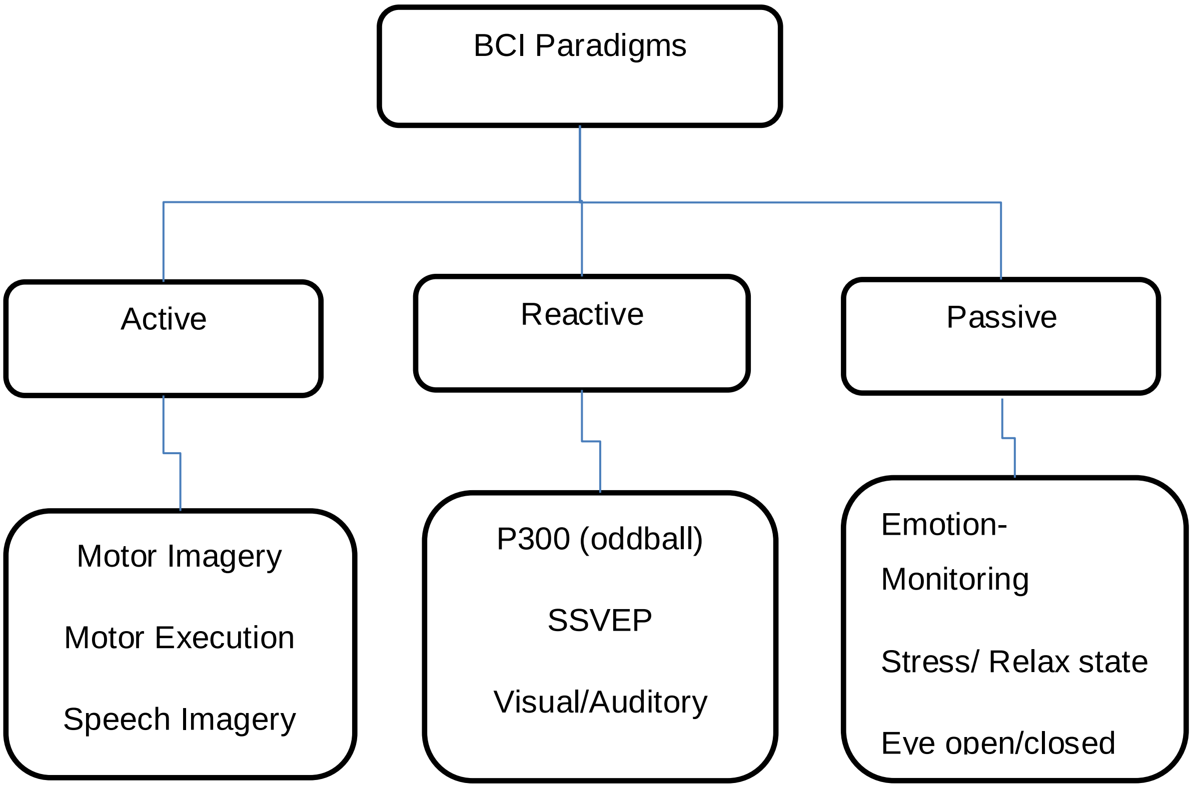
3.4 Classification of Brain-computer Interface Paradigms: -

Brain-Computer Interfaces (BCIs) are typically categorized into three major types based on how user intention is expressed: Active, Reactive, and Passive paradigms (Li, 2025). This classification helps researchers and developers choose the most appropriate interaction model for their specific application, whether it involves motor control, communication, or cognitive monitoring.

Active BCI: - The user intentionally generates specific brain patterns without relying on any external stimulus.

Reactive BCI: - The user focuses on external stimuli, and the brain's event-related responses are used for control.

Passive BCI: - Brain signals are interpreted without any intentional control, typically to monitor cognitive or emotional states.



3.5 Experimental Paradigm Description and Justification

In this study, we adopted a motor-related EEG paradigm, specifically based on motor execution, to distinguish between relaxed and focused mental states. During data collection, participants were instructed to relax with their eyes closed for a defined period, representing a calm, resting baseline. For the focus condition, participants were asked to open their eyes and squeeze a stress ball with their right hand, engaging in an intentional motor task.

This paradigm falls under the category of an Active BCI. In active BCI systems, users voluntarily generate specific brain activity patterns through intentional mental or physical actions, without relying on external stimuli. Here, the act of squeezing a stress ball represents a deliberate, controlled physical movement, which induces clear and consistent changes in brain activity, especially in the sensorimotor cortex that can be captured through EEG.

We selected motor execution instead of motor imagery (MI) or visual paradigms like P300 or SSVEP, due to several advantages. Motor imagery requires subjects to vividly imagine movement, a cognitive skill that varies across individuals and often demands extensive training. In contrast, motor execution provides a more robust and reliable neural signature, with minimal training requirements. When the participant physically performs a movement (e.g., squeezing the ball), it activates the primary motor cortex (M1) and related motor areas, resulting in event-related desynchronization (ERD), particularly in the mu (8–12 Hz) and beta (13–30 Hz) frequency bands. These desynchronization patterns are well-established indicators of motor activity in EEG research.

Moreover, using a real, tactile task during the focus condition ensures better user engagement and clearer labelling of mental states. The physical action enhances the signal-to-noise ratio in EEG recordings and reduces ambiguity during cognitive state classification. Since the right hand was used, cortical activation is primarily observed in the left hemisphere, providing a lateralized marker for focused activity.

This approach avoids the need for external visual stimuli, such as flashing lights or dynamic interfaces required by SSVEP or P300 paradigms. This makes the experiment more comfortable for participants, especially over long sessions, and less visually demanding, which is beneficial for naturalistic BCI settings or populations with visual or cognitive sensitivities.

Chapter 4

Environmental setup and Tools

4.1 Hardware Setup

Unicorn Hybrid Black

The hardware setup for this study involves the use of the Unicorn Hybrid Black headset. This specialized device is essentially a wearable tool that allows us to listen in on the brain's electrical activity. To capture these brain signals, the Unicorn Hybrid Black uses eight electrodes. These electrodes are carefully placed on specific spots on the user's head, following a standard map known as the International 10-20 system. This system is like a globally recognized grid for placing EEG electrodes, ensuring that researchers everywhere can accurately compare their findings. The numbers (10 and 20) refer to the percentages of the head's surface distance used to determine precise electrode locations, ensuring consistency regardless of head size.

Figure 4.1: Unicorn Hybrid Black Headgear.

(Source: https://www.gtec.at/wp-content/uploads/2023/09/unicorn-hybrid-black-bundle.jpg)

We placed electrodes at eight specific spots on the scalp to record brain activity. Each location gives us insight into different brain functions. Here's a simple breakdown of what each spot does:

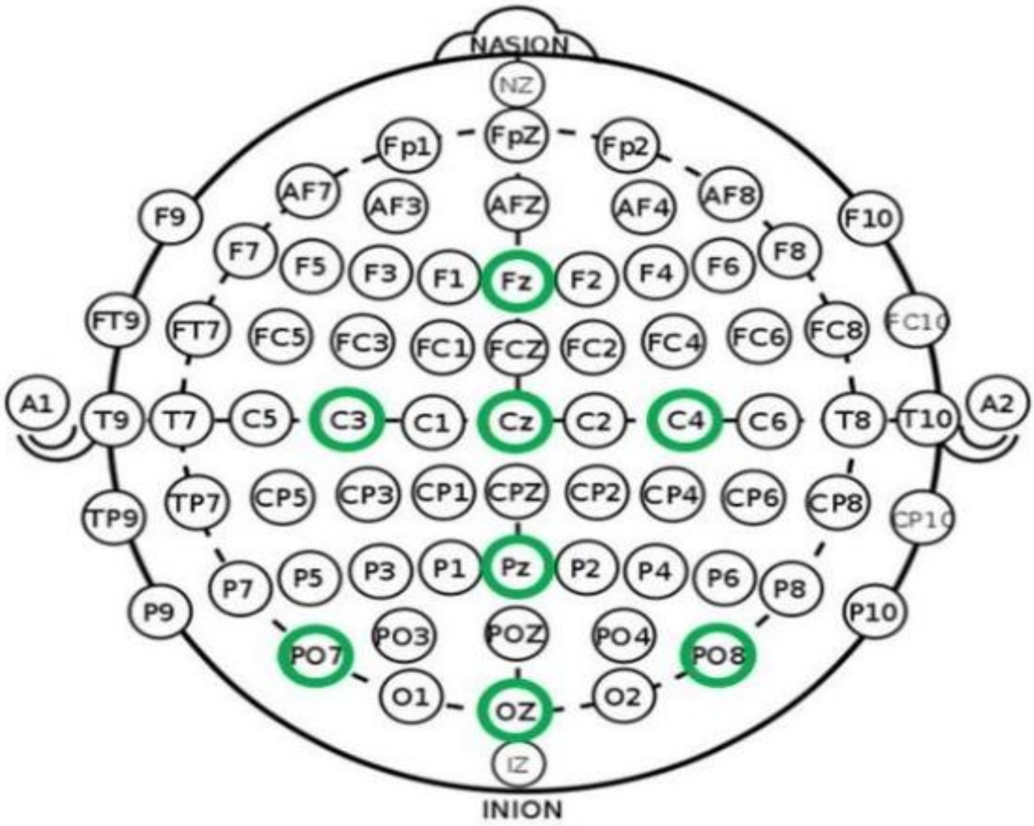


Figure 4.2: Electrodes position Unicorn Hybrid Black (Marked in green)

(Source: https://www.researchgate.net/figure/Location-of-the-eight-electrodes-Unicorn-Hybrid-Black-marked-in-green-Fz-C3-Cz-C4_fig5_385086223)

We used the following specific positions for our electrodes: FZ, C3, CZ, C4, PZ, PO7, OZ, and PO8. Each of these spots gives us a unique window into different parts of the brain and the specific functions they control:

- **FZ (Frontal-Midline):** This area is like your brain's control centre. It's active when you're focusing, making decisions, planning, or solving problems. Basically, whenever you're thinking hard or concentrating.
- **C3 (Central-Left):** This spot controls movement and feeling on the right side of your body. It's especially active when you move (or imagine

moving) your right hand or foot. Also picks up touch and sensation from your right side.

