Cortical Silent Period - Data Analysis for Concussion Evaluation in Contact Sports

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Abstract

Problem
Concussions are difficult to diagnose due to subtle symptoms and delayed manifestation. Existing methods like SCAT6 rely on human assessment, leading to potential errors. Early detection is crucial for proper treatment; faster, more objective methods are needed.
Objective
This project aims to develop a proof-of-concept model using data science and GPT-4 Vision for enhanced concussion detection in contact sports. The model focuses on accurately identifying the Cortical Silent Period (CSP) measured through Transcranial Magnetic Stimulation (TMS), a key indicator of concussions. This prototype integrates with existing screening methods, aiming to improve effectiveness without replacing them.
Methodology
The project utilises Artificial Intelligence to analyse signal patterns indicative of CSP within a controlled dataset. A key aspect involves integrating OpenAI's GPT-4 with its Vision Preview API.

- **Python as a Programming language for Data Analysis:** I used for its user-friendliness and extensive libraries, such as bioread (data import), NumPy, Pandas, SciPy (data analysis and preprocessing), and Matplotlib (visualisation). Annotations or highlights are incorporated to emphasise critical points identified during the analysis. Additionally, libraries such as datetime and os will manage timing information and file outputs, ensuring a well-organized data presentation.

- **Data Transmission and GPT-4 Integration:** Encoded image data (base64 format) is transmitted to GPT-4's API along with textual instructions via the requests library. This allows GPT-4's image recognition capabilities to be applied to the project. The data will be sent to OpenAI's API, and the necessary authentication details will be through JSON payloads.
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Thomas Di Virgilio of the Faculty of Health Sciences and Sport provided the dataset for this project. Initially offered in binary format, a standard text file format was also supplied to clarify the data structure. The data originates from measurements taken through the use of Transcranial Magnetic Stimulation (TMS) and Electromyography (EMG).

Achievements
This project demonstrates the feasibility of using AI to improve concussion detection at a manageable scale. The prototype minimises human error and provides a basis for more objective assessments. While limited by a single dataset, it showcases the potential for broader applications in sports medicine. This lays the groundwork for future research to transform athlete health assessments and create safer contact sports environments.

Attestation

I understand the nature of plagiarism, and I am aware of the University's academic integrity policy.

I certify that this dissertation reports original work by me during my University project except for the following:

The Time series that I mention in the project referred to as Channel_6 in Section 5 was developed in collaboration with Chris Grigson after I ran into difficulties with verifying the true scale and values of the source data.

When discussing the shift in the project to an AI based system I was shown an example of how to prompt the AI to look for data by my Professor Marc Cavazza. This was the basis for the start of Section 7. All work on prompting after the initial demo code of the API was my own work. The initial Prompt can be found in the appendix section.

The "True Values" that I refer to in my testing and evaluation sections from Chapters 8-10 were provided by Dr Thomas Di Virgilio.

Signature *Christopher Jack Foster* **Date** 24/04/2024

Acknowledgements

I could not have completed this project without the following. Firstly, I would like to thank Professor Marc Cavazza for the support that he has provided me during this project. His insight into AI and its capabilities and limitations gave me the support and knowledge to turn the project into a worthwhile endeavour that trod new ground in a field I had limited knowledge of before this assignment began. I would also like to thank Dr Thomas Di Virgilio for allowing me to carry out such a project. Despite being an active member of a rugby team, this field of concussion detection and measurement was completely new to me, and the opportunity for insight into this, as well as the data, knowledge of existing protocols and verification of results that I could not have completed this project without. I would also like to thank Chris Grigson for the support he provided in the project providing data and feedback about my methods. The support I have had from my friends and family alike has been invaluable, between discussions of my work and ensuring that my will to keep going remained intact. I cannot thank them enough for what they have done for me.

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1 Introduction

While thrilling and competitive, contact sports inherently pose various risks of injury to the participants [1]. Among these injuries, concussions represent a particularly complex challenge due to their subtle onset and potential long-term effects on athletes' health [1]. Recent advancements in medical protocols and the development of the SCAT6 test have marked significant progress in identifying and treating concussions [1].

This project introduces a novel approach leveraging data science and a GPT-4-Vision-based model for enhancing the detection of concussions. Specifically, it aims to accurately identify the cortical silent period (CSP)—a critical concussion indicator—through advanced pattern recognition techniques applied to signal patterns. This method is designed to pinpoint the start and end of CSP more accurately than current methods allow.

Through the use of Transcranial Magnetic Stimulation(TMS) readings for seamless integration with the existing observation-based screening methods utilised in professional sports, particularly emphasising the Rugby Union and its governing body, World Rugby [1]. By fitting into the established safety protocols, this project aspires to augment the efforts of medical staff, contributing to the overall safety and recovery processes of players without seeking to replace current systems. Given rugby's vibrant history with data analysis for enhancing player safety and performance, this innovative approach is expected to be well-received. However, integrating data science into sports also raises essential considerations regarding privacy and the potential impact on the game's dynamics.

1.1 Background and Context

To address the challenge of concussion detection effectively, it is essential first to understand what constitutes a concussion. Concussions are brain injuries that disrupt normal brain function, resulting from either direct blows to the head or rapid head movements that cause the brain to move within the skull [2]. The symptoms of concussions are varied, ranging from dizziness and imbalance to memory loss and difficulty concentrating [2].

While a single concussion might not lead to permanent damage, repeated concussions can have severe, long-lasting effects, such as second-impact syndrome or post-concussive syndrome [2].

A significant challenge in contact sports is the ability to detect concussions promptly and accurately at the time of impact [1]. For example, World Rugby's protocols highlight that concussion symptoms may not become apparent until 48 hours post-impact [1]. Despite the implementation of the SCAT6 to improve concussion assessments, the reliance on observable symptoms often results in delayed diagnoses [3].

A comprehensive analysis conducted by the United States National Library of Medicine has revealed the limitations of current concussion protocols, highlighting significant flaws and a stark lack of standardisation in assessment methods [3]. The urgency for a more standardised and efficient approach is evident, with the SCAT 6 tool utilised in fewer than half of the studies examined [3]. Moreover, this analysis focused predominantly on elite sports contexts.

1.2 Scope and Objectives

1.2.1 Scope

The project is focused on developing an automated system for detecting the (CSP) using a simplified artificial intelligence model. This user-friendly system will allow straightforward operation with a single click to initiate the analysis once the necessary data is inputted. It is tailored for quick and efficient use in sports environments, where promptness and simplicity are essential. The system will employ advanced time series analysis and AI pattern recognition to accurately identify CSP from transcranial waveform data, ensuring it is accessible to users regardless of their technical expertise.

1.2.2 Objectives

The project aims to craft a proof-of-concept system for concussion detection that simplifies the process for sports medical staff and coaches. This system will enable an efficient, streamlined analysis of concussion indicators through a user-friendly, one-click operation.

The system's core is an AI model designed to autonomously identify patterns in waveform data that signify a (CSP), akin to the automatic interpretation features of modern ECG machines.

This system's effectiveness will be rigorously evaluated for its accuracy in CSP detection and ease of use, especially for those without specialised training. Feedback from this assessment phase will refine the system further and identify avenues for future enhancements and research opportunities.

By achieving these objectives, this dissertation aims to contribute to sports medicine and software engineering by offering a novel, AI-based approach to concussion detection. The project combines technical innovation with practical usability, addressing the urgent need for improved concussion management in contact sports.

1.3 Achievements

This project successfully delivered a proof-of-concept system demonstrating the potential of AI to improve concussion detection in contact sports, aligning perfectly with the requirements of a bachelor's dissertation. The resulting system offers a user-friendly, AI-powered tool designed to minimise human error in concussion assessments, leading to faster and more effective concussion management for athletes. Although currently limited to a pre-defined dataset, it lays the groundwork for broader applications in sports medicine.

Enhanced Data Analysis with Combined Plotting Function:

The project benefited significantly from implementing a novel plotting function, provisionally named "combined_plotting_function_v3." This function proved instrumental in analysing specific time ranges within the dataset. Enabling focused visualisation of predetermined events facilitated a deeper understanding of the data and the identification of subtle patterns potentially linked to CSP.

GPT-4 Vision API Integration and AI-Driven Insights:

A key achievement of this project lies in the successful integration of OpenAI's GPT-4 Vision API. This innovative approach utilised AI-driven image analysis to enhance the detection and interpretation of CSP within waveform images. The GPT-4 Vision API was critical in extracting valuable qualitative insights from the image data.

A custom extraction function was developed to bridge the gap between qualitative insights and quantitative analysis. This function transforms the qualitative observations provided by the GPT-4 Vision API into quantitative data. This seamless flow of information from image analysis into numerical data allows for further exploration and statistical analysis, enriching the investigation.

The combined use of the GPT-4 Vision API and the custom extraction function establishes a robust framework for leveraging AI in the analysis of electrophysiological data. This paves the way for future research in this domain, potentially leading to significant advancements in concussion detection and sports medicine.The system at its core uses established libraries like bioread for reading biomedical signal files and numpy, pandas, and matplotlib for efficient data manipulation and insightful visualisations.

While the initial proposal envisioned a more complex Gpt-4-Vision model, the project successfully adapted to the constraints of an undergraduate project. The final system effectively utilises essential AI-driven pattern recognition and signal processing techniques. The system achieves noteworthy accuracy by applying high-pass filtering and a tailored peak detection function designed to identify the CSP within transcranial signal waveforms, which can be found in the testing section I did this by using the mean results of Thomas Di Vigillos control CSP readings in the following study [17] as a baseline before gaining the “True Values” later on. This accomplishment demonstrates the project's feasibility and paves the way for future iterations with more advanced AI models.

2 Overview of Dissertation

3 State-of-The-Art

This state of the art section will cover in broad terms the research surrounding Waveform Analysis in its various forms, the dissertation discusses the analysis of transcranial signals and the Cortical Silent Period (CSP), referencing studies by Locke et al. (2020) and Wilke et al. (2016) to develop a more precise concussion assessment system. This discourse branches into detailed discussions across several topics surrounding wavefroms analysis. Semi-Automatic Analysis will cover the integration of semi-automated systems using the insights from Locke et al. (2020) who introduced a semi-automated TMS system aimed at objective CSP measurement. Automatic Analysis meanwhile looks at the efficiencies of automated tools like cSPider.Wilke et al. (2016) are cited here for their development of cSPider the automated tool that generates CSP analysis date.

The Consistency In Waveform Analysis section underlines the necessity for standardised measurement protocols across studies to ensure reliable and reproducible CSP assessments, a critical step for advancing concussion diagnostics in sports medicine. The call for standardisation is supported by the review from Hupfeld et al., who emphasize the need for consistent methodologies in measuring TMS-induced silent periods across various research settings.This is made apparent even from the previous work noted where it has already been documented the various attempts for standardisation in this field.

Waveform Analysis in Python combined with a look into AI analysis provided me with technical challenges and solutions related to the integration of critical tools like BioRead within the Python programming environment, emphasising the practical aspects of implementing waveform analysis in software. The challenges of integrating Python tools for scientific computing, specifically for waveform analysis, are discussed with reference to the broader Python community resources. Waveform Analysis through AI addresses technical challenges and solutions related to the integration of critical tools like BioRead within the Python programming environment, emphasising the practical aspects of implementing waveform analysis in software. The challenges of integrating Python tools for scientific computing, specifically for waveform analysis, are discussed with reference to the broader Python community resources.

3.1 Waveform Analysis

The core of this project is an analysis of electromyographic (EMG) signals, which manifest as transverse waves, with the objective of advancing concussion detection techniques. These EMG signals, exhibiting sinusoidal patterns in a consistent quarter wave symmetry, provide valuable information on brain activity post-trigger event. The key focus is on the CSP, a specific phase within the EMG waveform that offers critical insights into brain function disruptions following a concussion. Leveraging the work of Locke et al. (2020) and Wilke et al. (2016), who have made significant strides in the semi-automated and automated analysis of CSP, respectively, this initiative seeks to enhance the precision and efficiency of concussion diagnostics. With the use of TMS as a method for generating a CSP event, as referenced in prior studies such as the work done by Thomas DiVigillo[16], the project aims to provide a new method for the collection of data for the assessment of concussions, building on existing knowledge to develop a more sophisticated measurement process through the use of a novel detection system based on new technology, GPT-Vision and providing us with an AI capable of reading waveform data and drawing informed conclusions.

3.1.1 Semi-Automatic Analysis.

Locke et al. introduce a semi-automated analysis system leveraging TMSfor the objective assessment of the CSP and additional neurophysiological parameters in individuals with post-concussion syndrome (PCS). Locke and colleagues developed a new system that uses a type of brain stimulation technology to measure brain activity objectively changes in people with post-concussion syndrome. This system moves away from relying on patients' descriptions of their symptoms. Instead, it provides precise, objective data about how the brain works, including how brain cells communicate and regulate each other. This method is beneficial because it could help us better understand and monitor the condition over time.

When developing such software, it is important to recognise pre-existing limitations, such as human error, which incites demand. An operator must manually complete specific steps or analyses when a system is only partly automated, and even well-trained individuals can make mistakes or interpret data differently, leading to potential inconsistencies. For example, when evaluators are required to measure responses induced by Transcranial Magnetic Stimulation (TMS), subjective factors may influence their judgment, or they might make an unintentional error. If different evaluators are involved, each may have a slightly different approach or criteria for measurement, which can result in a lack of uniformity in the data collected. This variability can affect the overall validity and reliability of the study's findings, as it could be challenging to determine if changes in results are due to the patient's condition or the evaluator's method.This is the issue with huiman error that is prevalent throughout CSP measurement.

The aim of my project is to enhance processing in the analysis system. With the aim of reducing the need for manual input and limit the potential for these human-related inconsistencies. A more automated approach would ensure that every evaluation is performed with the same standards and precision, regardless of who is operating the system, providing high-quality reliability and risk management in contact sports. This would improve the accuracy of the results and make it easier to implement the system in a broader range of clinical settings, as the requirement for specialised human expertise would be less critical.

The process outlined in the paper begins with TMS application to the motor cortex, inducing electrical currents that activate neural pathways, with CSP measurement serving as a primary metric for analysis.[5] The EMG data generated through this process is subjected to algorithmic analysis, supplemented by manual verification to ascertain the accuracy of CSP onset and offset determination. This waveform analysis, integral to the system's methodology, identifies peaks and troughs in the EMG signals to assess cortical excitability and inhibition. At the same time, examining EMG waveform symmetry and latencies contributes to evaluating the integrity of motor pathways, which is crucial for understanding PCS.

And Finally, we have Prompt Engineering which covers the process that focuses on crafting inputs to guide AI systems, particularly in natural language processing tasks, to produce desired outputs. It demands a comprehensive skill set, merging expertise in NLP, data science, and AI development frameworks. An important section of my dissertation that I cover due to its relevance to this dissertation.

3.1.2 Automatic Analysis

Traditionally, analysing waveforms has been a manual task fraught with potential inconsistency. As mentioned in this article, the difference between what professionals believe to be the onset and offset of a CSP event is quite subjective.[14] The advent of automated analysis tools like cSPider marks a significant advancement, offering increased precision and efficiency.

cSPider operates by acquiring data from TMS-induced motor evoked potentials (MEPs), which are recorded by stimulating the motor cortex and capturing the responses in peripheral muscles. The software then used sophisticated algorithms to automatically detect the onset of the MEP and the beginning of the CSP. These algorithms include matched filtering and spectral analysis, precisely identifying these pivotal events within the waveform. Once these points are established, cSPider calculates the duration of the MEP and CSP from the EMG data. It determines the offset of the CSP based on a high-pass filtered signal to pinpoint the end of the silent period accurately. To ensure accuracy and reliability, the results from cSPider are validated against manual analysis methods, focusing on achieving high intra-class correlation.

The efficiency of cSPider is one of its most compelling strengths. It drastically reduces the time required for waveform analysis, a boon for large-scale research studies and quick clinical assessments. Its user-friendly graphical user interface (GUI) is designed to be accessible to users with varying technical expertise, making it a valuable tool for many users. For those with more advanced technical skills, cSPider's open-source code offers the flexibility to customise the software, expanding its applicability to meet specific research needs.

Despite its strengths, cSPider does have some limitations. The requirement for Matlab could limit access for some users due to the software's cost[15]. Moreover, while cSPider's reliability is a notable feature, discrepancies between its automated analysis and manual methods have been observed, suggesting a need for further refinement for specific applications. [6]Additionally, adequate hardware specifications are required to run the software, which could present a barrier in resource-constrained settings.

Overall, cSPider symbolises the innovative future of waveform analysis. [6] By providing an automated, efficient, and reliable means of analysing the CSP, it holds the potential to enhance neurophysiological research and significantly improve clinical diagnostics. The output presented by cSPider will be a reference for the production style I want the Python part of my system to generate.

3.1.3 Consistency In Waveform Analysis

Recent scholarly work underscores the pressing need for standardised measurement practices in studying the CSP, especially given its pivotal role in concussion evaluation within contact sports. This standardisation is critical for enhancing the reliability of CSP assessments and fostering a more comprehensive understanding and diagnosis of concussions.

A study I found in this field is the review by Hupfeld et al., which explicitly called for consistency in the methodologies used to measure TMS-induced silent periods. The review highlights the considerable variability in measurement practices across different studies, which significantly impedes the ability to compare or generalise findings across the scientific community. This inconsistency is particularly problematic in fields like sports medicine, where precise and reproducible measurements are crucial for diagnosing and managing concussions.

Hupfeld et al. argue for a standardised protocol that includes uniform definitions of what constitutes the start and end of a CSP, the specific conditions under which CSPs should be measured, and the types of equipment that should be used. Such standardisation would not only improve the accuracy of concussion assessments but also enhance the reproducibility of research findings, thereby advancing our understanding of the neurophysiological impacts of sports-related head injuries.

The review also provides a set of detailed recommendations for future research, suggesting that these could serve as a foundation for developing a consensus on CSP measurement practices. Implementing these recommendations could lead to more reliable and effective use of CSP in concussion evaluation, ultimately contributing to safer sports environments and better health outcomes for athletes.

This call for standardised measurement protocols is crucial for my dissertation as it aligns with the objective of developing a proof-of-concept model that integrates advanced pattern recognition techniques to detect CSP accurately. The model can achieve greater reliability and validity by adhering to a standardised approach, as suggested by Hupfeld et al., making it a valuable tool in enhancing concussion detection in contact sports.

3.2 Waveform Analysis in Python

I initially planned to use Anaconda for package management and JupyterLabs to organise the workflow, particularly emphasising the SciPy library for its comprehensive signal processing capabilities. This approach harnessed the best technological tools for advanced concussion detection. However, the project encountered a challenge with the unavailability of the BioRead library, which is essential for processing and analysing biological signal data within the Anaconda repository. The decision was made to manually install Jupyter Notebook, facilitating the direct integration of the BioRead library. This adaptation ensured the project continued to use the essential tools I wanted to use for my project on concussion detection, demonstrating the project's flexibility and commitment to utilising the best resources available despite technical challenges.

More importantly, given how vital the use of AI will be in this assignment, GPT Vision Python is often the go-to language for AI, machine learning, and API interactions. OpenAI provides a Python client library that is well-documented and simple to use, making it an excellent choice for someone beginning to work with Prompt Engineering.[11]

3.3 Waveform Analysis through AI

OpenAI's GPT-4-Vision Preview API allows visual data analysis, marking a significant advancement from previous text-only interactions. This breakthrough paves the way for innovative applications, such as an automated system detecting the CSP in waveforms. By integrating the Vision API, the process can be streamlined, allowing the efficient processing of waveform images without the need to feed in large volumes of numerical data.

However, current regulations on AI usage prevent the system from offering what could be interpreted as medical advice, presenting a challenge for fully utilising this technology in healthcare contexts. Therefore, I must craft prompts carefully to align the system with automatic waveform analysis while adhering to these constraints. This involves avoiding specific language that triggers restrictions or designing the system within a framework within acceptable boundaries. This approach will enable us to use the AI's capabilities for waveform analysis without breaching its operational guidelines. The implementation of an impartial AI that is capable of explaining its findings and providing a printout and range of what it deems appropriate would be a great advancement on the current system.

3.4 Prompt Engineering

Prompt engineering represents an emerging field within AI that focuses on crafting inputs (or prompts) to guide AI systems, particularly in natural language processing tasks, to produce desired outputs. It demands a comprehensive skill set, merging expertise in NLP, data science, and AI development frameworks. This specialised discipline is pivotal in optimising AI-driven solutions, enabling more effective communication with AI systems and fostering innovative interactions. It's important to mention that in terms of the system that I am currently using the prompting that I am using in my system is not what I would deem true prompt enginerring due to the efficiency of the prompts that are generated in such cases far outclassing my own work. However in the prompts that I generate I do take some lessons form them.

In exploring "ChatGPT and Bard for Business Automation,"[4] I was particularly drawn to Chapter 4, which delves into prompt engineering. This chapter broadened my understanding of the field and highlighted its burgeoning significance in artificial intelligence (AI) landscape. Prompt engineering necessitates a unique blend of skills, including a deep understanding of natural language processing (NLP), data science, and familiarity with AI development frameworks.

Incorporating prompt engineering principles into my project promises to optimise the efficiency of the AI-driven solutions I'm developing and open new avenues for innovative interactions with AI. This approach will enable me to navigate the complexities of AI communication more effectively and contribute meaningfully to the evolving discourse on AI utilisation in software engineering and related fields.

4 System Overview

This section introduces the system I created, a novel, AI-assisted automatic detection system designed to identify the CSP from neurological waveforms. The system utilised standard data processing and analysis techniques to interpreting complex bio-signal data efficiently, with minimal input only the acq file provided by the user. This automation facilitates rapid and accurate concussion assessment in contact sports settings, ultimately contributing to athletes' immediate and long-term well-being. Figure[1] provides a visual representation of the system.

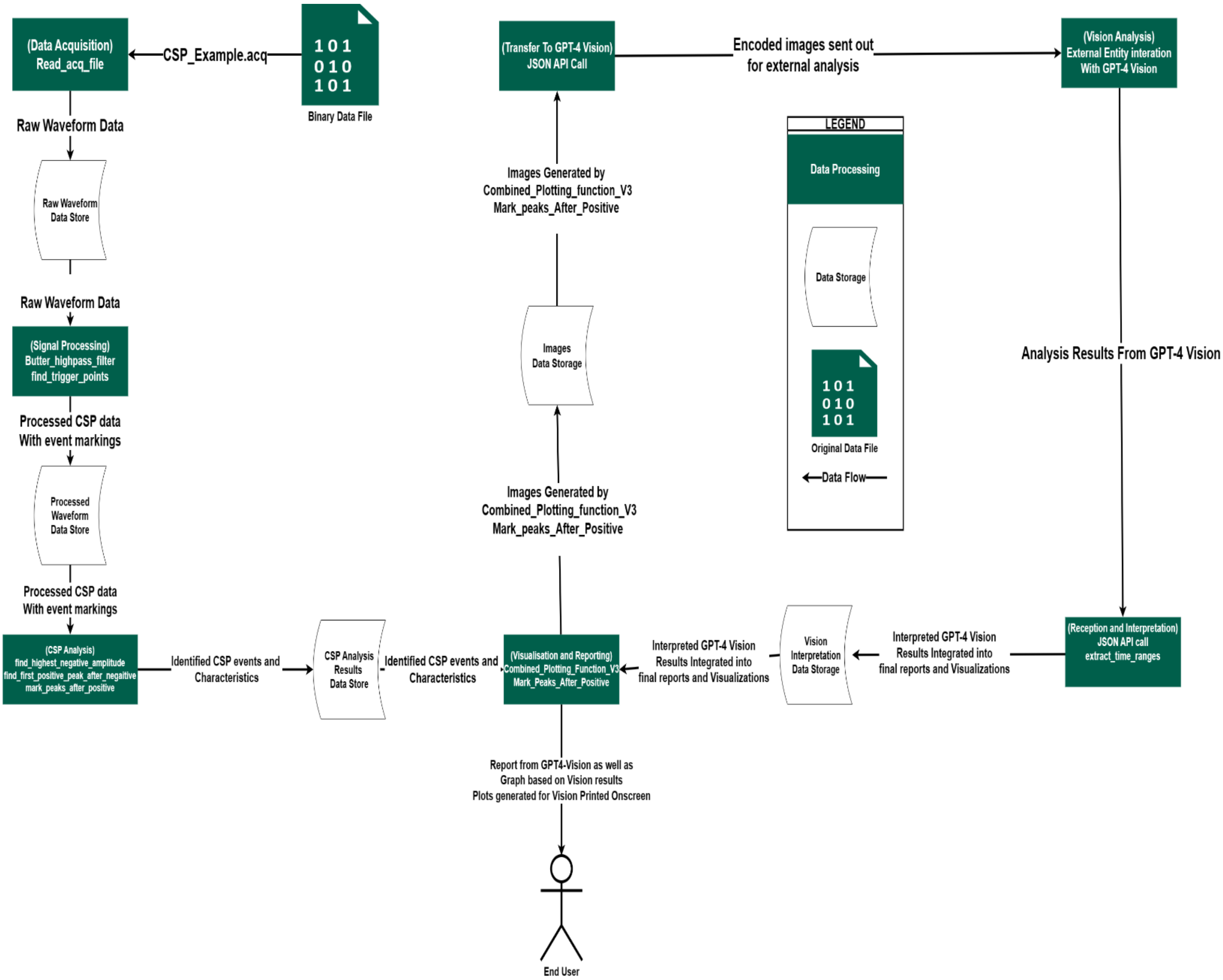

Figure 1: A data flow diagram of how the data is passed through the system.

4.1 System Functionality

As shown in Figure [1], the system begins by acquiring data from Acq files, a prevalent format for storing neurological recordings captured during biopotential assessments. These recordings represent the electrical activity of the brain and nervous system. Once the system accesses an Acq file, it intelligently extracts the relevant channels containing the bio-signal data of interest. This extracted data serves as the raw material for further analysis to identify the CSP.

Following data acquisition, the system enters the pre-processing stage. Here, the raw bio-signal data undergoes refinement to prepare it for accurate CSP detection. The first step involves identifying trigger points within the data stream. These trigger points mark the precise moments when TMS is applied. TMS pulses are brief, targeted bursts of magnetic energy delivered to the brain to induce controlled neural responses. The system establishes clear temporal landmarks within the data by pinpointing these trigger points, allowing it to focus on the brain activity immediately following the TMS pulse.

Next, the pre-processing stage employs a high-pass filter. This filter is a sieve that selectively allows specific frequencies to pass through while blocking others. In this case, the filter targets and removes low-frequency noise from the data. This noise can originate from various sources, including power line interference or physiological artefacts like muscle movements. By eliminating this noise, the system enhances the clarity of the bio-signal and minimises potential interference with subsequent analysis of the CSP.