- **CZ (Central-Midline):** This is a balanced spot that picks up activity from both sides of your body. It’s often used as a central reference because it sits over the areas that handle both movement and touch.
- **C4 (Central-Right):** Same job as C3, but for the left side of your body. It’s involved when you move or feel something with your left hand, arm, or leg.
- **PZ (Parietal-Midline):** Helps you understand touch, pain, temperature, and where things are around you. It’s important for awareness of your surroundings and integrating your senses.
- **PO7 (Parieto-Occipital Left):** This spot helps you process what you see on the right side of your visual field. It’s used when you’re judging distances, locations, or tracking things with your eyes.
- **OZ (Occipital-Midline):** This is the brain’s main visual centre. It lights up whenever you see anything shapes, words, faces, etc.
- **PO8 (Parieto-Occipital Right):** Like PO7, it's crucial for visual-spatial integration, but specifically handles visual information from the left half of your visual field.

Once the electrodes are positioned, a crucial step called an impedance check is performed. This ensures that each electrode is properly connected to the scalp and can pick up brain signals clearly, without interference or noise. In simple terms, impedance refers to the resistance between the electrode and the skin. For clean and accurate brain signal recordings, we need low impedance. When impedance is low, the tiny electrical signals from the brain can travel easily from the scalp to the electrode. But if impedance is high, it acts like a barrier weakening the signal and adding unwanted noise, which makes the data harder to interpret.

To achieve these optimal low impedance levels, a small amount of conductive gel is applied to each electrode. This gel works by improving the electrical contact between the electrode and the skin. Our skin naturally has some resistance, and the gel bridges this gap, allowing the electrical signals to flow much more freely. This simple step is fundamental for ensuring the high-quality data necessary for accurate BCI applications.

Once these brain signals are picked up by the electrodes and the impedance is confirmed to be good, the Unicorn Hybrid Black headset converts them into digital information very rapidly. It does this at a sampling rate of 250 Hz per channel, meaning it captures the brain's electrical activity 250 times every second for each individual electrode. This incredibly fast capture rate is essential because brain signals change very quickly, and a high sampling rate ensures we don't miss any subtle yet important fluctuations in activity.

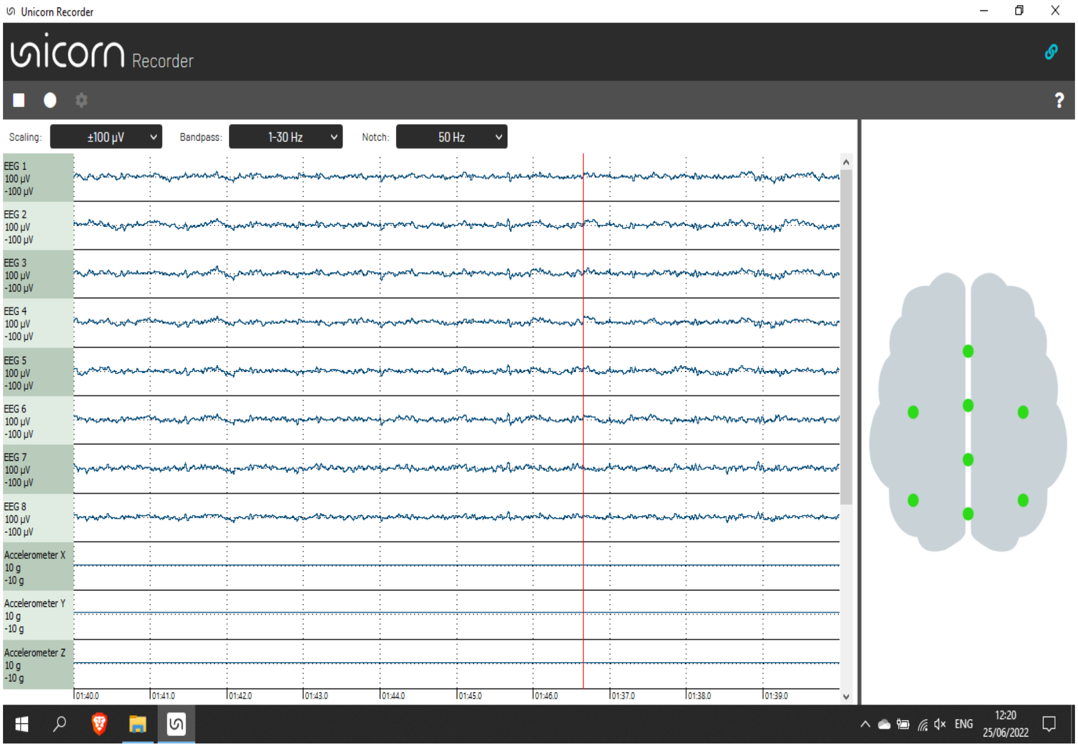


Figure 4.3: Impedance check of electrodes in Recorder software

(Source: https://robertoostenveld.nl/wp-content/uploads/2022/06/unicorn_eeg_quiet.png)

This digital information is then sent wirelessly via Bluetooth to a connected computer. On the computer, specialized software, part of the Unicorn Suite, takes these raw brain signals. Or we can collect the data through python script and store it. This software is designed to clean them up by removing any unwanted "noise" (like muscle movements or electrical interference that isn't from the brain) and then process them. This processing involves filtering the signals to highlight specific brainwave patterns (like alpha or beta waves) that are known to be linked to different mental states or intentions. This entire setup allows us to explore how these unique brain activity patterns can be translated into commands to control external devices or help us understand more about how the brain functions during specific tasks.

4.2 Why I Switched from OpenBCI to Unicorn Hybrid Black: -

In the starting of this project, I was using the OpenBCI headgear. It's a well-known open-source system and great for getting started with EEG experiments. But over time, I ran into some frustrating issues mainly with impedance. Every time I used it, the impedance levels were different. Even during the same session, they would fluctuate a lot, which made it hard to trust the data I was collecting.

The main reason for this inconsistency is that OpenBCI uses dry electrodes. While convenient, dry electrodes don't always make strong, stable contact with the scalp especially if there's hair in the way or if the skin is dry. That weak connection leads to higher impedance, more noise, and a less reliable signal. I found myself constantly adjusting the headset or repeating recordings just to get a clean readout.

Then, I decided to switch to the Unicorn Hybrid Black headset, and it made a huge difference. This system uses hybrid electrodes, which means you can apply conductive gel to improve the contact. Once I started using the gel, the impedance dropped significantly and more importantly it stayed stable throughout the session. That stability gave me much cleaner and more consistent brain signal recordings.

The data quality from the Unicorn system was noticeably better. The signals were clearer, with less noise and fewer artifacts, which made analysis much smoother and more reliable. For a BCI project, where precision really matters, this switch wasn't just helpful it was necessary.

In the end, moving to the Unicorn Hybrid Black gave me the confidence that I was collecting high-quality data I could trust, and it allowed me to focus more on the core goals of the project rather than constantly troubleshooting signal issues.

4.3 Software Setup

4.3.1 CARLA

CARLA is an open-source urban driving simulator specifically designed for the development, training, and validation of autonomous driving systems. It provides realistic virtual environments, diverse scenarios, and flexible sensor configurations, making it a powerful platform for researchers and developers to test perception, planning, and control algorithms. (Koltun, 2017).

Chapter 5

Data Acquisition and Pre-processing

After completing the hardware setup and ensuring low, stable impedance through proper electrode placement and the use of conductive gel, the next step was to begin data acquisition. This is the stage where actual brain signals are recorded using the Unicorn Hybrid Black headset.

At this point, the system is ready to capture raw EEG data in real time. The goal during data acquisition is to ensure that the signals collected are clean, consistent, and relevant to the task or mental state being studied. This involves careful planning of the experimental conditions, minimizing movement artifacts, and monitoring the signal quality throughout the session.

To make sure the data I collected was consistent and well-organized, I built a custom Python program with a simple, user-friendly interface (GUI). This wasn't just for convenience it was a key part of the experiment. The program helped guide me through each step of the process and ensured everything ran smoothly. One important feature was the use of short "beep" sounds. These audio cues clearly signalled when to start and stop each phase of the experiment. This kept the timing precise, so I knew exactly when to begin or end a task, and the recording system could capture my brain activity at just the right moments. Accurate timing like this is essential for linking brain signals to specific mental states.

The experiment followed a repeating cycle (or "epoch") that lasted 30 seconds and was designed to highlight different mental states. Each cycle had three parts:

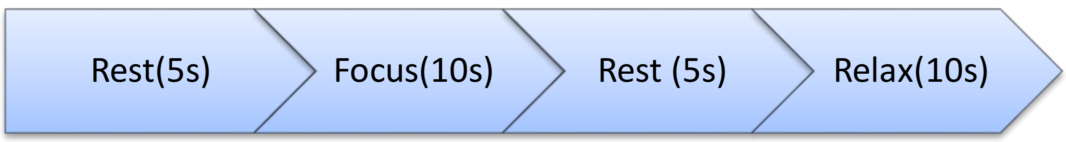


Figure 5.1: Data collection paradigm Cycle

Focus Phase (10 seconds): I opened my eyes and squeezed a stress ball. This simple and consistent activity helped shift my brain into a more alert and focused state, typically associated with beta waves. By comparing these two phases, I could train the BCI system to recognize the difference between being relaxed and being focused.

Relaxation Phase (10 seconds): After that, I started by sitting still with my eyes closed, simply relaxing. This helped capture a calm, resting state in the brain usually seen as alpha waves, which are common during quiet wakefulness.