After the pre-processing phase cleans and prepares the data, the system's core functionality is CSP detection. This stage hinges on identifying the CSP within the biosignal. The CSP is a critical window with significantly reduced neural activity following the TMS pulse. Here, the system employs two complementary techniques to pinpoint this period accurately.

Firstly, the system will attempt to detect any heightened activity immediately proceeding to the point following a trigger event caused by (TMS) in "Channel_3"[18]. The task that follows is to locate specific peaks or spikes within the waveform that represent heightened levels of brain activity. By identifying these peaks, particularly those occurring shortly after the TMS trigger point, the system can establish a temporal reference for the onset of the CSP.

Once the system has marked as many key events around the csp event as it can the data is then passed to the OpenAI's GPT-4-Vision API. This innovative integration utilises the power of a pre-trained AI. The system transmits waveform images, visual representations of the bio-signal data, directly to the GPT-4-Vision API. This API, trained on massive datasets, can interpret these images and glean insights about the underlying neural activity. By incorporating this AI-powered analysis, the system bypasses manual data entry, streamlining the process and potentially enhancing the robustness of CSP detection, especially when dealing with complex EEG data that might pose challenges for traditional algorithms.

In essence, the system employs a two-pronged approach, combining the analytical power of peak detection algorithms with the intelligent image interpretation capabilities of GPT-4-Vision to achieve a highly accurate and efficient identification of the CSP.

Following the core detection phase, the system enters the post-processing stage, refining the identified CSP window and presenting the results for further exploration. Here, the system delves deeper into the data surrounding the CSP, Analysing the peaks and troughs it previously pinpointed. These peaks and troughs would be akin to topographical features on a biological landscape; peaks represent heightened activity, while troughs signify dips or periods of reduced activity. By closely examining these features flanking the CSP, the system can potentially refine the temporal boundaries of the silent period, ensuring the most accurate possible window is captured.

An integral aspect of post-processing involves data visualisation. The system generates informative plots that depict the processed bio-signal data. These plots serve a dual purpose. Firstly, they provide a clear visual representation of the identified CSP, allowing medical professionals to examine the reduced brain activity period easily. Secondly, the visualisations often include zoomed-in sections offering a magnified CSP view. This magnified view enables a more granular examination of the silent period, potentially revealing subtle details that might be less apparent in the broader view. By generating these comprehensive visualisations, the system empowers medical professionals with the necessary tools to analyse the identified CSP and make informed decisions.

4.2 Underlying Technology

The system's functionality is built upon the use of specialised libraries tailored to specific tasks within the system. The core platform is Python, a versatile programming language preferred for its simplicy and data analysis capabilities. Within this framework, a suite of specialised libraries empowers the system's operations.

The Bioread library has been used due to its speciality in being capable of reading practically any version of Acqknowldge software files[10]. It's important that the system is capable of this. It is the preferred format of the Faculty of Health Sciences and Sport and, in general, is a common format used for the storage and recording of neurological data. Therefore, efficient reading of information stored in Acq files is a necessity. Once this raw data is accessible, the NumPy and Pandas libraries are utilised. These powerful tools provide the muscle for numerical computations and data manipulation, allowing the system to organise and prepare the information for further analysis.

The SciPy library is the next one to be used[9], offering a comprehensive toolbox for signal processing. This library equips the system with functionalities for filtering, a crucial step that removes low-frequency noise that might obscure the underlying neural activity. SciPy also boasts advanced peak detection algorithms, Scanning the data structure to detect the peaks and troughs that mark significant changes in brain activity[18].

Following this initial data preparation, I used the Matplotlib library[19]. This library empowers the system to generate informative visualisations. These visualisations act as maps that translate the complex bio-signal data into a clear visual representation. These plots provide a greater view of the processed data and include zoomed-in sections for a microscopic examination of the CSP. By offering these detailed visualisations, the system equips medical professionals with the tools to delve deeper into the data and make informed decisions. Or in the case of the system a better view for the Vision AI to make an decision.

Finally the unique selling point of this system which sets it apart is the use of OpenAI's GPT-4-Vision API. Leveraging the power of machine learning. The system transmits waveform images, visual representations of the bio-signal data, directly to the GPT-4-Vision API. With the knowledge gleaned from massive datasets, this API can interpret these images and extract insights about the underlying neural activity. By incorporating this AI-powered analysis, the system bypasses manual data entry. It enhances the robustness of CSP detection, especially when dealing with intricate EEG data that might challenge traditional algorithms.

The connection between these underlying technologies provided a multitude of benefits. Automated processing, a cornerstone of the system, significantly reduces reliance on manual analysis. This minimises the risk of human error and eliminates variability between evaluators, ensuring consistent and reliable results. Furthermore, the system streamlines the concussion assessment process, enabling faster and more timely decisions about an athlete's well-being.

By presenting the results in a user-friendly manner, the system empowers medical professionals and non-specialist users, to better understand the identified CSP window and its potential implications. Generating a collaborative approach to athlete care, ensuring everyone involved clearly understands the situation. For a system such as this the most significant benefit lies in the system's accuracy of measurement. The combination of advanced algorithms and the potential for AI integration aims to improve the accuracy of CSP detection. This enhanced accuracy translates to more informed detection and, in theory better care for athletes who may have sustained a concussion.

Finally, the core reason for a project such as this is mentioned in the State Of The Art section. The system promotes standardisation. By providing a consistent and reliable approach to concussion assessment across different contexts, the system ensures that athletes receive a fair and objective evaluation regardless of location or available resources. This technology paves the way for a more uniform and effective approach to athlete safety in sports. A requirement that this paper calls for expressly[16].

5 Development of visual representation of Concussion Data

5.1 Toolbox

The analysis employed a diverse toolbox comprising libraries such as bioread for reading biomedical data files, numpy and pandas for data manipulation, and matplotlib for visualisation. Additionally, the scipy library facilitated signal processing tasks, including filtering and peak detection, which served as the foundational tools for this study. While initially, I wanted to use the Anaconda Python distribution platform to manage my Python libraries and interact with the Jupyter Notebook, it did not support the “bioread” package. I worked around this with a manual installation of the required packages, including bioread, through a command prompt using the pip package manager; this allowed me to develop still using both bioread and the Jupyter Notebook.

5.2 Initial Data Acquisition and Structuring

The cornerstone of this dissertation's analysis pipeline lies in the initial data acquisition and structuring stage. This crucial step paves the way for subsequent in-depth exploration of the electrophysiological data.Through the use of the bioread library in Python to providing the valuable information contained within acq (AcqKnowledge) files, a file format commonly employed in neurophysiology.

Acq files are the common format for recording neural data, in the case if this project it contained information from five separate channels. However, a well-organised and structured format is essential to analyse this intricate data effectively. This is precisely where the bioread library comes into play. Its purpose is quite simple. The translation of the raw data from the acq files into a structured pandas DataFrame.

The significance of this transformation cannot be overstated—a pandas DataFrame offers a robust and well-established data structure within the Python ecosystem. By converting the acq files into DataFrames, we establish a clear and organised representation of the neural recordings. Each channel's data is compared against a corresponding temporal axis, ensuring perfect synchronisation across all five channels. This synchronisation is paramount for accurate analysis, as it allows me to precisely correlate the activity observed in one channel with the activity coinciding in other channels.

Initial data acquisition and structuring stage layed the groundwork for the subsequent feature extraction and analysis techniques employed throughout this dissertation. By transforming the raw data into a structured format, I am able to manipulate the information contained in the acq files, ultimately enabling me to examine the data and better understand the underlying neurophysiological processes.

From the graph below you can see how the data appeared In this early part of the design stage.

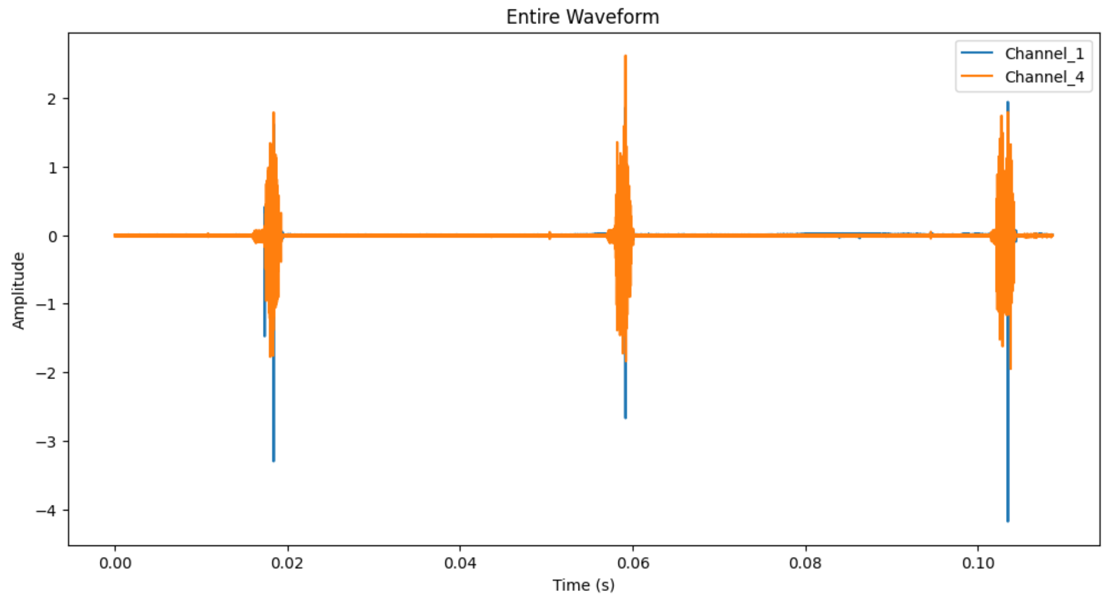

Figure 2: Data provided after basic visualisation

5.3 Signal Preprocessing and Event Detection

At the heart of our analysis lies the critical detection of trigger points within the neural recordings—points defined by their surpassing a predetermined amplitude threshold, suggesting potential neural responses to stimuli. The subsequent application of a Butterworth high-pass filter serves to pick out the frequency components most pertinent to the study of (CSPs), thereby eliminating lower-frequency noise and augmenting the clarity of the signal for further analysis.

The initial phase of signal preprocessing centres on identifying trigger points embedded within the neural recordings. These trigger points represent crucial junctures where the signal amplitude exhibits a marked and rapid surge, exceeding a predefined threshold value. This threshold is a critical marker which was established through rigorous experimentation and knowledge of the source data finding the point at which the trigger wave spikes to above a certain threshold value in the trace. Values surpassing this threshold indicate significant neural responses potentially triggered by external stimulant.

The markings of these trigger points lie in their ability to demarcate the boundaries of potential CSP events within the continuous stream of neural data. By pinpointing them, we effectively isolate segments of the recording that warrant closer scrutiny for the presence of CSPs. Here, the find_trigger_points function takes centre stage, sifting through the designated trigger channel within the DataFrame. It calculates the difference between consecutive data points, effectively transforming the continuous signal into a sequence of differences. Significant deviations exceeding the established threshold are then flagged as potential trigger points, furnishing us with a roadmap to navigate the intricate landscape of the neural recordings.

The signal is further processed after successfully detecting trigger points using a Butterworth high-pass filter. This filter acts as a sophisticated tool, eliminating low-frequency noise from the signal while permitting high-frequency components to pass through relatively unscathed. The rationale behind this selective filtering process stems from the inherent characteristics of CSPs. These events in brain activity are primarily associated with high-frequency neural activity, and by attenuating low-frequency noise and extraneous elements, the filter effectively enhances the signal-to-noise ratio and provide smoother lines to be able to better determine when a flattened period has truly stopped without setting off any false positives. Consequently, the filtered signal offers a more precise representation of the high-frequency neural dynamics most pertinent to the study of CSPs.

The butter_highpass_filter function Is what I use to handle the removal of noise. It takes the raw signal, the desired cutoff frequency, and the sampling frequency as input parameters. The cutoff frequency marks the boundary between the frequency components that pass through the filter and those that are attenuated. When selecting a cutoff frequency that aligns with the known frequency range of CSPs, we ensure that the filter hones in on the most relevant parts of the signal, discarding extraneous information that could obfuscate the analysis.

The combination of trigger point detection and high-pass provide a more precise and focused analysis of the neural recordings. By strategically isolating potential CSP events and enhancing the high-frequency components most indicative of such phenomena, we equip ourselves with a refined signal ready for the subsequent stages of analysis, where the intricacies of CSPs can be displayed.