Rest Phase (5 seconds): I included a short break between the two main phases to give my brain a moment to reset. This helped prevent one phase from affecting the next and kept the data cleaner.

I repeated this cycle around 20 to 30 times to collect enough data for both mental states. The better-quality data I had, the better the system could learn to tell the difference between relaxed and focused brain activity.

Throughout the whole process, I paid close attention to signal quality to avoid "artifacts" unwanted noise in the EEG data caused by things like blinking or small movements. I stayed as still as possible and watched the signals in real time to keep the data clean.

I used the Unicorn Hybrid Black EEG headset, which I connected to my Python program using the UnicornPy library. This allowed me to collect brainwave data live, with each data point automatically marked with a precise timestamp. These timestamps were key for analysing how my brain activity changed over time. I saved all the data in CSV files, which are easy to use and compatible with many analysis tools.

Overall, this setup helped me collect reliable, well-structured data that I could use confidently in the next steps of my project.

5.1 Data Preparation

The raw EEG dataset consisted of approximately 1,080,000 samples, collected during repeated cycles of three experimental phases: *Ready*, *Relax*, and *Focus*. Each sample included multichannel EEG recordings, along with metadata columns such as timestamps, trigger markers, and phase labels.

As an initial step, all samples corresponding to the Ready phase were excluded. This phase was designed only as a brief transitional period and did not represent a meaningful mental state for classification. In total, 330,250 samples were removed, leaving only data from the Relax and Focus phases these two categories formed the core of the dataset used for training and evaluating the brain-computer interface (BCI) model.

Following this, two metadata columns timestamp and trigger were also dropped. The timestamp column, used to synchronize recordings during real-time data acquisition, was not informative for classification and was unnecessary for offline model training. Likewise, the trigger column, which marked the onset of each phase, had served its purpose during segmentation and labelling and was no longer needed in the final dataset. Removing these columns helped reduce dimensionality and simplify the input features for the model.

To prepare the data for binary classification, the categorical values in the phase column were encoded as numerical labels:

- Relax was replaced with 0
- Focus was replaced with 1

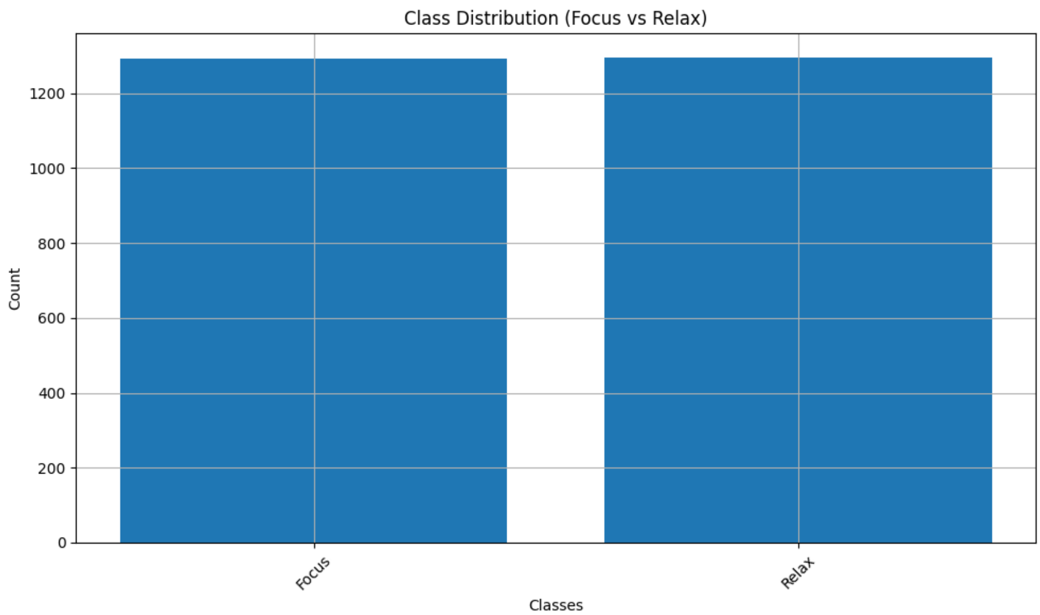


Figure 5.2: Class Distribution of Data sample into Focus and Relax

This transformation enabled the use of standard machine learning algorithms that require numerical target variables. The resulting dataset consisted entirely of EEG signal values and a binary class label, providing a clean and structured input for the subsequent preprocessing and model development pipeline.

5.2 EEG Signal Preprocessing: -

EEG (Electroencephalography) signals are naturally very weak and constantly changing, which makes them challenging to work with. They are also easily affected by noise from various sources like eye movements, muscle activity, and even electrical devices nearby. Because of this, raw EEG data can't be used directly for analysis or classification as artifacts overshadow the neural activity (Soria-Frisch, 2025)

To extract meaningful information, the data must first go through a careful preprocessing pipeline. This step is essential for cleaning the signal and preparing it for further analysis. In this section, we'll walk through the main stages of EEG preprocessing, including re-referencing, filtering, frequency-domain analysis, and Independent Component Analysis (ICA). For each step, we'll explain the reasoning behind it, how it's typically done in practice, and include any important mathematical concepts.

5.2.1 Data Loading and Initial Inspection

The EEG dataset is imported from a cleaned .csv file containing multichannel EEG recordings sampled at 250 Hz. Initial visualization of the raw signals is conducted to qualitatively evaluate the signal quality, detect the presence of artifacts, and establish a baseline for subsequent comparisons.

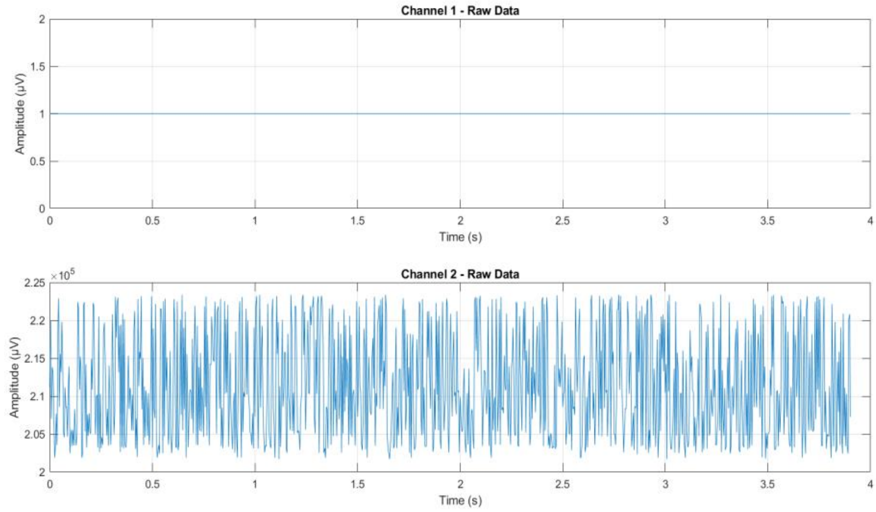


Figure 5.3: Raw EEG Data from Channels 1 and 2.

This plot shows typical raw electroencephalography (EEG) signals as initially recorded, illustrating the inherent noise and high amplitude fluctuations often present before any preprocessing steps.

5.2.2 Re-referencing

EEG measures the difference in voltage between each electrode and a reference electrode. But the signal you get depends heavily on which reference you choose. A poor choice can distort the data and make it harder to detect real brain activity.

To reduce this problem, a method called the Common Average Reference (CAR) is often used. Instead of using just one electrode as a reference, CAR uses the average of all electrodes. This helps reduce bias and makes the signal more balanced across the scalp by minimizing noise that is common to all channels (Ludwig KA, 2008)

5.2.3 Filtering

Raw EEG signals often contain unwanted noise. This includes slow drifts (very low frequencies below 0.5 Hz), high-frequency interference (above 45 Hz), and power-line noise (typically at 50 or 60 Hz, depending on the country). These noise sources can make it hard to focus on the actual brain rhythms we're interested in like delta, theta, alpha, beta, and low gamma waves.

To clean up the data and highlight meaningful neural activity, we use a combination of bandpass filtering and notch filtering.

5.2.3.1 Bandpass Filter

We apply a 4th-order Butterworth bandpass filter to keep only the frequencies between 0.5 Hz and 45 Hz. This range captures most of the brain's physiological rhythms while filtering out slow drifts and high-frequency noise.

The Butterworth filter is a good choice because it has a flat response in the passband, which means it doesn't distort the frequencies we want to keep. In practice, we use the butter function (e.g., in MATLAB or Python) to design the filter, and filtfilt to apply it in zero-phase mode, so that the signal isn't shifted in time.

Mathematically, the transfer function for a Butterworth filter is:

$$H(s) = 1 / \sqrt{(1 + (s/\omega c)^{(2n)})}$$

Where:

- $s = j\omega$ (complex frequency),
- ωc is the cutoff frequency,
- $n = 4$ is the filter order.

5.2.3.2 Notch Filter

To specifically remove power-line interference at 50 Hz, we use a second-order notch filter. This type of filter sharply removes just one frequency while leaving the rest of the signal mostly untouched.

The digital form of the notch filter looks like this:

$$H(z) = (1 - 2\cos(\omega_0)z^{-1} + z^{-2}) / (1 - 2r\cos(\omega_0)z^{-1} + r^2z^{-2})$$

Where:

- $\omega_0 = (2\pi \times 50) / 256$ (assuming a 250 Hz sampling rate),
- r determines how wide or narrow the notch is (usually close to 1 for a narrow filter).

By applying both the bandpass and notch filters, we can significantly clean up the EEG signal, making it easier to analyze real brain activity without interference from unwanted frequencies.