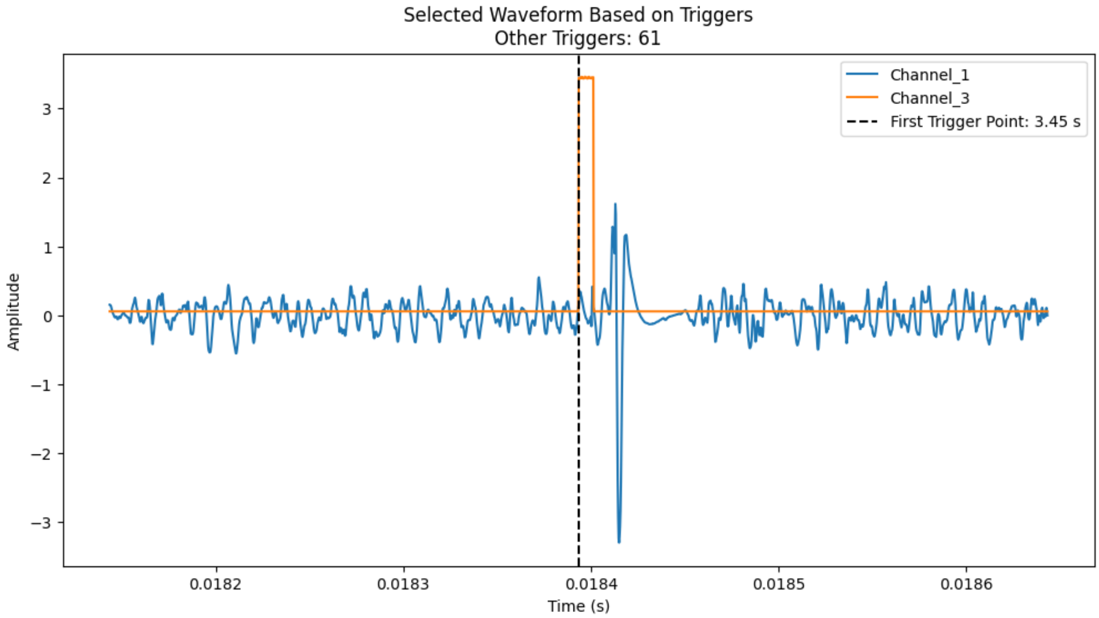

Figure 3: The first trigger point found by looking in Channel 3 for stimulus events

5.3.1 Sophisticated Signal Analysis

Following the crucial groundwork laid by signal preprocessing, we move into more sophisticated signal analysis. This stage past the basic identification of trigger points and filter application. The system goes a little further, dissecting the neural signal to pinpoint the hallmarks characterising CSPs. Displaying the key events that surround the CSP event

The analysis applied a high-pass filter to the signal. This filtering stage is pivotal in isolating the frequency components most relevant to the CSP analysis. High-pass filters effectively attenuate the lower-frequency noise and irrelevant signal components, enhancing the clarity of the neural signals under scrutiny. Focusing on frequencies above a certain cutoff point ensures that the signal analysis concentrates on the fluctuations most indicative of concussion-induced neural responses.

Central to this analysis is the adept identification of significant neural events. These events serve as critical markers, demarcating the onset and offset of CSPs within the continuous stream of neural data. The find_peaks function takes centre stage in this endeavour as a powerful tool for uncovering the hidden peaks and troughs embedded within the signal.

The initial focus is identifying the most pronounced negative amplitude after the previously detected trigger point. This negative deflection signifies a pivotal moment—the commencement of neural inhibition within the cortex, a hallmark of the impending CSP. The find_highest_negative_amplitude function examines the designated data window, pinpointing the exact time instance and amplitude value corresponding to this crucial negative peak.This negative amplitude is a potent indicator of the brain's response to the external stimulus or event that triggered the neural activity. It signifies a temporary dampening of neural activity, paving the way for the subsequent period of reduced neural firing characteristic of CSPs.

After identifying the negative peak, the analysis strives to locate the first positive peak that emerges after this deflection. This subsequent positive peak signifies the dtart of the flatlining which is the core identifier of a CSP event. The find_first_positive_peak_after_negative function handles this phase of the analysis, sifting through the data segment following the negative peak. It searches for the initial positive deflection, pinpointing the precise time instance and amplitude value associated with this marker.

This positive peak is significant because it marks the boundaries of the CSP. Its presence signifies the transition from the initial neural inhibition to the subsequent period of reduced brain activity that defines a CSP. By pinpointing this positive peak, we effectively delineate the duration of the CSP within the recordings of brain function.

Beyond isolating discrete events, sophisticated signal analysis provides the abuility to better understand the neural response's return to normal wave function. This is achieved through carefully examining the sequence of peaks and troughs surrounding the identified negative deflection and subsequent positive peak. The mark_peaks_after_positive function plays a pivotal role in this endeavour. It delves into the CSP data segment, identifying the prominent positive peak and subsequent peaks and troughs that unfold within this timeframe.

By charting these additional peaks and troughs, we gain a more comprehensive understanding of the waves return to normal activity post CSP event. This visualisation below provides valuable insights into how the wave activity returns gradually to normal function after the series of core events that have been marked In the image.

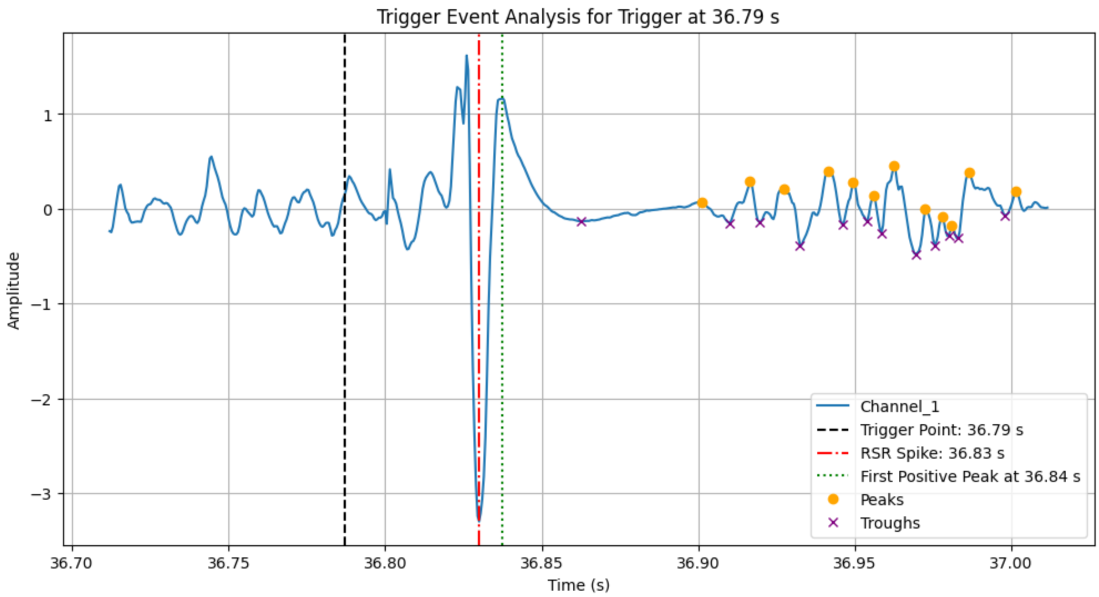

Figure 4: The first CSP event with key events and processes labelled

In essence, sophisticated signal analysis provides the user and the AI with a better vision of the neural activity within the context of CSPs. By analysing the signal to identify critical events, we understand the wave function associated with these neurophysiological phenomena. This knowledge provides opportunities for further investigation into the physiological underpinnings of concussions and the potential for utilising CSPs as a diagnostic tool for concussion severity.

5.3.2 Visualisation and Interpretation of Neural Dynamics

The culmination of our signal processing and analysis efforts finds its fruition in visualisation. Here, the raw data transcends its numerical form, blossoming into a captivating narrative that illuminates the intricate story of the neural response post-concussion. Visualisation is a cornerstone of interpretative data analysis, offering a window into the complex interplay of neural processes during a CSP.

By harnessing the power of visual representations, we effectively translate the neural data's intricacies into a format readily interpretable by both scientific experts and audiences seeking a deeper understanding of concussions. Here, the focus shifts from the underlying code (find_peaks, etc.) to the overarching concepts and the resulting visualisations.

A cornerstone of visualisation involves depicting the wave function of the neural response. This is achieved by generating time-series plots that chart the fluctuations in neural activity over time. These plots serve a critical purpose—unveiling the precise sequence of events unfolding during a CSP. The negative deflection, the subsequent positive peak, and additional peaks and troughs are represented as a line and plots on the timeline, respectively, providing a straightforward visual narrative of the cortical response.

researchers can glean valuable insights into the duration of the CSP by looking at the way waves behave under stimulation, the relative prominence of the negative and positive peaks, and the overall pattern of neural activity post-stimulus. This visual representation facilitates comparisons between different subjects or experimental conditions, aiding in identifying potential biomarkers or group-specific characteristics of CSPs.

Beyond the temporal realm, visualisation extends to portraying the amplitude characteristics of the neural response. Here, the focus shifts to the magnitude of the voltage fluctuations within the neural signal. By incorporating amplitude information into the visualisation, we gain a deeper understanding of the intensity of the neural activity throughout the CSP.

The negative deflection, for instance, can be visualised in its temporal placement and depth, signifying the extent of the neural inhibition. Similarly, the positive peak's amplitude provides insights into the strength of the rebound excitation that follows the initial inhibition. By examining these amplitude variations, researchers can differentiate between mild and severe concussions or track the recovery process over time.

The power of visualisation lies not just in the presentation of data but also in its ability to weave a compelling narrative. Combining temporal and amplitude information into a cohesive visual representation can effectively communicate the complex neural response postconcussion story. This is useful in the case of educating medical professionals, raise public awareness, and foster a deeper understanding of the physiological impact of concussions to those who are lacking the required specialist.

Visualisation serves as a transformative tool within the analysis pipeline. It breathes life into the raw data, transforming it into an interpretable narrative that unveils the intricate dynamics of neural activity during a CSP. Through this visual storytelling, researchers gain profound insights into the physiology of concussions, paving the way for advancements in diagnosis, treatment, and our overall understanding of these complex brain injuries.

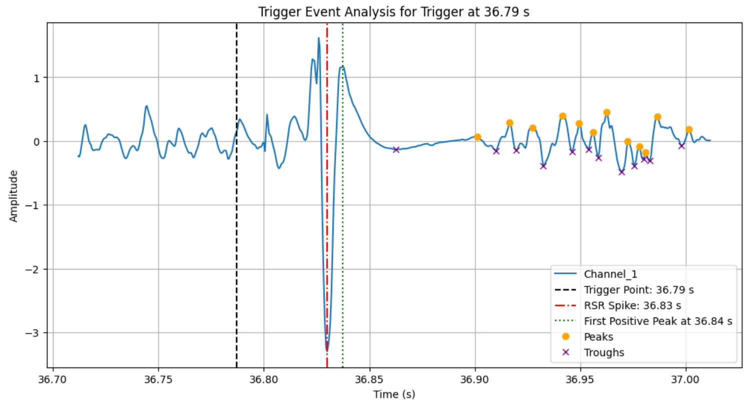

Figure 4

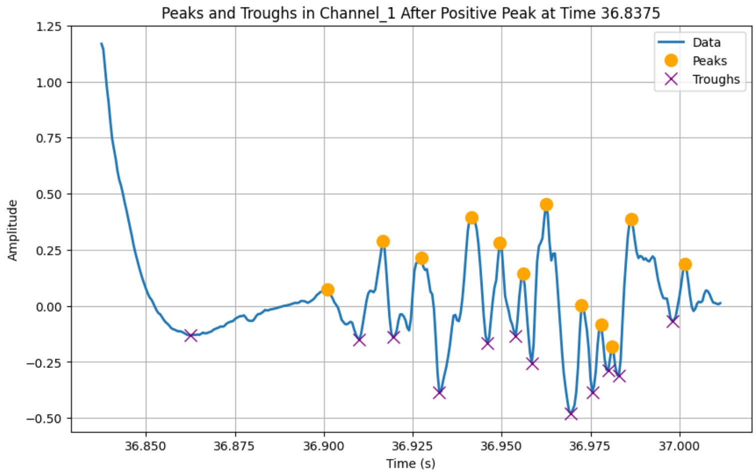

Figure 5: A plot of the time immediately following the first Positive peak

6 Utilisation of the data representation by Vision-API to provide results.

6.1 Toolbox

This project successfully integrated AI-powered analysis into the concussion detection system. To achieve this, a carefully curated toolbox of Python libraries was employed, enabling communication with OpenAI's Vision API [11] and processing image data for AI-driven CSP detection.

Base64: Streamlining Image Transmission and API Compatibility

The core of this toolbox lies in the base64 library. This library is critical in preparing the EEG waveform images for interaction with the machine-learning model. Traditionally, these images exist in a binary format. However, base64 facilitates their conversion into a text-based representation using base64 encoding. This compressed format offers two significant advantages. Firstly, it streamlines data transmission; by significantly reducing file size, base64 encoding allows efficient image data transmission via HTTP requests. This is crucial for communication with cloud-based machine learning models like OpenAI's Vision API. Secondly, base64 encoding ensures compatibility with many machine-learning APIs. These APIs are often designed to process text-based data, and base64 encoding ensures seamless communication and analysis between the local system and the API.

Requests: Communication with the Vision API

The requests library forms another essential component of the toolbox. It empowers researchers to construct and transmit HTTP requests, establishing a vital communication channel with OpenAI's Vision API. This library offers three key functionalities:

1. **Request Construction:** Requests allow researchers to construct detailed HTTP POST requests. These requests encapsulate the base64-encoded EEG waveform data alongside any additional parameters or instructions the machine learning model requires for analysis.
2. **Secure Transmission:** Each HTTP request incorporates an API key within its headers to safeguard data integrity during communication. This critical functions as a secure access token, authenticating the user and authorising them to leverage the capabilities of the cloud-based machine learning model.
3. **Dispatching Requests:** Once constructed and authenticated, the requests are dispatched to the designated endpoint of the Vision API. This initiates the communication channel between the local system and the cloud-based AI model.

6.2 AI-Driven CSP Detection

This section delves into the heart of the AI-driven approach to CSP detection. Here, we move beyond traditional signal processing techniques and embrace the power of machine learning algorithms. This section highlights the intricate interplay between data preparation, communication protocols, and the underlying AI analysis.

6.2.1 Image Encoding and Preparation

Effective AI integration begins with the preparation of the EEG data for seamless interaction with machine learning models. Unlike previous sections' traditional signal processing methods, this AI-driven approach necessitates a data transformation stage. Here, the raw EEG data, often visualised as waveforms, undergoes a crucial metamorphosis.

The base64 library in Python takes centre stage, bridging the world of raw EEG data and the machine learning realm. This library facilitates the encoding of EEG waveform images into a text-based format. This encoding process transforms the bulky binary image files into streamlined text strings. This transformation offers two key benefits.

Streamlined Transmission

We significantly reduce the file size by converting the data into a text-based format. This compressed format becomes eminently suitable for transmission via HTTP requests, a critical aspect of communication with the cloud-based machine learning models.

Compatibility with Machine Learning APIs

Many machine learning APIs, such as the Vision API employed I this project, are designed to process text-based data. Encoding the EEG waveform images as text strings ensures compatibility with these APIs, paving the way for seamless communication and analysis.

6.2.2 Communication with Vision-API

Following the data preparation stage, the system establishes a vital connection with the cloud-based machine learning model. This communication channel hinges on the requests library within Python. This library offers a robust suite of tools for constructing and transmitting HTTP requests. Here's how it orchestrates the communication flow:

The requests library is employed to construct HTTP POST requests. These requests encapsulate the base64-encoded EEG waveform data alongside any additional parameters or instructions the machine learning model requires for analysis. Each HTTP request contains an API key within its headers. This API key serves as a safe access token, authenticating the user and authorising the use of the cloud-based machine learning model.

Once constructed and authenticated, the HTTP request is sent to the designated endpoint of the Vision API. This effectively initiates the communication channel between the local system and the cloud-based AI model. However, several aspects merit consideration when evaluating whether the prompts utilised in this project meet the standards of being prompt-engineered. Firstly, while ensuring detailed instructions, the complexity and specificity of the prompts need to align with prompt engineering's emphasis on simplicity and precision. Effective prompt engineering advocates for creating inputs easily interpretable by AI and users, suggesting that simplification and clarification could benefit the project's prompts. Furthermore, the current prompts are static and lack the dynamic flexibility highlighted in prompt engineering principles. This flexibility is crucial for adapting to varying data scenarios and user inquiries; enhancing the AI system's responsiveness and utility across diverse applications would result in a more flexible system capable of consistent detection and measurement, as well as an explanation of how it came across these findings.

Moreover, the project's prompts could be more user-centric, an essential facet of prompt engineering. This principle involves designing prompts that are intuitive and accessible, minimising technical jargon and focusing on user engagement. The detailed and technically dense nature of the project's prompts might only partially accommodate users with different levels of expertise or familiarity with AI systems, suggesting an area for improvement.

Lastly, the efficiency of the prompts in guiding AI analysis without introducing unnecessary complexity or potential for user error is a critical aspect of prompt engineering. The project's approach, necessitating multiple steps and detailed observations, indicates an opportunity to streamline the prompts. This streamlining could enhance the speed and accuracy of AI analyses, reducing the cognitive load on users and improving the overall efficiency of the AI-driven solution.

6.2.3 AI-Driven Analysis

Upon receiving the HTTP request from the local system, the Vision API decodes the base64-encoded data, transforming it back into its original EEG waveform image format. Here, the true power of machine learning comes into play. The Vision API harnesses pre-trained machine learning algorithms specifically designed to identify the characteristic patterns of CSPs within the EEG data. These algorithms carefully scrutinise the waveforms, searching for Trigger Points the AI model pinpoints the precise moments within the signal where it surpasses a predefined threshold, potentially indicating the onset of a neural response,rSR Spikes The AI analysis examines the signal for (rSR) spikes, often associated with concussive events. These spikes can be found immediately before a drop in brain activity and Signal flattening paying close attention to characteristic dips or flattenings within the signal, a hallmark of reduced neural activity during a CSP.

The Vision API extracts valuable insights from the complex neurophysiological recordings by dissecting the EEG data through these AI-powered algorithms. This refined analysis empowers researchers to glean a deeper understanding of the presence and characteristics of CSPs within the data, ultimately aiding in concussion diagnosis and management.

An AI-driven approach such as this offers a novel and potentially transformative avenue for analysing EEG data in the context of concussions through data preparation, secure communication protocols, and the expertise of pre-trained algorithms.

However, this approach has limitations and difficulties. The data presented through the API must be of good quality for analysis. Inconsistent or noisy data can cause significant issues for the vision system. Consistent pre-processing techniques will be required for consistent results from the AI model.

The pre-trained nature of the Vision API's algorithms means they are not initially custom-tailored to the specific nuances of CSP detection in concussion analysis. To address this, we engaged in extensive prompt engineering and iterative testing to guide the AI towards a more precise interpretation of the EEG waveforms related to CSPs. Building on this issue are the safeguards that Openai has placed on the system to ensure that the GPT is not misused. If the AI believes that the data is in any way related to medical data, then the system will flag medical ethics and refuse to provide an answer to the system, which provides the balancing act that the system has to struggle with. How much can it know before it figures out too much and refuses to cooperate?

It is also important to mention that as this is an external product the system is interfacing with and to note that there is an associated cost[15]. As my system got more advanced the cost increased. In the original prototype of the system a single image was sent. By the end, six images would be sent along with a further request to format an array of ranges from the report that it has generated.

6.3 Output and Data Presentation

6.3.1 Result Interpretation and Enhancement

The Vision API is a powerful tool for interpreting the intricate details of CSPs within neural recordings. Its output delves beyond raw data points, offering a nuanced and visually compelling representation of the underlying neurophysiological phenomena. This section explores the core functionalities of the API's interpretation and delves into potential avenues for further refinement using the Python Imaging Library(PIL).
The cornerstone of the Vision API's interpretation lies in its ability to pinpoint and annotate critical events within the waveform images. These annotations act as a roadmap, guiding researchers towards a deeper understanding of the wave function of CSPs. Here's a breakdown of the critical elements revealed by the API:

The API assigns timestamps to crucial events within the CSP, such as trigger points, rSR spikes (reflecting specific neural activity patterns), and positive peaks. These timestamps provide a quantitative understanding of the temporal sequence of these events, enabling researchers to measure the duration of CSPs and analyse the intervals between different neural markers.

The API doesn't rely solely on numerical data. It overlays visual indicators directly onto the EEG waveform images, highlighting the abovementioned events (trigger points, rSR spikes, positive peaks). This visual representation fosters a more intuitive grasp of the temporal relationships between these events within the broader context of neural activity. Essentially this means that the system is reading the data in the same practice that is the standard for CSP waveform analysis

The Vision API comprehensively interprets the neural response during a CSP by combining precise timestamps with visual indicators. This interpretation empowers researchers to delve deeper into the complex interplay of neural processes following a concussive event. While the Vision API provides a robust interpretation, there's always room for further refinement. Here's where the PIL library enters the picture. PIL offers a versatile toolkit for image manipulation, potentially enhancing the interpretability and clarity of the API's output:

The API's output images might benefit from increased resolution, particularly when zoomed in for detailed analysis. PIL's image-resizing functionalities could generate higher-resolution versions of the EEG waveform plots, facilitating a closer examination of specific neural events.

In essence, the Vision API and PIL offer a powerful synergy for interpreting and refining the visualisation of CSPs within EEG recordings. By leveraging the strengths of both tools, researchers can gain a deeper and more nuanced understanding of the neurophysiological processes associated with concussions. Simplifying the prompts, making them more dynamic and user-friendly, and optimising efficiency could align the project more closely with the ideals of prompt engineering. Such improvements would elevate the project's technical achievements and contribute to AI's broader application and effectiveness in complex data analysis tasks.

6.3.2 Visual Data Presentation

OpenAI's text generation offers a compelling avenue for crafting textual summaries of the detected CSPs. These summaries can encapsulate critical characteristics such as the duration, frequency, and prominence of the silent periods within the EEG data. By presenting this information clearly and concisely, researchers can effectively communicate their findings to audiences needing a deeper understanding of electrophysiological data visualisations.

For instance, if a medical professional who is unfamiliar with the intricacies of EEG analysis needs to be briefed on a patient's CSP results, OpenAI-generated text summaries can provide a concise and informative overview, highlighting the detected cortical silence's presence, duration, and severity. This empowers medical professionals to make informed patient care decisions without requiring extensive EEG interpretation expertise.

```
[181]: content = response.json()['choices'][0]['message']['content']
       print(content)
```

```
Based on the information provided and the examination of the standard and zoomed-in graphs provided for each trigger event, we can identify th
e range of times specifically requested. We're asked to find the range from the dashed vertical line (indicating the trigger point) through th
e spike (noted by the red dashed line) until the wave activity returns to normal after a flat period.

1. For the first set of images, the trigger event is at 36.79 seconds as indicated by the black dashed line. The red dashed line, indicating t
he spike in the non-zoomed image, is at 36.83 seconds. The normal wave activity appears to resume shortly after 36.91 seconds where the flat p
eriod ends. Thus, the first CSP range is from 36.79 to 36.91 seconds, which is a duration of 120 milliseconds.

2. In the second set of images, the trigger event is at 118.32 seconds. The spike occurs at 118.36 seconds. The flat period ends and normal wa
ve activity seems to start around 118.44 seconds. Therefore, the second CSP range is from 118.32 to 118.44 seconds, which is a duration of 120
milliseconds.

3. In the third set of images, the trigger starts at 206.91 seconds. The spike is at 206.95 seconds. The flat line period concludes, and the w
ave activity appears to return to normal just after 207.03 seconds. So the third CSP range is from 206.91 to 207.03 seconds, resulting in a du
ration of 120 milliseconds.

In summary, we have the following list for each of the CSP ranges:

- CSP_1: 120 ms
- CSP_2: 120 ms
- CSP_3: 120 ms

These durations are consistent with the expected range of 100ms-130ms as mentioned in the instructions.
```

Figure 6: Report of the API finding

The versatility of text generation extends beyond essential summaries. OpenAI's capabilities allow researchers to tailor their narratives to resonate with specific audiences. For instance, a scientific report might delve deeper into the technical details of the CSP analysis, outlining the criteria used for detection and the statistical significance of the findings. This level of detail caters to researchers seeking a comprehensive understanding of the methodology and results.

On the other hand, presentations aimed at a broader audience, such as patients or the general public, might benefit from a more accessible narrative. OpenAI can generate text that explains the concept of CSPs in layperson's terms, highlighting their potential implications and the overall significance of the research findings. This approach fosters public awareness and understanding of concussions and their underlying physiological processes.

6.3.3 Output Integration

Following the processing and analysis of the electomyographic data, the focus shifts towards integrating these findings into the broader narrative of the dissertation. Here, the emphasis lies in weaving a clear and concise textual tapestry that effectively communicates computational analysis results.

While potential future endeavours might explore visualisation techniques, the current approach prioritises textual integration. This is achieved by generating descriptions of the identified CSPs.
A cornerstone of this textual integration involves generating detailed descriptions for each detected CSP event. These descriptions capture key characteristics such as the duration of the silent period, and the relative prominence of the associated negative deflection and positive peak. By incorporating this level of detail, researchers can ensure clear communication of the nature and extent of the observed neural inhibition.

In the event that a researcher needs to highlight a specific CSP event within the dissertation. The textual description can pinpoint the moment in the neural recording where the silent period commences and concludes, specifying its duration. Additionally, the description can elaborate on the depth of the negative deflection, indicating the extent of neural inhibition and the amplitude of the positive peak, providing insights into the subsequent rebound excitation.

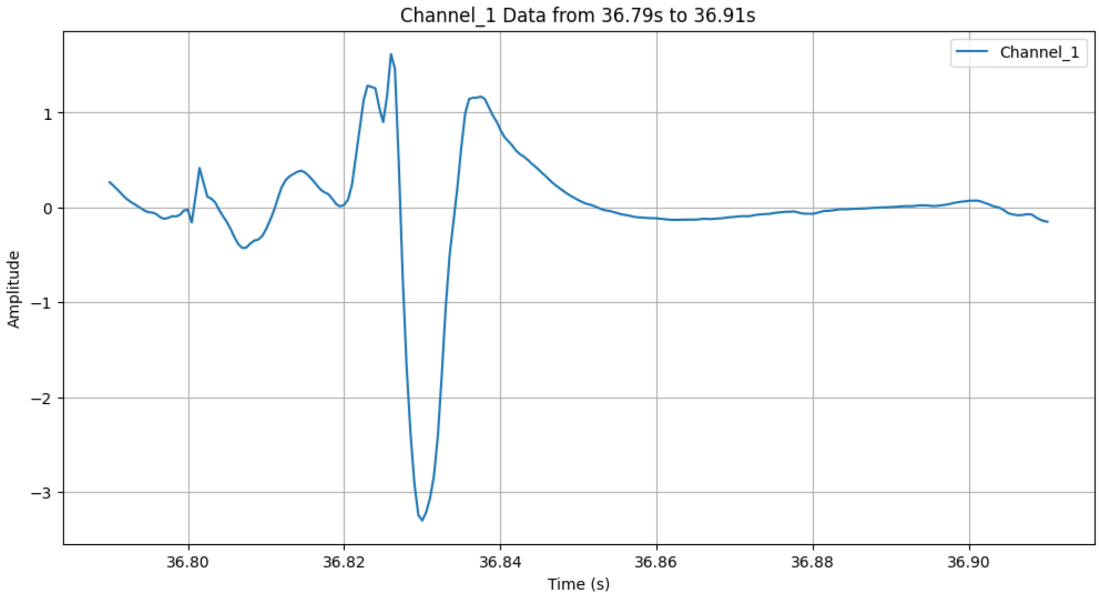

Figure 7: A graphical display of what the AI believes is the CSP range of Channel 4 data

While the current focus is on textual integration, future endeavours have the potential for a more multimodal approach. This could involve integrating the textual descriptions with future visualisation techniques. Imagine combining the detailed narratives with strategically generated figures highlighting the identified CSPs within the EEG data. This would provide a comprehensive picture, catering to readers who prefer a combination of textual and visual representations of the data.