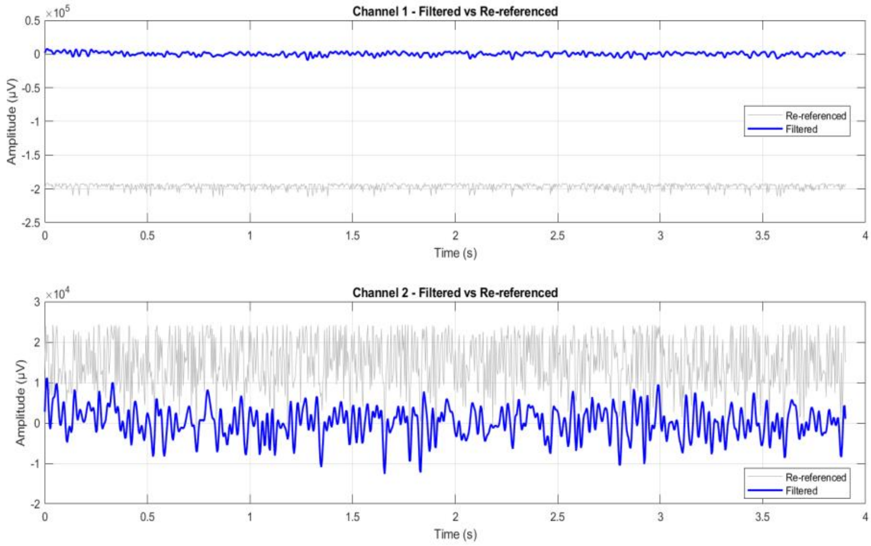


Figure 5.4: Visual Comparison of Re-referenced vs. Filtered EEG Signals

This figure shows the impact of bandpass and notch filtering (blue line) on the re-referenced EEG signal (grey line) for Channels 1 and 2. The filtered signal is noticeably smoother and cleaner, especially in Channel 2 (bottom graph), where much of the high-frequency noise has been effectively removed. This visual comparison highlights the effectiveness of filtering in enhancing signal quality and isolating meaningful brain activity.

5.2.4 Frequency-Domain Analysis (FFT)

While EEG signals are recorded in the time domain, their interpretation often relies on their frequency content. Different brain states are associated with specific frequency bands like alpha waves during relaxation or beta waves during focused activity. To better understand these patterns and to verify that our filtering step worked correctly, we convert the signal into the frequency domain using the Fast Fourier Transform (FFT).

The FFT breaks down the EEG signal into its frequency components, showing how energy is distributed across different bands.

For a discrete-time signal x[n] with length N, the FFT is defined as:

$$X[k] = \Sigma\, x[n] \times e^{(-j2\pi kn/N)}, \text{ for } k = 0 \text{ to } N-1$$

Where:

- X[k] is the complex spectrum at frequency bin *k*,
- x[n] is the time-domain EEG signal.

To analyze the results, we plot the magnitude spectrum |X[k]|, which shows how much energy is present at each frequency. This helps us identify key brain rhythms in the following bands:

- Delta (0.5–4 Hz)
- Theta (4–8 Hz)
- Alpha (8–13 Hz)
- Beta (13–30 Hz)
- Low Gamma (30–45 Hz)

A clean spectrum showing clear peaks in the expected bands and no significant spike at 50 Hz confirms that our filtering step was effective and that the signal is ready for further analysis.

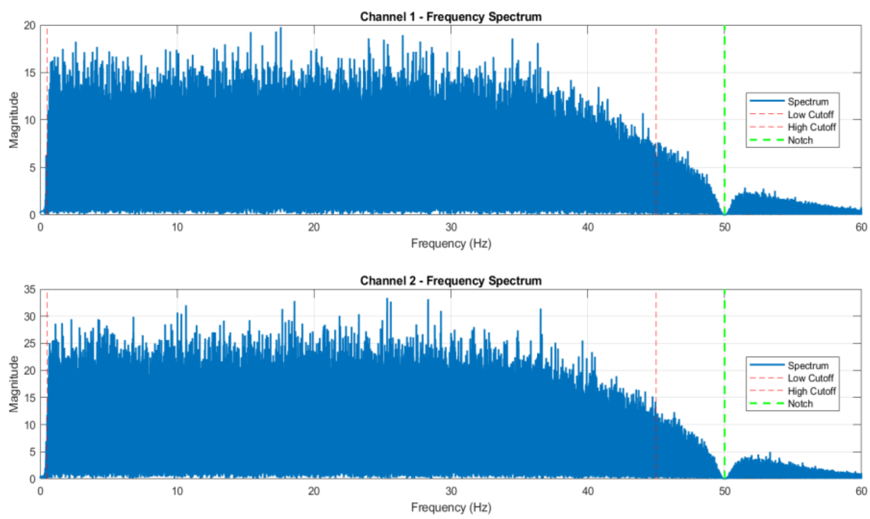


Figure 5.5: Frequency Spectrum of EEG Signals Post-Filtering for Channels 1 and 2.

This Fast Fourier Transform (FFT) plot shows the power distribution of the EEG signal across frequencies, providing a clear view of how energy is concentrated in different bands. The red dashed lines at 0.5 Hz and 45 Hz mark the cutoff points of the bandpass filter, indicating where low-frequency drifts and high-frequency noise were removed. The green dashed line at 50 Hz highlights the notch filter's effect, showing a sharp drop where power line interference was successfully suppressed. This spectral view confirms that the filtering process effectively cleaned the signal while preserving key brainwave components such as alpha and beta rhythms.

5.2.5 Independent Component Analysis (ICA)

Each EEG electrode captures a linear mixture of brain activity, eye movements, and muscle artifacts. (Yin, 2017) proposed a BCI system to control a four wheeled electric vehicle using motor imagery. ICA is a blind source separation technique that decomposes these mixed signals into statistically independent components. (X. Gong, 2021) used ICA as a feature extraction method to extract the source of the measured signals and classify the motor imagery information. This allows for selective removal of artifacts without compromising brain activity, making ICA an essential step in EEG preprocessing.

The Fast ICA algorithm is commonly used to perform ICA. It identifies independent components by iteratively maximizing statistical non-Gaussian, typically measured using kurtosis or negentropy. Once the components are extracted, those corresponding to artifacts are identified based on their spatial topography (e.g., strong activity at frontal electrodes like Fp1 and Fp2), their spectral properties (e.g., high power in frequencies below 4 Hz), and their correlation with reference electrooculography (EOG) channels.

Components with artifact scores above a predefined threshold (e.g., 0.5) are removed. The EEG signal is then reconstructed by projecting the remaining components back into the sensor space.

Comparison with PCA

While Principal Component Analysis (PCA) also performs dimensionality reduction and decorrelation, it does not ensure independence between components. (Sadiq, Yu, Yuan, & Aziz, 2020) uses multi-scale principal component analysis for de-noising and successive decomposition index was used to extract features. PCA finds orthogonal directions based on maximum variance, whereas ICA finds statistically independent components using higher-order statistics. For EEG data where the goal is to isolate specific biological and non-biological sources, ICA is superior to PCA.

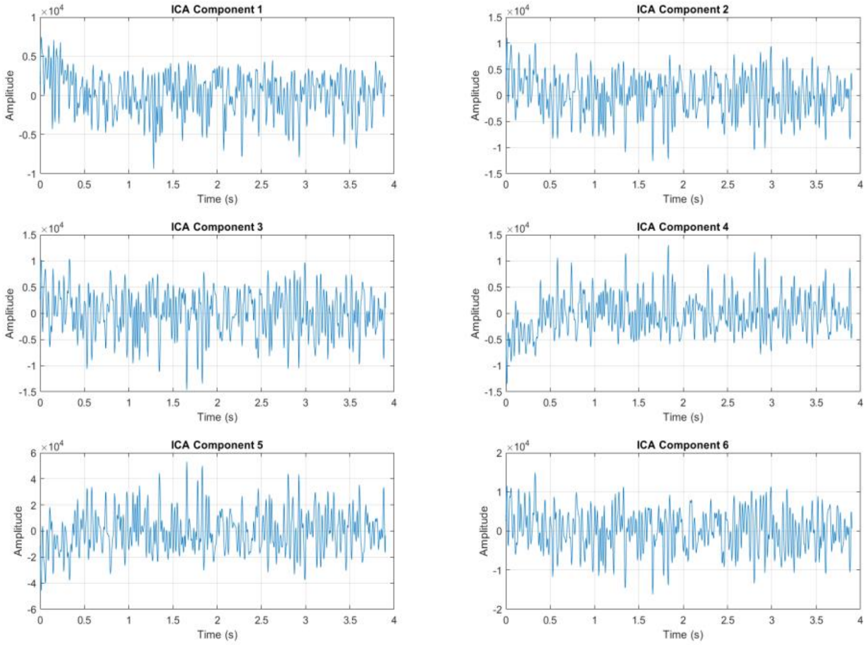


Figure 5.6: Independent Components Derived from EEG Data via ICA

This plot shows six independent components extracted from the EEG data using Independent Component Analysis (ICA). Each component represents a distinct source of activity separated from the mixed EEG signals. By visually inspecting these components, we can identify and remove artifacts such as eye blinks or muscle noise while preserving genuine brain activity.

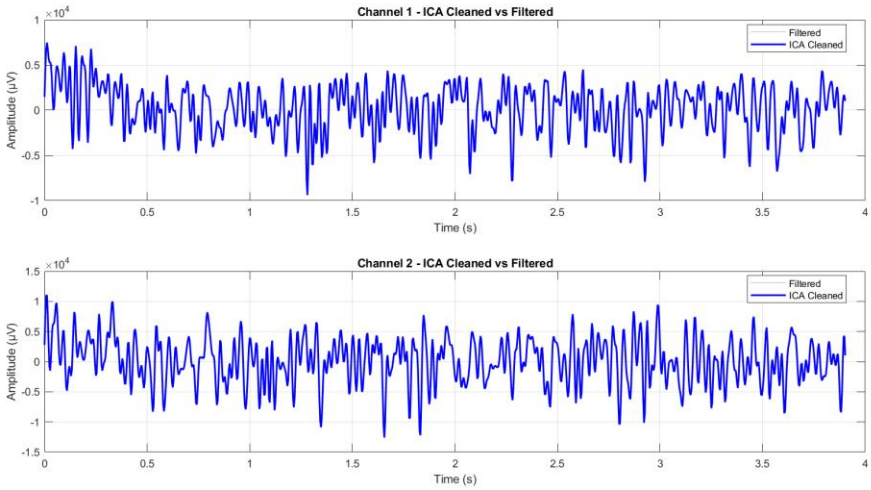


Figure 5.7: Comparison of Filtered EEG Data Before and After ICA Cleaning

This plot compares the EEG signals before (grey line) and after (blue line) cleaning with Independent Component Analysis (ICA) for Channels 1 and 2. The ICA-cleaned signals are visibly smoother and free of sudden spikes present in the filtered signals, clearly illustrating ICA's effectiveness in removing residual artifacts and refining the EEG data.

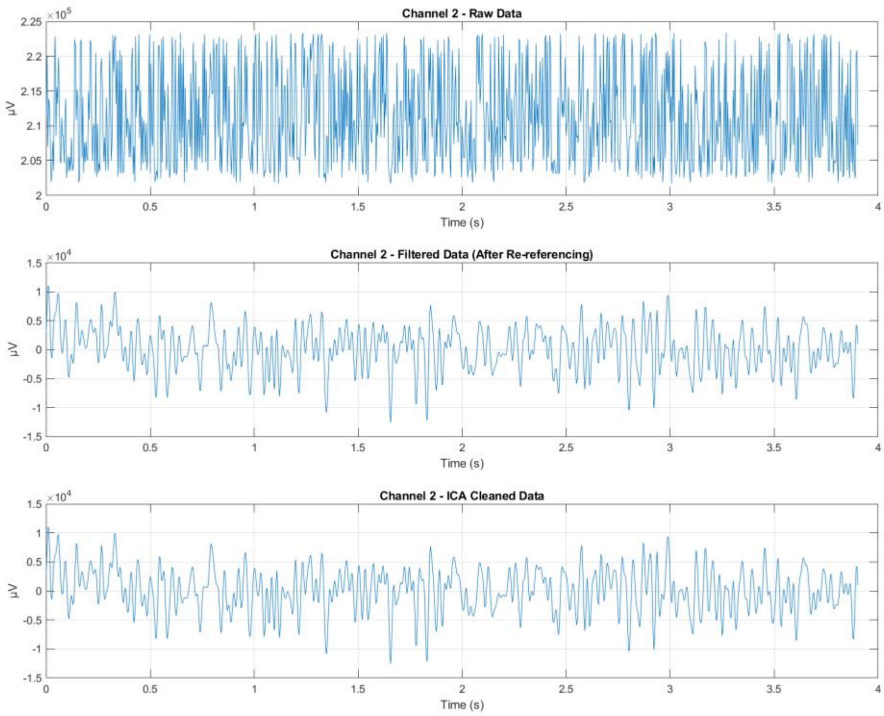


Figure 5.8: Progressive Transformation of EEG Signal through the Preprocessing Pipeline for Channel 2.

This comprehensive illustration demonstrates the progressive enhancement of EEG signal quality. The top panel displays the raw EEG data, the middle panel shows the signal after filtering and re-referencing, and the bottom panel presents the final cleaned signal following artifact removal with Independent Component Analysis (ICA).

Chapter 6

Feature Extraction and classification

After the EEG signals have been pre-processed to remove noise, drifts, and common artifacts like eye blinks and muscle movements, the next important step is feature extraction. This step involves identifying and computing meaningful characteristics from the EEG signals that can help distinguish between different mental or physical states. These features are then used by machine learning models to recognize the user's motor execution intention such as turning throttle or brakes.

In this chapter, we describe the feature extraction and classification methods used in our project. These methods are commonly applied in EEG-based Brain-Computer Interface (BCI) systems and have been shown to perform well in different motor execution tasks. We apply and evaluate these methods in a simulated vehicle control scenario using the CARLA autonomous driving simulator. In our system, EEG signals are processed and classified in real-time using Python scripts, which then send driving commands to a virtual vehicle in CARLA.

Unlike some other BCI systems that use Robot Operating System (ROS) to control robots or vehicles, our setup directly uses Python to interact with CARLA. After classifying the motor execution signal, commands such as "throttle" or "brake" are generated and sent to the vehicle, enabling a form of mind-controlled driving in a simulated environment. This approach allows for flexible development and testing in the field of human-computer interaction for intelligent transport.

Several recent studies support the effectiveness of the approaches used in this work. For example, (Padfield, Zabalza, Zhao, & Masero, 2019) provides an overview of modern signal processing pipelines for BCI systems, discussing various feature extraction and classification methods. The study highlights common challenges such as low signal quality and differences between individuals, which our system also addresses.

In a related study, (al, 2019) explores how a 96-channel intracortical BCI can control vehicle actions like accelerating, braking, and steering within the CARLA simulator. They use Python-based interfaces similar to our approach and even tested their methods on a physical small-scale vehicle to validate their results.

Another study (Ashima Khosla, 2020) compares different EEG processing and classification techniques and examines how well they perform in real-time systems. Their analysis highlights the trade-offs between speed, accuracy, and ease of interpretation, which are important considerations in our project.

Although (G. Beraldo, 2018) uses ROS and adds more advanced robotic functions like obstacle avoidance, the key idea using EEG signals to control navigation is similar to our work. While we do not use ROS, our Python-based control system achieves comparable goals within the CARLA environment.

This chapter outlines the feature extraction techniques employed in the study. These include frequency-based features, such as alpha and beta band powers, as well as statistical features like mean, variance, skewness, and kurtosis. It also introduces the classification methods evaluated, which include Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) models. The chapter provides detailed descriptions of the implementation procedures, the rationale behind selecting each classification method, and the criteria used to assess their performance.

These techniques are essential for decoding brain signals and converting them into meaningful control commands for the simulated car, forming the core of our BCI system.

6.1 Feature Extraction: Transforming Brainwaves into Meaningful Numbers

Feature extraction plays a vital role in Brain-Computer Interface (BCI) systems, particularly in translating raw EEG signals into a structured format that machine learning algorithms can interpret (Luis, 2012). Since EEG signals are complex, noisy, and non-stationary, effective feature extraction is necessary to capture the most relevant information that reflects motor execution activity, such as hand or arm movements.

In this study, we use a combination of frequency-domain and statistical features extracted from the pre-processed EEG signals. These features are widely used in BCI research and are selected based on their proven ability to reflect physiological patterns associated with motor-related brain activity.

6.1.1 Frequency Band Power Features

In this study, frequency-domain features are extracted from the EEG signals to capture changes in brain activity that occur during motor execution. Since specific brain rhythms are known to be modulated during physical movements, analysing the power within key frequency bands (such as alpha and beta) provides useful information for distinguishing between different motor tasks.

To compute frequency band power, the pre-processed EEG signal is transformed from the time domain to the frequency domain using the Fast Fourier Transform (FFT) (Cohen, 2014). This allows us to measure how much energy is present in each frequency range during a particular time window.

The Power Spectral Density (PSD) is then calculated for each EEG segment, and the average power is computed within predefined frequency bands of interest. These band powers serve as key features, reflecting how the brain's electrical activity changes in response to physical movement of the hands.

Mathematically, the power in a specific frequency band *b* is computed as:

$$P\_b = (1/N) \times \Sigma\ |X[f]|^2, \text{ for all } f \in b$$

Where:

- P_b is the power in the frequency band *b*
- *X[f]* is the magnitude of the FFT at frequency bin *f*
- *N* is the number of frequency bins within that band

By comparing the power in these bands across different motor execution tasks (e.g., moving the left or right hand), we can identify patterns that help the classifier distinguish between intended actions. These band power features are widely used in Brain-Computer Interface (BCI) applications due to their robustness and physiological relevance.

6.1.2 Statistical Features

After preprocessing the EEG signals to remove noise and artifacts, the next important step is to extract meaningful features that can help in identifying different brain states. While frequency-based features (such as band powers) are commonly used, time-domain statistical features also play a critical role in capturing patterns that reflect the user's mental or motor activity.

6.1.2.1 Why Use Statistical Features in EEG-Based BCI?

Statistical features like mean, standard deviation, maximum, minimum, skewness, and kurtosis provide a simple yet informative summary of how the EEG signal behaves over time. These features describe the average value, how much the signal fluctuates, and whether its shape is symmetrical or contains sharp peaks. This kind of information helps in identifying subtle variations in brain activity that might be linked to different motor actions.

Sensitive to Motor Execution Changes

During motor execution tasks such as moving the left or right hand the brain's electrical activity changes slightly in ways that might not always appear in frequency analysis. For example, there might be an increase in variance or a change in the skewness of the signal. Statistical features are particularly good at capturing these time-domain changes, making them valuable for classifying different motor commands.

Complements Frequency Features

Frequency-based features focus on rhythmic or oscillatory brain activity (like alpha or beta waves). In contrast, statistical features capture the shape and structure of the signal in the time domain. When used together, these two types of features offer a more complete view of the EEG data, improving the performance of machine learning models used for classification.

Efficient and Interpretable

One of the key advantages of statistical features is that they are simple to calculate and easy to understand. They do not require complex mathematical transformations, which makes them suitable for real-time applications. Additionally, if a model relies on, say, an increase in signal variance during movement, this can be interpreted in terms of actual physiological activity, which is useful in understanding the system's behaviour.

6.1.2.2 How Statistical Features Are Used in This Project

In this project, statistical features are an essential part of the EEG signal processing pipeline for motor execution-based control of a vehicle in the CARLA simulator. The methodology comprises the following key stages:

Feature Extraction:

The continuous EEG signals are segmented into short, overlapping time windows to capture temporal dynamics. For each time window and each EEG channel, a set of descriptive statistical features is computed to characterize the underlying signal distribution. The extracted features include:

- Mean
- Standard deviation
- Maximum and minimum values
- Skewness
- Kurtosis

These features capture both the central tendency and the higher-order statistical properties of the EEG signals, providing a rich representation of neural activity.