By crafting descriptions of the CSP events and contextualising them within the broader body of concussion research, researchers can effectively communicate their findings and contribute to a deeper understanding of the physiological correlates of concussions. This paves the way for advancements in diagnosis, treatment, and our overall understanding of these complex brain injuries.

7 Prompting for Concussion Detection

The introduction of the use of AI elements came about after discussions with my supervisor, who deemed that to make the most out of the opportunities that were available to create a proof of concept using a new novel technology, it was an opportunity that could not be missed. Made available in November 2023, the technology and its capabilities are still being tested and discovered, and for the project, a pivotal change in the scope from purely a Python-based data analysis project with a new focus on providing data and supporting images and refining prompts for greater use by the Vision API.

7.1 Introduction

A significant aspect of this integration is the application of Artificial Intelligence (AI), particularly in data analysis and interpretation. Within this context, Prompt Engineering emerges as a critical discipline, bridging the gap between complex AI capabilities and the nuanced requirements of concussion detection.

Prompt Engineering fundamentally involves the strategic formulation of inputs designed to guide AI systems towards generating desired outputs. This process is particularly crucial when working with OpenAI's GPT-4 Vision API, as it involves crafting precise and effective prompts that can accurately interpret and analyse complex neural signals indicative of the CSP. Given the intricacies of neurophysiological data and the critical nature of concussion assessments, the role of Prompt Engineering cannot be overstated. It is a technical endeavour and a nuanced art form that balances clarity, specificity, and adaptability.

This section's inception delves into the principles of Prompt Engineering, underscoring its significance in the context of this project. It elaborates on how carefully engineered prompts can enhance the AI-driven analysis of CSP by ensuring that the AI interprets the waveform images with the requisite precision, thereby facilitating a more accurate and efficient identification of concussion indicators. This introduction sets the stage for a deeper exploration into the methodologies employed in Prompt Engineering, the challenges encountered in crafting effective prompts, and the innovative strategies developed to surmount these challenges.

As we navigate the nuances of Prompt Engineering, it becomes evident that this discipline is not merely a component of the project's methodology but a transformative approach that augments its core objectives. It encapsulates the synergy between human ingenuity and artificial intelligence, heralding a new era of concussion detection that is both refined and accessible. Thus, the exploration of Prompt Engineering within this dissertation enriches our understanding of AI's potential in sports medicine and exemplifies the iterative process of innovation that drives the field forward.

In this discussion about the intricacies of Prompt Engineering, we aim to illuminate the path towards a more nuanced and effective application of AI in concussion detection. By dissecting this discipline's process, challenges, and solutions, we endeavour to contribute a valuable perspective to the ongoing dialogue on the intersection of artificial intelligence, data science, and sports medicine.

7.2 Designing Effective Prompts

Crafting effective prompts for AI, particularly within concussion detection using the CSP, requires an iterative design process. This process is paramount in ensuring that the AI system[20], such as OpenAI's GPT-4 Vision API, can accurately interpret complex neural signals and provide valuable insights into CSP analysis. This section delves into the methodologies adopted for designing these prompts, the iterative design process involved, and the criteria employed to evaluate the efficacy of these prompts.

7.1.1 Methodologies for Crafting Prompts

Crafting effective prompts begins with a deep understanding of the problem domain and the specific capabilities of the AI system in use. In the context of CSP analysis for concussion detection, prompts must be designed to accurately guide the AI in recognising and interpreting specific patterns in electromyographic (EMG) signal waveforms[14]. The methodology had to address the following concerns.

It must have the capability of referencing termanology from neurophysiology and sports medicine to define key features of CSP that the AI must identify. This includes understanding the wave function, amplitude characteristics, and typical patterns associated with concussions. Prompts must be clear and specific to avoid ambiguity in AI interpretation. This involves defining precise criteria for what constitutes CSP in EMG waveforms. Maintain simplicity in prompts to make them accessible for AI understanding without oversimplifying the complexity of the neurophysiological signals.

7.1.2 Iterative Design Process

The design of effective prompts is inherently iterative, involving cycles of development, testing, and refinement. Based on the project's objectives and the AI's capabilities, initial prompts are developed as hypotheses on how best to guide the AI's analysis.A series of A/B Tests involving creating variations of prompts to test their performance in guiding the AI. Each variation is evaluated on how well it helps the AI identify and interpret CSPs within the data.

Based on feedback and testing results, prompts are refined to enhance clarity, specificity, and effectiveness. This cycle repeats until the prompts achieve the desired level of efficacy and then move onto the next criteria.

7.2.3 Criteria for Evaluating Prompt Efficacy

The primary criteria is the accuracy with which the AI interprets the prompts to identify CSPs in the waveform data. This is measured against known outcomes in a controlled dataset. Effective prompts must yield consistent results across various datasets, including those with mixed-quality signals, to ensure the AI's performance is stable and reliable. While not compromising accuracy, the prompt should enable the AI to quickly process and respond to the input data, enhancing the efficiency of concussion detection.

Domain experts in sports medicine and neurophysiology evaluate the clinical relevance and applicability of the AI's interpretations, guided by the prompts. Their feedback is crucial for assessing the AI-driven CSP analysis's real-world applicability. However in the limited scope of this project the system evaluation was as simple as it looks correct and the results are within acceptable levels of deviation.

By adhering to these methodologies,and engaging in an iterative design process, employing rigorous evaluation criteria, this project aims to craft effective prompts that significantly enhance the AI-driven analysis of CSP for concussion detection. This contributes to the academic field and has the potential to revolutionise the way concussions are detected and managed in contact sports, thereby safeguarding athlete health and well-being.

7.3 Integrating Prompts with GPT-4-Vision

Integrating carefully crafted prompts with GPT-4-Vision is a pivotal component in leveraging AI's potential for detecting the CSP in concussion evaluation. This integration is about feeding data into an AI system and crafting a dialogue that guides the AI to analyse complex neural signals accurately. This section investigates the nuances of designing prompts for the GPT-4-Vision API, specifically tailored to CSP detection, and the inherent challenges of ensuring these prompts align effectively with the objectives of medical data analysis.

7.3.1 Designing Prompts for GPT-4-Vision

The task of designing prompts for the GPT-4-Vision API involves a synthesis of neurophysiological knowledge, AI interaction principles, and an understanding of the API's capabilities and constraints. The process encompasses

Prompts direct GPT-4-Vision's focus towards key features indicative of CSP within EMG waveform images. This includes instructions to identify specific signal patterns characteristic of CSP, such as the sudden onset and cessation of neural activity.Given GPT-4-Vision's capability to analyse image data, prompts are designed to exploit this feature, asking the AI to interpret visual representations of EMG data. This might involve instructions to discern between normal neural activity and the reduced activity periods indicative of CSP.To enhance the AI's analytical precision, prompts include contextual information about the data, such as the type of sport involved, the typical incidence of concussions, and any relevant physiological considerations. This context aids the AI in making more informed interpretations of the waveform images.

7.1.2 Challenges of Aligning Prompt Responses with Medical Data Analysis

Integrating AI-driven analysis with medical data analysis presents unique challenges, especially when dealing with nuanced and complex data like CSP in EMG waveforms. Ensuring that the AI's interpretation of prompts leads to precise and reliable identification of CSP is challenging. This is due to the subtle variations in EMG signals and the need for high specificity in detecting concussion-related changes.Another challenge is aligning the AI's interpretations with clinical relevance. The AI might accurately identify patterns specified in the prompts, but interpreting these patterns in the context of concussion severity and prognosis requires a nuanced understanding that AI currently cannot fully replicate.The variability in EMG data quality, such as noise levels or differences in signal amplitude, poses a challenge in designing prompts that consistently lead to accurate CSP detection across diverse datasets. It is paramount to ensure that the AI-driven analysis, guided by prompts, adheres to ethical standards and regulatory guidelines for medical data analysis. This includes avoiding any implication of medical advice or diagnosis beyond the AI's scope of study.

Addressing these challenges involves an iterative refinement of prompts[13], continuous evaluation against clinical benchmarks, and collaboration between AI developers and medical professionals. The goal is to balance leveraging AI's analytical capabilities and ensuring that the insights generated are clinically meaningful, ethically sound, and aligned with the overarching objectives of concussion management in contact sports. This collaborative approach not only enhances the efficacy of CSP detection using GPT-4-Vision but also paves the way for broader applications of AI in medical data analysis, where accuracy, reliability, and clinical relevance are paramount.

7.4 Prompt Testing and Refinement

Prompt Testing and Refinement play a critical role in ensuring that the prompts designed for the GPT-4-Vision API effectively and accurately aid in detecting the CSP within the context of concussion analysis. This iterative process involves testing protocols, test results analysis—including unexpected AI responses and subsequent refinements to enhance prompt efficacy. This chapter delves into these aspects, illustrating the continuous effort to fine-tune the interaction between AI and medical data analysis.

7.1.1 Testing Protocols for Prompt Performance

The evaluation of prompt performance necessitates a systematic approach, ensuring that the prompts elicit the desired AI responses for CSP detection. The testing protocols include. A diverse and comprehensive set of EMG waveform images representing various CSP instances is utilised to test the AI's ability to generalise across different data qualities and conditions.I implemented controlled variations in the phrasing and detail level of prompts to assess their impact on AI response accuracy and relevance. Establishing clear metrics for success, such as the accuracy of CSP detection, the specificity of AI-generated annotations, and the relevance of the AI's textual descriptions to the CSP characteristics.

7.4.2 Insights from Testing Results

Testing results often reveal insightful patterns and occasional surprises in the AI's responses, Initial testing rounds highlighted variability in the AI's accuracy across different waveform images, suggesting that the AI was more easily recognisable by certain visual characteristics of CSP than others.

Some tests yielded unexpected responses, where the AI focused on irrelevant signal aspects or misinterpreted the waveform features, underscoring the necessity for prompt refinement.

The testing underscored the sensitivity of AI responses to prompt phrasing, where subtle changes in wording could significantly alter the focus and depth of the AI's analysis.

7.1.3 Refinement Process Based on Test Outcomes During Development

The insights from testing necessitate a rigorous refinement process aimed at enhancing prompt precision and AI interpretative accuracy. Based on testing feedback, prompts are iteratively optimised for clarity, specificity, and contextual relevance, ensuring that the AI's focus aligns closely with key CSP features. An in-depth analysis of instances where the AI's responses deviated from expected outcomes helps identify prompt elements that may lead to confusion or misinterpretation. Leveraging ongoing advancements in AI and prompt engineering research to refine prompts further, accommodating new insights into AI interpretation and analysis capabilities.

This iterative process of testing and refinement ensures that the prompts continually evolve to meet the challenges of accurately detecting CSP using GPT-4-Vision. It underscores the dynamic nature of AI applications in medical data analysis, where constant iteration and collaboration between AI experts and medical professionals are pivotal in harnessing AI's potential to enhance concussion management strategies.

7.5 Ethical Considerations and Compliance in Prompt Engineering for Concussion Detection

Ethical considerations and regulatory compliance are pivotal in the construction of a system for concussion detection through CSP analysis using the GPT-4-Vision API, albeit within a narrower scope focused on the project's specific context. This section outlines the guiding principles and compliance strategies tailored to the project's scale and objectives, ensuring ethical integrity without overly complicating the framework with broader, large-scale concerns.

7.5.1 Ethical Design in Prompt Engineering

The design of prompts, a critical component of this project, is approached with ethical principles tailored to its educational and research context

Recognising the sensitivity of medical data[13], even within a controlled project setting, prompts are engineered to process anonymised datasets, emphasising the protection of individual privacy. This approach ensures the system can be developed and tested without compromising personal data integrity.The potential implications of AI-assisted diagnosis highlight the necessity for reliability. The prompt design focuses on the clear, unambiguous language that guides the AI in analysing CSP data accurately. This approach minimises errors, aiming for precision within the project's scope.

Within the project's confines, transparency regarding AI decision-making is paramount. Prompts are designed to elicit detailed explanations from the AI, allowing for a clear understanding of how conclusions are drawn. This transparency facilitates project evaluations and educational insights while maintaining the anonymity of of the test subjects.

7.5.2 Compliance with Ethical Guidelines

The project complies with the ethical standards of academic research, ensuring that data use, AI application, and research methodologies are conducted with integrity. This includes obtaining necessary approvals for data use and adhering to principles of honesty and transparency in research.

Guidelines from relevant bodies on the ethical use of the project data was layed out in the ethics request that approved this project and those guidelines were adhered to regarding prompt design and system implementation. While the project does not directly engage with patients or clinical data, it nonetheless upholds principles of non-maleficence and beneficence, ensuring the technology is used responsibly and constructively within its research context.

This project adopts a focused approach to ethical considerations and compliance tailored to its research and development context. By prioritising privacy, reliability, and transparency and aligning with academic and AI ethical standards, the project aims to navigate the ethical landscape effectively. This approach ensures that the development and application of AI for concussion detection through CSP analysis are conducted with a strong moral foundation appropriate to its scope and objectives.

7.6 Impact of Prompt Engineering on System Performance

Implementing prompt engineering within the context of our concussion detection system, specifically designed to analyse the CSP using the GPT-4-Vision API, has showcased substantial impacts on the system’s performance and user interaction. This section delves into how prompts tailor made enhance detection capabilities and influence the system's usability and accessibility.It is important to note that as more prompts are added to the system the run time is increased greatly.Based on my own personal experience the system its roughly an extra 20 seconds per prompt that is added to the project, this highlights the importance of efficient prompting of the system.

7.6.1 Enhancing Detection Capabilities through Precision and Contextualization

Prompt engineering significantly improves the system's ability to detect CSP accurately and efficiently. By designing prompts that precisely and contextually guide the GPT-4-Vision API, we optimise the AI's focus on relevant features within the electromyographic (EMG) data images.

Well-engineered prompts direct the AI’s analysis towards specific waveform characteristics indicative of CSP, thereby reducing the likelihood of misinterpretation or oversight. This focused attention enhances the detection of CSP, minimising false negatives or positives.The AI can process the data more efficiently by clarifying the task at hand through detailed prompts. This optimisation leads to quicker turnaround times in analysing CSP data, facilitating timely assessment without sacrificing accuracy.Dynamic prompts can notably improve the system’s capacity to handle data variability, such as differences in waveform quality or CSP intensity. These prompts adapt the AI’s analysis parameters to the specifics of each dataset, ensuring reliable detection across diverse data conditions.

7.1.2 Influencing Usability and Accessibility through Intuitive Interaction

The role of prompt engineering extends beyond the technical performance of the system, significantly impacting its usability and accessibility.Engineering prompts that translate complex AI functionalities into straightforward operations make the system more accessible to users without extensive AI knowledge. This simplicity enables medical professionals and researchers to utilise the system effectively, focusing on interpreting the CSP data rather than navigating complex AI interactions. The system’s output, influenced by the specificity and clarity of the prompts, becomes more interpretable. Users can understand the basis of the AI’s analysis, fostering trust in the system’s accuracy and facilitating informed decision-making based on the CSP detection results. Prompt engineering allows customisation according to user feedback and evolving needs. This adaptability enhances the system’s long-term usability, as it can be refined to meet specific user preferences or to incorporate advancements in concussion detection research.

This concussion detection system's strategic application of prompt engineering significantly bolsters its performance and user interface. By enhancing the AI’s focus and efficiency in CSP detection and simplifying user interaction, prompt engineering emerges as a critical component in developing accessible, reliable, and efficient AI-assisted medical analysis tools. The direct impact on system performance and the positive influence on usability and accessibility underscore the value of integrating prompt engineering in the design and implementation phases of AI-driven healthcare technologies.

8 Evaluation and Future Work

8.1 Testing and Evaluation Strategy for Robustness

This section outlines the revised testing and evaluation plan to assess the system's performance on data reflecting real-world variability. We introduce a mixed-quality dataset combining precise data from Channel 1 and less clear data from Channel 5. This approach aims to validate the system's robustness and adaptability across different data qualities.

8.1.1 Testing Accuracy with Mixed-Quality Data

Objective

The goal is to evaluate the system's accuracy in detecting critical signal points (CSP) when provided with a dataset comprising mixed-quality signals. In specific terms the aim is for the system to achieve an accuracy of 85% in terms of the standard deviation compared to the “True Values” that were provided by Thomas DiVigillo. This dataset includes:

- Channel 1: Raw EMG Rectus Femoris muscle
- Channel 2: Force
- Channel 3: Stimulator trigger
- Channel 4: Raw EMG Vastus Lateralis muscle
- Channel 5: Dynamometer Torque
- Channel 6: Time Series (Added by myself during the development)

Channel 1 represents high-quality data, while Channel 4 contains less clear data. This simulates varying conditions that may affect the CSP detection process in real-world applications.

Note: I incorporated a sixth channel containing the time series data for analysis to aid in plotting the data.

Test Method

The testing process will incorporate data from all channels, with particular attention given to preprocessing steps for Channel 4's data (Raw EMG Vastus Lateralis muscle). Preprocessing will include noise reduction techniques to enhance the clarity of the less clear data without altering its integrity. After preprocessing, the system will conduct CSP detection tests on the integrated dataset. The outcome will be compared to the results obtained when only Channel 1's clear data (Raw EMG Rectus Femoris muscle) is used, thus assessing the robustness and effectiveness of the system across data of varying quality.

Success Criteria

For the test to succeed, the system must demonstrate an accuracy of at least 85% when analysing the mixed-quality dataset. An in-depth analysis will be conducted to understand performance variances observed between the two channels. Specifically, the system's ability to maintain high accuracy levels in detecting CSP is crucial despite the inherent challenges presented by the less clear data in Channel 4.

Sample Results

The performance in these tests is quantified by the accuracy percentages for each trace (individual signal) and the overall accuracy for each channel. The trace accuracy for Channel 1 ranged between 90.96% and 92.01%, with an overall accuracy of 91.33%.

Channel 4 displayed trace accuracies between 88.09% and 89.19%, with an overall accuracy of 88.71%. These results exceed the 85% threshold set for the success criteria, indicating that the system can reliably detect CSP in mixed-quality datasets. Performance variances will be noted and further examined to optimise the system's accuracy across all data conditions.

8.1.2 Usability and Readability Testing with Mixed-Quality Data

Objective

My task is to assess the usability and readability of the system's results when dealing with datasets of mixed quality. A subjective test however it is important to determine if the system is still capable of generating readable graphs when the system gets noisy.

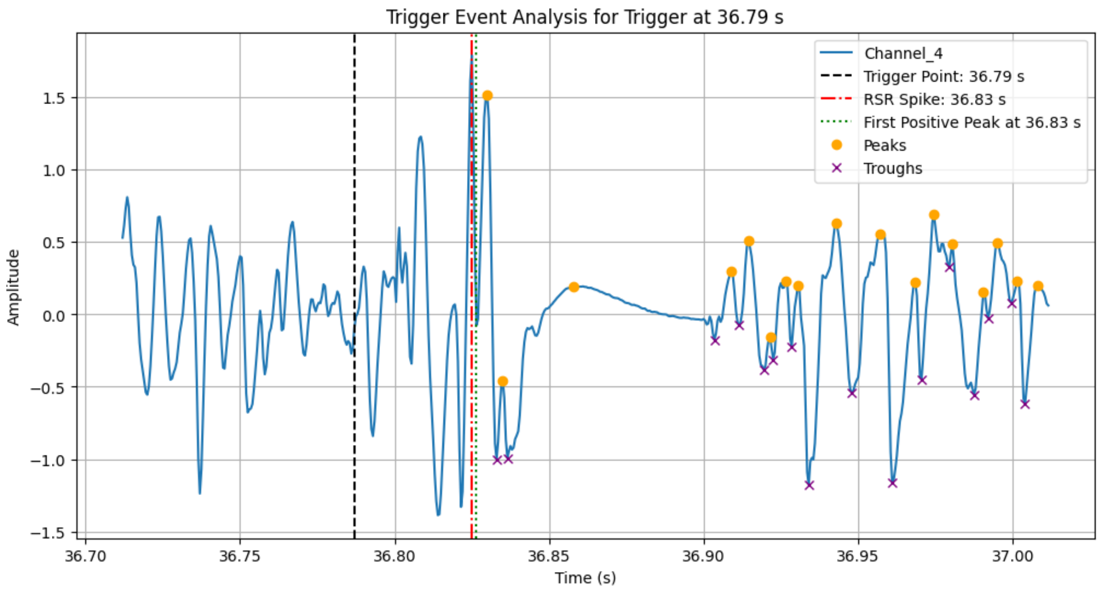

Figure 8: Standard View of a Channel 4 CSP event

Test Methods

I examined the system's outputs from analysing clear and noisy datasets. Through the graphical representations for Channel 1 and Channel 4, I reviewed the signal's peaks and troughs for clarity and definition. These graphical outputs will be interspersed throughout this document to illustrate the points of interest. Additionally, I tested the system's one-click functionality to ensure a seamless transition from data input to visual output and that the results were displayed clearly.

Success Criteria

The benchmark for success is based on my ability to discern the critical information from the mixed-quality dataset within a maximum of two additional minutes over the time it would take with high-quality data. The interface should aid in this efficiency, with the one-click operation facilitating a swift and intuitive analysis process.

This testing showed that the system meets the established usability and readability criteria when confronted with mixed-quality data. The outputs for Channel 1, representing high-quality data, displayed sharply defined features that allowed for quick identification of CSPs. Channel 4's less clear data yielded understandable graphs after preprocessing, which were readable despite the increased noise levels.

The success criteria also highlight the importance of system efficiency and intuitiveness, maintained across the board. The one-click operation and user interface elements proved to be user-friendly. I could navigate the system without difficulty, reinforcing the system's effectiveness in providing clear, actionable results regardless of data quality.

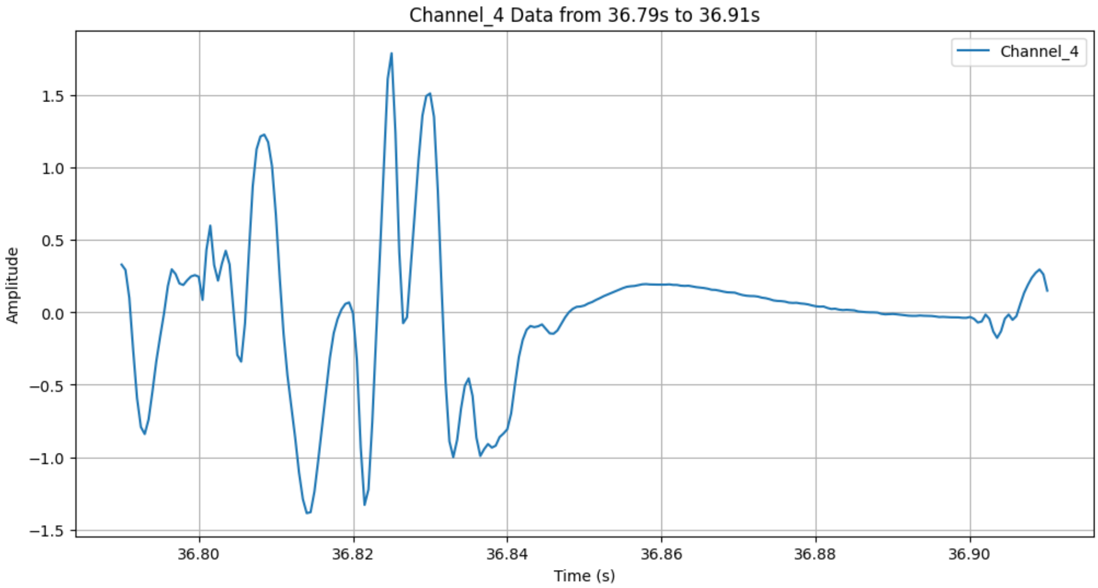

Figure 9: Zoomed in display of Channel 4 CSP event

8.1.3 Evaluation of System Adaptability and Robustness

Introduction

Based on the initial feedback I received from the internal demos and the iterations that followed. My reliance in the early stages of the development on the use of Channel_1 data over Channel_4 data made it evident to me that I would have to address this in the system's design at a later stage.
The system's scale was also adjusted to reflect the data's "True Values" and better mark the key events apparent in the waveform: the rSR, where the trigger event begins, the first peak post-rSR, and better clarity of the waveform during the CSP event.

Objective

I aim to pinpoint areas for system enhancement to better analyse mixed-quality data, which is common in real-world scenarios. As per my introduction, it is important that data from different sources and different clarity can still be accurately detected and measured.

Test Methods

Upon analysing the outputs from Channel 1 and Channel 4, When first designing the system I noted the clarity of Channel 1's data compared to the more challenging, noisier Channel 4 data. Despite the system's current preprocessing measures, which included basic noise reduction techniques, Channel 4's results still lacked the precision found in Channel 1's outputs. To tackle this, I'm considering recommending the integration of advanced filtering techniques that could better isolate signal from noise, particularly for lower-quality data streams. Moreover, adjustments to the user interface, such as incorporating visual cues that highlight areas of lower data confidence or potentially erroneous detections, could significantly aid users in interpreting results more accurately.

Success Criteria

The key measure of success will be my ability to derive actionable enhancements that refine the system's processing of less clear data. The noise reduction techniques must be capable enough to handle varying signal quality, and the user interface should offer clear indicators of data reliability. Identifying and implementing these enhancements will directly contribute to the system's robustness.