Advantages in the Context of This Study

1. **Better Classification Performance**:

Statistical features provide additional information that helps the models more accurately differentiate between different motor states.

2. **Improved Generalization**:

These features are relatively stable and less sensitive to minor noise or changes between subjects, helping the model perform well across different individuals or sessions.

3. **Ease of Interpretation**:

If the model is found to rely on specific statistical changes (e.g., increased skewness in a certain brain region during movement), these patterns can be related back to actual brain processes, adding to the interpretability of the system.

1.2.4 Summary of Key Statistical Features

Feature	What It Describes	Why It's Useful in EEG/BCI
Mean	Average amplitude of the signal	Detects baseline shifts or slow drifts
Standard Deviation	Amount of signal fluctuation	Indicates overall signal activity or movement levels
Maximum/Minimum	Extreme values in the signal	Useful for detecting spikes or transient events
Skewness	Asymmetry of the signal distribution	Highlights unusual signal patterns or artifacts
Kurtosis	Sharpness or flatness of signal peaks	Detects bursts or sharp changes in brain activity

Table 6.1 Summary of Statistical Features

6.2 Feature Vector Construction

All the computed features frequency band powers and statistical measures are combined into a single feature vector for each EEG window. This vector is then used as input to machine learning models during the classification stage.

To ensure consistency, feature vectors are normalized (e.g., using z-score normalization) across the dataset so that all features contribute equally to the learning process.

6.3 Classification

Once the most informative features are extracted from the EEG signals whether frequency-based, statistical, or connectivity features they are used to train classifiers (Luis, 2012). This final stage in the Brain-Computer Interface (BCI) pipeline involves translating the neural features into discrete motor intentions such as "go" or "stop" movements, which can then control an external system like a simulated vehicle in CARLA.

A wide range of classification algorithms have been proposed and evaluated in BCI research. Among them, Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA) are among the most frequently used due to their strong performance and relatively low computational requirements (Lotte F, 2007). Deep learning methods, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, can also be employed, although they often perform both feature extraction and classification within a unified architecture. (Craik A, 2019)

Several studies have explored the use of machine learning models in BCI pipelines. For instance, (K.-R. Muller, 2004) discusses a range of machine learning approaches applied to BCI, highlighting the importance of model validation and the role of regularization in improving classification performance on noisy EEG signals. Similarly, (G. Dornhege, 2007) investigates the use of machine learning techniques in motor execution and imagery classification with real-time feedback.

Although neural networks are often used for both feature extraction and classification, they can also be applied solely for classification. However, this can sometimes be inefficient, especially when simpler methods perform comparably. Still, in some studies, neural networks have been used exclusively as classifiers to model complex, nonlinear decision boundaries in EEG data.

6.3.1 Support Vector Machine (SVM):

Support Vector Machines (SVM) are one of the most popular machine learning algorithms used in EEG-based BCI systems (Lotte F, 2007). SVMs are particularly well-suited for problems where the data has clear margins between classes, such as distinguishing between different mental or motor tasks. The main idea behind SVM is to find the best possible boundary that separates the data into different classes with the widest possible gap.

SVMs work well with EEG data because they can handle high-dimensional input and are robust to noise. When EEG signals are complex or nonlinear, SVMs can still perform effectively by transforming the data into a higher-dimensional space using what’s called a "kernel" function. This makes it possible to find a separation even when the classes are not clearly divided in the original space.

SVMs are computationally efficient and do not require large amounts of training data, making them ideal for real-time applications. These qualities have made SVMs a standard choice in many BCI systems.

6.3.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is another widely used method for EEG classification due to its simplicity and speed (Lotte F, 2007). LDA works by finding a straight line (or a hyperplane in higher dimensions) that best separates different classes of data based on their statistical properties.

The strength of LDA lies in its ability to work efficiently with high-dimensional data while remaining easy to implement and interpret (Lotte F, 2007). It assumes that the data for each class comes from a normal distribution and that all classes have the same variability. Although these assumptions are rarely fully met in real EEG data, LDA still performs surprisingly well in practice.

One major advantage of LDA is that it is computationally lightweight, making it suitable for real-time EEG classification. It is often used as a baseline method and has shown competitive performance in many BCI applications.

To improve its performance when dealing with noisy or limited data, a regularized version known as Shrinkage-LDA is often used. This variant helps to stabilize the model and avoid overfitting by slightly adjusting the statistical estimates.

6.3.3 Random Forest (RF):

Random Forest is an "ensemble" model, meaning it combines the predictions of many individual decision trees. Each tree makes its own prediction, and then the

Random Forest takes a "vote" to decide the final classification. This approach makes Random Forests very robust, less prone to overfitting, and excellent at handling complex relationships within the data, often providing very accurate results.

6.3.4 Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) are a type of deep learning model that excels at automatically learning spatial patterns in data (Roy Y, 2019). Originally developed for image processing, CNNs have been successfully adapted for EEG signal classification, especially when working with raw or minimally processed signals (Craik A, 2019).

CNNs are particularly good at detecting local patterns—such as changes in signal strength or shape across time and electrodes—which may correspond to specific brain activities. In EEG-based BCI systems, CNNs can automatically extract complex features from the data, which often results in higher accuracy compared to traditional methods like SVM or LDA.

Although CNNs require more computational power and training data, their ability to learn directly from raw signals without hand-crafted features makes them a powerful tool for EEG classification, particularly in offline or research settings.

6.3.5 Long Short-Term Memory (LSTM):

Long Short-Term Memory (LSTM) networks are a special type of Recurrent Neural Network (RNN) designed to capture patterns that unfold over time. Unlike traditional neural networks, LSTMs have a memory mechanism that allows them to remember past information, making them highly effective for sequential data such as EEG signals (Gers, 2000) .

EEG signals are naturally time-dependent, and motor tasks often involve changes that evolve over several seconds. LSTM networks are able to capture these temporal dynamics, learning when and how patterns occur over time (Craik A, 2019; Roy Y, 2019). This makes them particularly well-suited for tasks like detecting motor execution or intention from EEG recordings.

Although LSTMs are more complex to train and require more data, they offer superior performance in scenarios where the timing of brain activity is important.

For each of these models, we used a portion of our feature-extracted dataset for training, where the model learned the underlying relationships. The remaining portion was reserved for evaluation, where we tested how well the trained model could correctly classify new, unseen data. Key performance metrics (e.g., accuracy, precision, recall, F1-score) were used to objectively compare the effectiveness of each model in distinguishing between the relaxation and focus mental states.

Chapter 7

Result and Discussion

7.1 Classification Performance of EEG Signals

This section looks at how different machine learning and deep learning models performed when used to classify EEG brain signals. The goal was to figure out which model could best tell the difference between the “go” and “stop” mental states an essential part of controlling the simulated car. We tested several models, including Linear Support Vector Machine (SVM), Random Forest (RF), Linear Discriminant Analysis (LDA), as well as deep learning models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. To see how well each model worked, we evaluated them using both offline testing (on a separate dataset) and real-time performance during actual use.

7.1.1 Offline (Test Set) Performance

The initial evaluation involved assessing the models' performance on a held-out test set, providing a measure of their generalization capability on unseen, but similarly distributed, data. Figure 7.1 summarizes the accuracy and F1 score for each model.

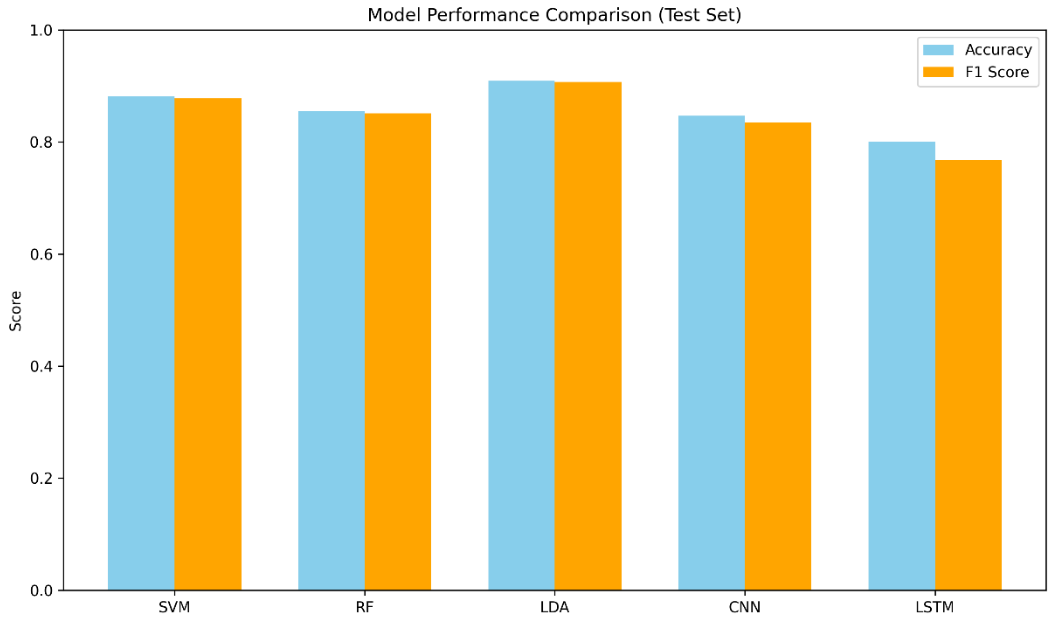


Figure 7.1: Offline Performance Metrics of EEG Signal Classification Models

As shown in Figure, Linear Discriminant Analysis (LDA) achieved the highest accuracy (0.909) and F1 score (0.907) on the offline test set, closely followed by SVM and Random Forest. Conversely, the deep learning models, CNN and LSTM, did not outperform the classical machine learning approaches in this offline evaluation. This outcome is likely attributable to factors such as the relatively limited size of the training dataset or the specific characteristics of the hand-crafted features extracted, which may not have fully leveraged the complex pattern recognition capabilities typically associated with deep learning architectures.

7.1.2 Real-Time Performance and Generalization

While strong offline metrics are indicative of a model's potential, real-time performance is paramount for practical BCI applications. Despite the promising offline results for models like LDA and SVM, real-time testing revealed significant discrepancies and highlighted critical differences in generalization capabilities.

During real-time inference, the Random Forest (RF) model consistently demonstrated the most robust and balanced performance. It maintained a commendable level of accuracy and exhibited less susceptibility to overfitting or class bias, providing reliable predictions in dynamic, live EEG streams.

In contrast, other models (SVM, LDA, CNN, and LSTM), despite their high-test set accuracy, exhibited notable issues with overfitting and class bias during real-time operation. This was particularly evident from their respective confusion matrices and prediction distributions, which frequently showed a strong tendency to predict only one class, irrespective of the actual input mental state. This suggests that these models struggled to generalize effectively to the inherent variability and slight distributional shifts present in continuous, real-time EEG signals, a common challenge in BCI research.

7.1.3 Interpretation and Implications

The observed discrepancy between offline and real-time performance underscores a critical consideration in BCI system development. The overfitting and class bias seen in SVM, LDA, CNN, and LSTM models suggest that while they learned the training data effectively, they failed to capture the underlying patterns that generalize robustly to the unpredictable nature of real-time EEG. This phenomenon is often attributed to the non-stationary characteristics of EEG signals and the subtle variations in data distribution between controlled offline recordings and live acquisition.

The superior robustness of the Random Forest model in real-time scenarios can be attributed to its ensemble nature. By aggregating predictions from multiple decision trees, RF inherently reduces variance and is more resilient to noise and feature variability. This ensemble approach enabled it to provide more balanced predictions across classes and rendered it less sensitive to the minor distributional changes encountered in the continuous data stream.

7.1.4 Recommendation for EEG Classification

Based on these findings, for practical, real-time EEG classification in BCI applications, the Random Forest model is strongly recommended due to its superior generalization capabilities and demonstrated robustness against overfitting and class bias. This analysis highlights that relying solely on offline metrics is insufficient; rigorous real-time validation is essential to ensure the reliability and practical utility of BCI models in deployment scenarios. Future work should focus on strategies to improve the generalization of deep learning models in real-time EEG contexts (e.g., through advanced data augmentation techniques, regularization methods, or domain adaptation) and further investigate the specific causes of class bias observed in SVM, LDA, CNN, and LSTM.

Model	Test Accuracy	Test F1	Real-Time Generalization	Class Bias in Real-Time
SVM	0.882	0.878	Poor	Yes
RF	0.855	0.851	Good	No
LDA	0.909	0.907	Poor	Yes
CNN	0.847	0.834	Poor	Yes
LSTM	0.800	0.767	Poor	Yes

Table 7.1 Summary of Model Performance and Real-Time Characteristics

7.2 BCI-Controlled Vehicle Performance in CARLA

Figure 7.2: Car standing still in Carla Simulation.