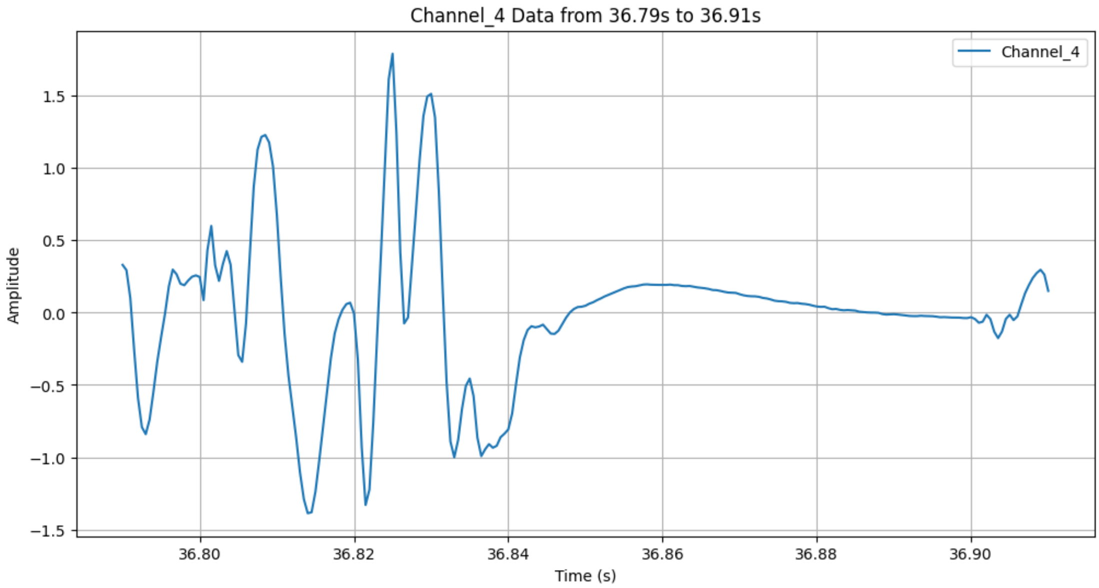

Figure 10: CSP length from Trigger to normal wave funcion according to the AI

Summary of Evaluation Strategy

For this evaluation strategy, I am centring the approach on tests that reflect the diversity and complexity of data encountered in practical settings, such as sports medicine. This encompasses a focus on accuracy, usability, and robustness to comprehensively assess the system's capabilities. The clear delineation of Channel 1's peaks and troughs versus the noisier profile of Channel 4 has revealed the system's current strengths and areas for improvement.

Applying refined digital signal processing methods, such as adaptive filtering or machine learning-based noise classification, could benefit algorithmic enhancements. On the interface front, features like interactive graphs, where users could adjust the noise threshold and instantly see the effects of CSP detection, may provide a more hands-on approach to data analysis.

By striving for a system that is not only technically adept but also intuitive and efficient for users, we cater to the needs of our target audience within the sports medicine community. The valuable insights from this expanded testing will be instrumental in refining the system to excel in real-world conditions, supporting efforts in concussion management and beyond.

9 Conclusion

9.1 Summary

In this dissertation, I embarked on the task of finding an application of a Gpt-4-Vision-based model to detect the CSP a promising indicator for concussion evaluation in contact sports. Leveraging advanced data science methodologies and the prowess of artificial intelligence, I aimed to develop a proof of concept that supplements existing concussion detection protocols and paves the way for reducing human error in manual screening methods.

Python was the cornerstone of this project, providing the structure of the system with its comprehensive libraries and user-friendly nature. The integration of the Vision Preview API allowed me to delve into the sophisticated realms of automatic analysis, combining Python's robustness with AI's advanced capabilities.

The dataset, provided by Thomas Di Virgilio of the Faculty of Health Sciences and Sport, comprised intricate measurements obtained through TMS and Electromyography (EMG). My analysis demonstrated a system capable of achieving commendable accuracy in identifying the CSP from this dataset, fulfilling the stringent requirements set forth at the beginning of the project.

9.2 Evaluation Of Project Achievement

My achievements within this project reflect a successful demonstration of how AI can enhance concussion detection in contact sports. Even when challenged with mixed-quality datasets, the system's accurate CSP detection supports its potential for real-world application. However, this process also uncovered the system's limitations, particularly with less clear data, offering valuable insights into areas ripe for future development.

The project's adaptability was tested by implementing sophisticated signal processing and AI-driven insights, showcasing my ability to pivot and innovate in the face of technological constraints. Despite these successes, I recognise the necessity for ongoing refinement, particularly in algorithmic precision and user interface design, to ensure the system's resilience and efficiency in varied conditions.

9.3 Reflection on the Project

Reflecting on the entirety of this project, I acknowledge the complexities involved in joining the detailed, process-driven world of concussion detection with the fast-evolving landscape of AI technology. This project was a technical exercise and a lesson in the delicate balance between innovation and practical application.

The system's design and execution highlighted the importance of intuitive user experience and the role of AI as an augmentative tool rather than a replacement for human expertise. As I reviewed the outputs for Channels 1 and 4, it became apparent that AI's role is to support and enhance human decision-making, providing a safety net that could potentially save lives if the technocology is developed further and sees real time use on the side of the playing field.

The adaptability and robustness testing underscored the necessity for a system that can handle the variability inherent in real-world data. The system's performance with mixed-quality datasets signified a promising start. Yet, it also charted the path for enhancements that would make the system not just a concept but a practical tool for medical professionals.

Looking forward, this dissertation lays the groundwork for future exploration into how AI can be and should be integrated into the fabric of sports medicine. It sets a precedent for interfaculty innovation that could redefine athlete safety and healthcare.

This dissertation was a combination of research techniques, technical achievement through implementation, and the vision to create a tool with the potential to positively impact the real world. As AI continues to evolve, its integration into the field of sports medicine holds promise for advancements in the safety and well-being of athletes across the globe. This project is a testament to the strides made and the miles yet to travel on this exciting frontier.

References

[1] "World Rugby," Player Welfare - Medical - Concussion Management for Doctors and Health Care Professionals - SCAT6, 2024. [Online]. Available: https://passport.world.rugby/player-welfare-medical/concussion-management-for-doctors-and-health-care-professionals/scat6/. [Accessed: 24-Mar-2024].

[2] "N. Agarwal, R. Thakkar, and K. D. Than, 'Concussion – Symptoms, Diagnosis and Safety Guidelines,' American Association of Neurological Surgeons, [Online]. Available: https://www.aans.org/en/Patients/Neurosurgical-Conditions-and-Treatments/Concussion.

[Accessed: 24-Mar-2024]."

[3] E. Daly, A. J. Pearce, E. Finnegan, C. Cooney, M. McDonagh, G. Scully, M. McCann, et al., "An Assessment of Current Concussion Identification and Diagnosis Methods in Sports Settings: A Systematic Review," in *BMC Sports Science, Medicine and Rehabilitation*, vol. 14, 2022. [Online]. Available: https://doi.org/10.1186/s13102-022-00514-1. [Accessed: Mar. 24, 2024].

[4] Taulli, T., "Gpt-4 and Bard for Business Automation: Achieving AI-Driven Growth", Monrovia, CA, USA: Apress, 2023. DOI: 10.1007/978-1-4842-9852-7.

Gpt-4 and Bard for Business Automation: Achieving AI-Driven Growth | SpringerLink (stir.ac.UK)

[5] M. B. Locke, S. L. Toepp, C. V. Turco, D. H. Harasym, M. P. Rathbone, M. D. Noseworthy, and A. J. Nelson, "Altered Motor System Function in Post-concussion Syndrome as Assessed via Transcranial Magnetic Stimulation," Clinical Neurophysiology Practice, vol. 5, pp. 157-164, 2020, Accessed March 24, 2024. [Online].

Available: https://doi.org/10.1016/j.cnp.2020.07.004

[6] S. Wilke, D. Groenveld, U. Grittner, J. List, and A. Flöel, "CSPider – Evaluation of a Free and Open-Source Automated Tool to Analyze Corticomotor Silent Period," PLOS ONE, vol. 11, no. 6, e0156066, 2016. [Online]. Available: https://doi.org/10.1371/journal.pone.0156066. [Accessed: Mar. 24, 2024].

[7] Anaconda Inc., "Anaconda Software Distribution." [Online]. Available: https://www.anaconda.com/

[Accessed: Mar. 24, 2024].

[8] Project Jupyter, "JupyterLab." [Online]. Available: https://jupyter.org/.

[Accessed: Mar. 24, 2024].

[9] SciPy developers, "SciPy: Open-source scientific tools for Python." [Online]. Available: https://scipy.org/

[Accessed: Mar. 24, 2024].

[10] BioRead Library, "BioRead: A library for processing and analysing biological signal data." [Online]. Available: https://pypi.org/project/bioread/

[Accessed: Mar. 24, 2024]

[11] OpenAI, "Gpt-4-4 Vision Preview," 2024. [Online].

Available: https://platform.openai.com/docs/guides/vision

[12] A. Conway, “How to jailbreak Gpt-4: Get it to do anything you want,” *XDA Developers*, Jan. 18, 2024.
Available: https://www.xda-developers.com/how-jailbreak-gpt-4

[13] M. Kofler, U. Ziemann, and V. K. Kimiskidis, “CSP,” in *Oxford University Press eBooks*, 2021. doi: 10.1093/oxfordhb/9780198832256.013.12.
Available: CSP | The Oxford Handbook of Transcranial Stimulation: Second Edition | Oxford Academic (oup.com)

[14] M. A. Garvey, U. Ziemann, D. A. Becker, C. A. Barker, and J. J. Bartko, “New graphical method to measure silent periods evoked by transcranial magnetic stimulation,” *Clinical Neurophysiology*, vol. 112, no. 8, pp. 1451–1460, Aug. 2001, doi: 10.1016/s1388-2457(01)00581-8.
Available: New graphical method to measure silent periods evoked by transcranial magnetic stimulation - ScienceDirect
[15] “Pricing.” https://openai.com/pricing

[16] K. E. Hupfeld, C. W. Swanson, B. W. Fling, and R. D. Seidler, “TMS-induced silent periods: A review of methods and call for consistency,” *Journal of Neuroscience Methods*, vol. 346, p. 108950, Dec. 2020, doi: 10.1016/j.jneumeth.2020.108950.

[17] T. G. Di Virgilio *et al.*, “Evidence for acute electrophysiological and cognitive changes following routine soccer heading,” *EBioMedicine*, vol. 13, pp. 66–71, Nov. 2016, doi: 10.1016/j.ebiom.2016.10.029.
Available:
https://www.sciencedirect.com/science/article/pii/S235239641630490X?via%3Dihub

[18] A. Ns, “What is Data Analysis? How to Visualize Data with Python, Numpy, Pandas, Matplotlib & Seaborn Tutorial,” *freeCodeCamp.org*, Oct. 28, 2021.
Available: https://www.freecodecamp.org/news/exploratory-data-analysis-with-numpy-pandas-matplotlib-seaborn/

[19]“Quick start guide — Matplotlib 3.8.4 documentation.” Available: https://matplotlib.org/stable/users/explain/quick_start.html

[20] "OpenAI API Documentation," OpenAI, 2024. [Online]. Available: https://platform.openai.com/docs/api-reference. [Accessed: Jan-20-2024].

10 Appendix 1 – Testing results from Channels 1 and 4 accuracy measurement

10.1 Channel 1 Testing

Iteration	trace1(ms)	trace2(ms)	trace3(ms)
1	120	120	120
2	100	100	100
3	140	120	120
4	120	120	120
5	130	120	100
6	120	120	120
7	135	130	125
8	120	120	120
9	120	120	120
10	130	130	130
	123.5	**120**	**117.5**

benchmark1(ms)	benchmark2(ms)	benchmark3(ms)
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5
123	124	124.5

deviation1(ms)	deviation2(ms)	deviation3(ms)
3	4	4.5
23	24	24.5
17	4	4.5
3	4	4.5
7	4	24.5
3	4	4.5
12	6	0.5
3	4	4.5
3	4	4.5
7	6	5.5
8.1	**6.4**	**8.2**

10.2 Channel 4 Testing

Iteration	trace1(ms)	trace2(ms)	trace3(ms)
1	100	100	100
2	120	120	120
3	130	130	130
4	105	110	110
5	130	130	110
6	115	90	90
7	100	100	100
8	130	130	130
9	120	130	120
10	80	100	100
	113	**114**	**111**

benchmark1(ms)	benchmark2(ms)	benchmark3(ms)
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5
114.5	119.5	118.5

deviation1(ms)	deviation2(ms)	deviation3(ms)
14.5	19.5	18.5
5.5	0.5	1.5
15.5	10.5	11.5
9.5	9.5	8.5
15.5	10.5	8.5
0.5	29.5	28.5
14.5	19.5	18.5
15.5	10.5	11.5
5.5	10.5	1.5
34.5	19.5	18.5
13.1	**14**	**12.7**

Appendix 2 – User Guide

Due to the simplicity of the system simply run the script from a folder containing the CSP_Example.acq file and it should run accordingly. You will need to provide an api key in order to run the system as well as money in an OpenAI API account.

Appendix 3 – Initial JSON Prompt

```
import base64
import requests

# OpenAI API Key
api_key = ""

from openai import OpenAI

# Function to encode the image
def encode_image(image_path):
  with open(image_path, "rb") as image_file:
    return base64.b64encode(image_file.read()).decode('utf-8')

# Path to your image
image_path = "CSP.jpg"

# Getting the base64 string
base64_image = encode_image(image_path)

headers = {
  "Content-Type": "application/json",
  "Authorization": f"Bearer {api_key}"
}

payload = {
  "model": "gpt-4-vision-preview",
  "messages": [
    {
      "role": "user",
      "content": [
        {
          "type": "text",
          "text": "Look at Channel 1 (blue line): can you identify the period of lowest fluctuation after the rsr' spike at 0.01841, and give very rough estimate of its duration based on the X values?"
```

```
      },
      {
        "type": "image_url",
        "image_url": {
          "url": f"data:image/jpeg;base64,{base64_image}"
        }
      }
    ]
  }
],
"max_tokens": 300
}

response = requests.post("https://api.openai.com/v1/chat/completions", headers=headers, json=payload)

print(response.json())
content = response.json()['choices'][0]['message']['content']
print(content)
```