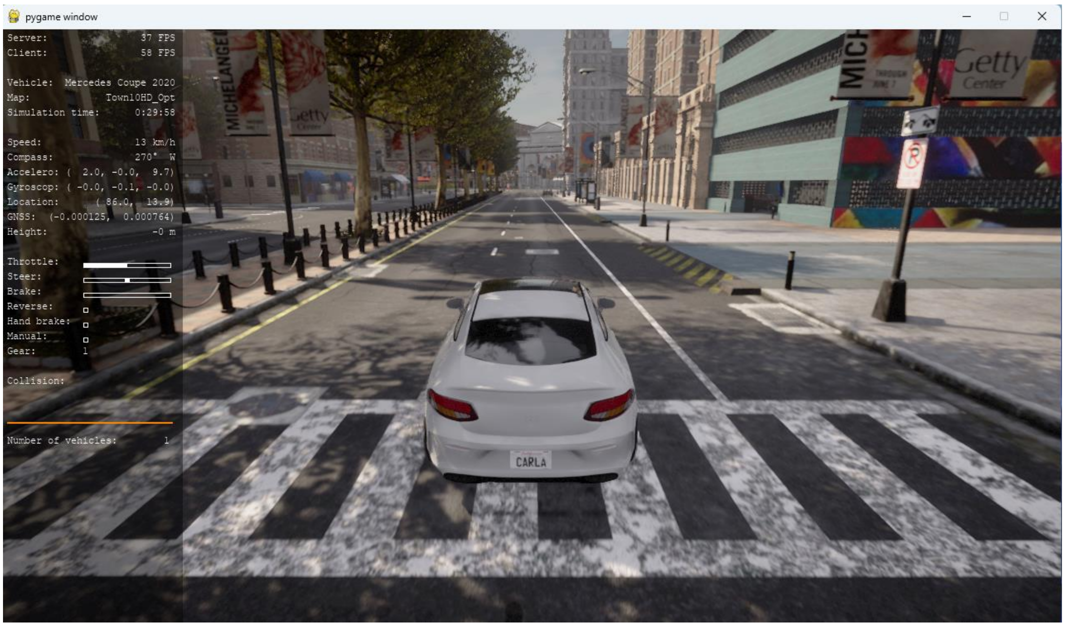


Figure 7.3: car moving

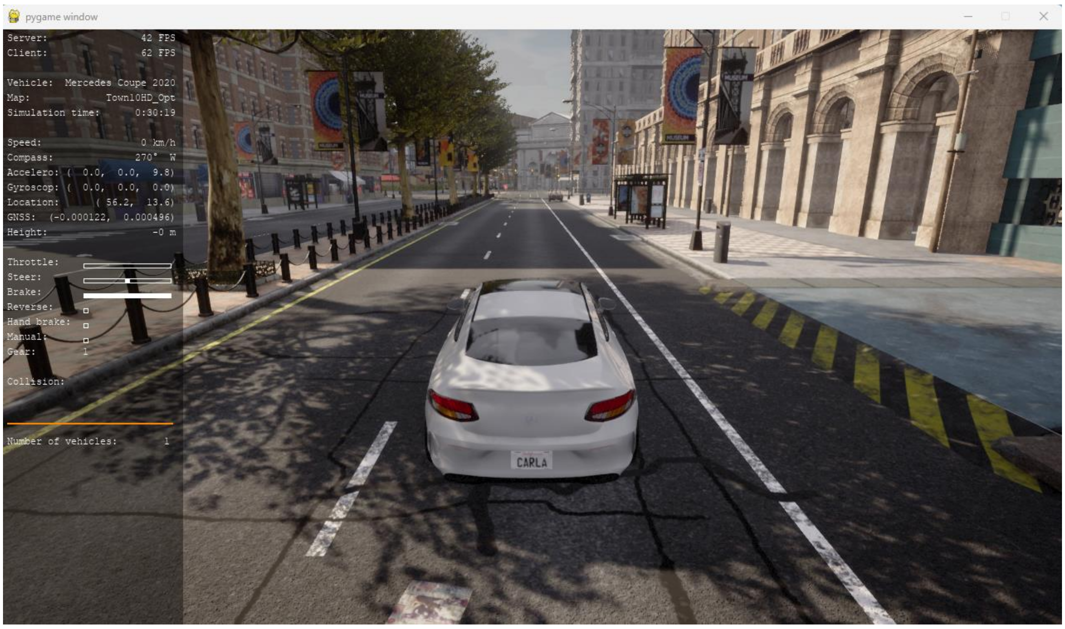


Figure 7.4: Brake applied to car when model output is stop

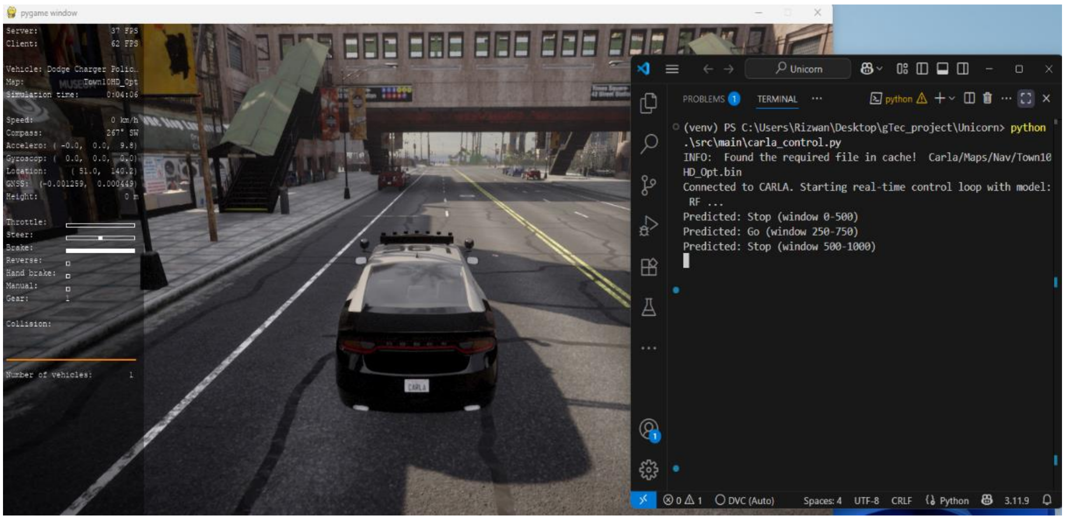


Figure 7.5: Brake applied to moving car when model output is Stop

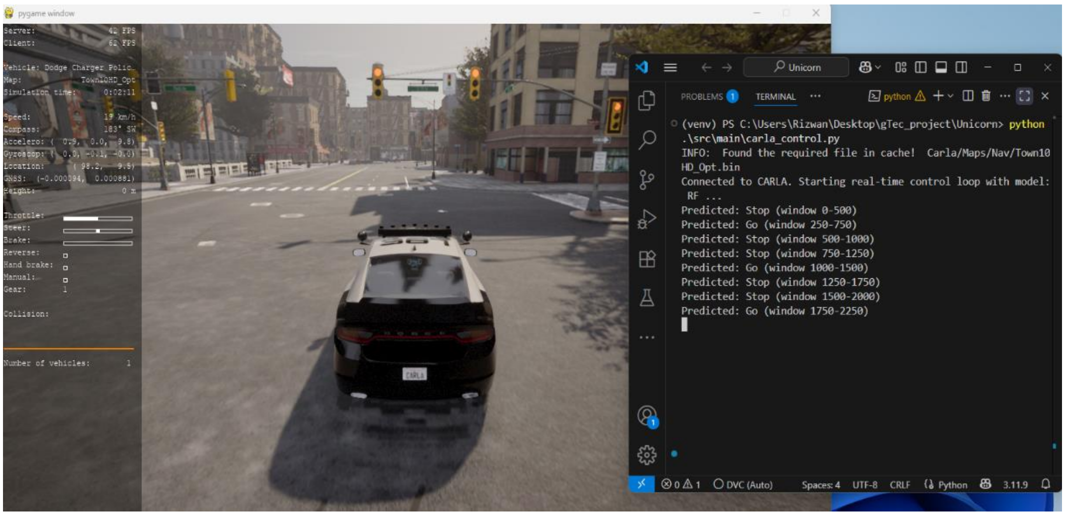


Figure 7.6: Throttle applied to car when model output is Go

7.2.2 Real-time "Go/Stop" Command Execution

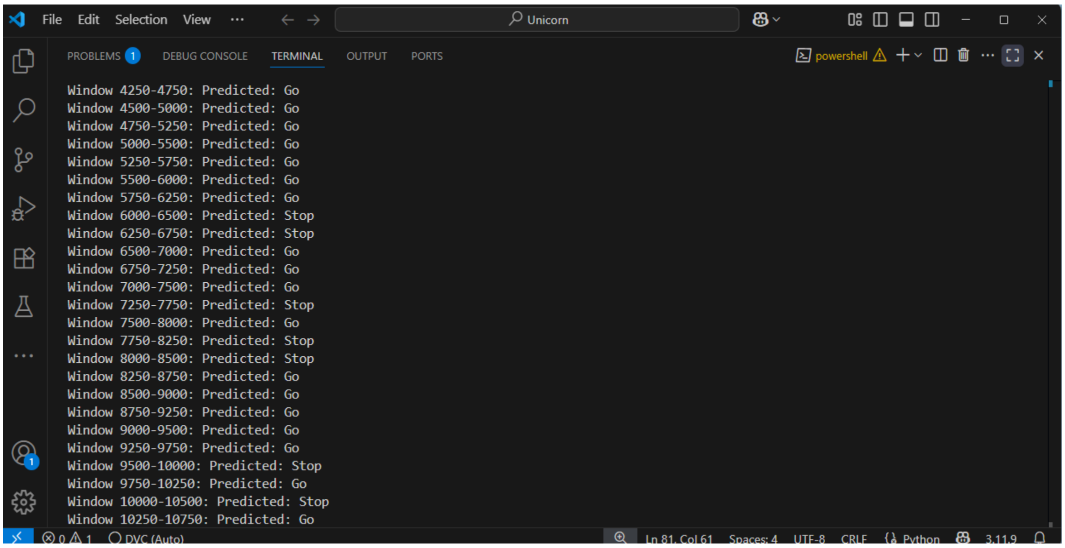


Figure 7.7: Go/stop prediction on real-time (online) data

7.3 Limitations and Future Works

This thesis successfully demonstrated the feasibility of an EEG-based BCI system for real-time "go" and "stop" commands in the CARLA simulation environment, leveraging a motor execution paradigm. While the system achieved its primary objective, several limitations were identified during its development and evaluation, which present opportunities for future work.

7.3.1 Limitations:

1. **Limited Command Set:** The current system is restricted to binary "go" and "stop" commands. This limited control vocabulary significantly constrains the complexity of interactions possible within the CARLA environment, preventing nuanced driving actions such as steering, acceleration control, or braking intensity.

2. **Single-Subject Dependency:** The data acquisition and model training were primarily conducted on a single subject. While this allowed for focused development and initial validation, the generalizability of the trained models to other individuals is a significant concern. EEG signals exhibit high inter-subject variability, meaning a model trained on one person's brain patterns may not perform effectively for another without extensive recalibration or retraining.

3. **Controlled Environment and Task Simplicity:** The motor execution paradigm, involving a stress ball squeeze, was chosen for its robust neural signatures. However, this task is relatively simple and performed in a controlled, static environment. Real-world driving scenarios are dynamic, complex, and require continuous, fine-grained control, which may not be adequately captured by a discrete, intentional motor execution task.

4. **Artifact Sensitivity:** Despite rigorous preprocessing (re-referencing, filtering, ICA), EEG signals remain susceptible to various artifacts (e.g., muscle movements, eye blinks, environmental noise). While ICA helps, complete artifact removal without distorting genuine brain activity is challenging, potentially impacting real-time classification accuracy, especially in less controlled settings (Soria-Frisch, 2025).

5. **Lack of Adaptive Learning:** The current classification models are static once trained. They do not adapt to changes in the user's mental state, fatigue, or long-term variations in EEG signals, which can lead to a degradation of performance over extended usage periods.

6. **Simulated Environment Only:** The system was validated exclusively in the CARLA simulation. Translating BCI control from a simulated environment to a physical vehicle introduces a new set of challenges, including latency, safety considerations, and the integration with vehicle control systems.

7.3.2 Future Work:

1. **Expanding the Command Set:** Future work should aim to increase the complexity of control by incorporating additional mental states or motor imagery tasks to enable multi-directional control (e.g., left/right turns, variable speed control). This could involve exploring more sophisticated EEG paradigms or combining multiple paradigms (hybrid BCIs) to generate a richer set of commands.

2. **Enhancing Generalizability and Robustness:** To address inter-subject variability, research should focus on developing subject-independent BCI systems or employing domain adaptation techniques. This could involve transfer learning, where models pre-trained on large datasets are fine-tuned for new users with minimal calibration data, or developing adaptive algorithms that continuously learn and adjust to individual users over time.

3. **Advanced Feature Extraction and Deep Learning Architectures:** Investigate more advanced feature extraction techniques beyond traditional frequency band powers and statistical features, such as Common Spatial Patterns (CSP) or time-frequency representations (e.g., Continuous Wavelet Transform). Further exploration of deep learning architectures, including more complex CNN-LSTM hybrids or transformer-based models, with larger and more diverse datasets, could potentially unlock higher classification accuracies and better generalization, especially in real-time scenarios. (Roy Y, 2019) (Craik A, 2019)

4. **Integration of Biofeedback and User Training:** Implement real-time neurofeedback mechanisms to help users optimize their mental strategies for generating distinct EEG patterns. Structured training protocols, combined with visual or auditory feedback, can significantly improve user proficiency and consistency in BCI control. (Blankertz, 2007)

5. **Real-World Application and Validation:** The ultimate goal is to transition from simulation to real-world applications. Future steps include testing the BCI system with a physical, scaled-down vehicle or a robotic platform to evaluate its performance in a tangible environment, addressing practical challenges such as latency, safety, and integration with hardware.

6. **Addressing Fatigue and Long-Term Use:** Develop strategies to mitigate user fatigue and maintain long-term performance. This could involve incorporating passive BCI components to monitor user cognitive load or fatigue levels, adjusting the system's sensitivity, or providing breaks.

7. **Multi-Modal BCI Systems:** Explore combining EEG with other physiological signals (e.g., EOG, EMG, fNIRS) to create multi-modal BCI systems. This could provide complementary information, improve signal-to-noise ratio, and enhance the overall robustness and accuracy of control.

8. **Improved Data Collection and Device Utilization:** Future efforts should focus on optimizing data collection protocols to acquire cleaner and more representative EEG signals. This includes exploring the use of advanced EEG devices with higher channel counts, improved signal quality, or specialized features, such as the g.tec USBamp or other research-grade systems. Better data quality and more comprehensive datasets, obtained through refined collection methods and superior hardware, are expected to significantly enhance model performance and the overall reliability of the BCI system.

Conclusion

This thesis successfully developed and evaluated a non-invasive Brain-Computer Interface (BCI) system utilizing Electroencephalography (EEG) for real-time control of a simulated car in the CARLA environment. By employing a motor execution paradigm, specifically distinguishing between "relaxed" and "focused" mental states induced by a stress ball squeeze, the system enabled intuitive "go" and "stop" commands. The methodology involved rigorous EEG signal preprocessing, including re-referencing, bandpass filtering, notch filtering, and Independent Component Analysis (ICA), to ensure signal quality and remove artifacts.

The processed signals were then used for binary classification, with various machine learning and deep learning models evaluated. While offline testing showed high accuracy for several models, real-time validation revealed that the Random Forest classifier demonstrated superior robustness and generalization capabilities, effectively translating mental states into discrete commands for the CARLA vehicle. This successful implementation underscores the feasibility of using EEG for direct control in complex simulated environments, contributing to the advancement of assistive technologies and innovative neurorehabilitation platforms.

The findings highlight the significant potential of EEG-based BCIs to offer new avenues for human-computer interaction, particularly for individuals with physical disabilities, by providing a direct communication pathway with external devices. Although the current system is limited to basic "go" and "stop" commands and was evaluated in a simulated environment, it lays foundational groundwork. Future research will focus on expanding the command set, enhancing generalizability across users, exploring more advanced deep learning architectures, and transitioning towards real-world applications to unlock the full potential of brain-controlled systems. This work represents a crucial step towards more seamless, intuitive, and effective brain-computer interaction, paving the way for transformative applications in various fields.

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