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Original Article

A Novel Approach for Non-Invasive, Brain-Computer Interaction Using Electroencephalogram Signals

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Abstract *- This paper presents a novel approach for non-invasive, brain-computer interaction using signals acquired from an end user. The proposed system employs a hybrid Machine Learning (ML) model to analyze EEG (Electroencephalogram) signals from the user's brain, which are then digitized, processed, and mapped to appropriate outputs, ultimately enabling users to control a video game environment and play a game without needing any physical inputs. This paper also aims to develop a video game that seamlessly integrates with and masks the limitations of a BCI. This innovative approach opens up new possibilities for human-computer interaction, offering an intuitive and efficient means of control. By using P300 signals along with mu rhythms, the system maximizes functionality and provides a seamless and immersive user experience. The non-invasive nature of the sensors ensures comfort and ease of use.*

Keywords – *Machine Learning, BCI, Electroencephalogram, OpenBCI.*

1. Introduction

In recent years, the convergence of neuroscience and technology has paved the way for groundbreaking advancements in human-computer interaction. One compelling avenue of exploration within this intersection is the development of Brain Computer Interfaces (BCIs) for gaming applications. A brain-computer interface, often known as a BCI, is a device that collects signals from the brain, processes them, and then converts those signals into commands that are then transmitted to output devices that carry out the intended tasks. Neuromuscular output channels are not utilized by BCIs in the conventional manner[11]. BCIs offer the tantalizing prospect of direct communication between the human brain and virtual environments, transcending traditional input methods. This synergy of neuroscience and gaming has the potential to revolutionize the gaming experience by allowing players to seamlessly control and navigate game environments using their neural activity.

This research endeavors to propel the optimization of BCI specifically tailored for gaming contexts. Employing a sophisticated approach, the study integrates the power of hybrid machine learning techniques to enhance the accuracy, adaptability, and real-time responsiveness of these interfaces. By combining classical signal processing methodologies with modern deep learning architectures, the aim is to create a synergy that unlocks the full potential of extracting meaningful information from Electroencephalogram (EEG) signals. This fusion of techniques seeks not only to decode the intricacies of the human brain's electrical patterns but also to map these patterns to precise and intuitive controls within the gaming realm.

2. Literature Survey

Brain Computer Interfaces (BCIs) are emerging as a significant technology in the realm of gaming, providing new ways for users to interact with games through brain activity alone. In the 1970s, the first research articles on brain-computer interfaces, or BCIs, were published. These studies focused on an alternate transmission channel that is independent of the brain's typical muscle and peripheral nerve output pathways [1]. A prosthetic limb could be controlled to perform a desired action by measuring and decoding brainwave signals, according to the original notion of a brain-computer interface [2]. Subsequently, a direct communication channel between the human brain and an external device was defined as "BCI" in a formal definition [3]. The research and technical challenges involved in developing BCI games differ significantly based on the type of BCI paradigm used, the game genre, and specific gameplay challenges. BCI control strategies [4] [5] are crucial areas of focus for advancing the field, especially for gaming and other interactive applications.

[12] Focuses on the art of employing Brain-Computer Interaction (BCI) in games and examines the implications of using knowledge from Human-Computer Interaction (HCI) to the design of BCI for entertainment purposes. It has been demonstrated that the majority of BCI games have

underwhelming performance in terms of both accuracy and speed. Furthermore, utilizing the research methods that are now available, it has been challenging to find a commercial product that has been effective.[13]

2.1. BCI Control Strategies

2.1.1. Signal Processing and Feature Extraction

Preprocessing

This involves cleaning the raw EEG signals to remove noise and artifacts (e.g. muscle movements, eye blinks). Several techniques like filtering, Independent Component Analysis (ICA) and Common Spatial Patterns (CSP) are used [6].

Feature Extraction

The signal that has been preprocessed gives rise to the extraction of essential characteristics, including amplitude, frequency, and phase. Methods such as the Fourier Transform, Wavelet Transform, and Time-Frequency Analysis are examples of standard approaches.

In addition, various methods make use of skewness, kurtosis, or root mean square measurements in order to identify and eliminate artifacts.

2.1.2. Classification and Pattern Recognition

Machine Learning Algorithms

These are used to classify different mental states or commands from the extracted features. Common classifiers include Support Vector Machines (SVM), Linear Discriminant Analysis (LDA) and Neural Networks.

Deep Learning Approaches

CNNs and RNNs, which stand for convolutional neural networks and recurrent neural networks, respectively, have demonstrated significant potential in enhancing classification accuracy through the process of automatically learning useful features from raw EEG data.

2.1.3. Control Paradigms

Event-Related Potential (ERP) Based Control

Uses specific brain responses to stimuli, such as the P300 wave [7], to make selections or trigger actions.

Motor Imagery (MI)

Includes picturing particular actions in order to elicit equivalent brain activity, which is subsequently translated into orders for the game [8]. Studies conducted in recent years have demonstrated that motor imagery can excite neurons and generate neuroplasticity, making it an effective method for post-stroke rehabilitation [9].

Steady-State Visually Evoked Potentials (SSVEP)

Utilizes brain responses to flickering visual stimuli of different frequencies to enable control based on the user's focus on specific targets.

2.1.4. Feedback Mechanisms

Visual Feedback

Providing visual cues [10] or changes in the game environment based on the user's brain activity to enhance control and learning.

Haptic Feedback

Using tactile sensations to give users a sense of touch or pressure, enhancing the immersive experience.

Auditory Feedback

Using sound cues to indicate successful commands or changes in the game state.

3. Materials and Methods

OpenBCI is an organization dedicated to promoting the open-source development of BCI systems and lowering the barrier of entry for Brain-Computer Interfacing. Hence, documentation and research are abundant and publicly available from OpenBCI and other sources, enabling researchers to develop a system based on OpenBCI's schematics, along with the signal processing system and machine learning algorithm to classify and map the brain signals to a custom-made video game which is being developed for BCI. Given the challenges and gaps discussed in the previous section, the proposed solution is MINERVA. MINERVA is a lower-cost and more accessible BCI system augmented with Machine Learning. MINERVA is subdivided into two modules: the EEG module and the Machine Learning (ML) module. MINERVA, in conjunction with the Video Game, makes up the complete project. The system is subdivided into modules, aiming to minimize the noise and errors at each stage while also maximizing and optimizing the throughput at each stage. This research aims to set up a functional BCI-ML system (MINERVA). It is chosen to limit the scope of the paper to playing a game due to both time and budget constraints. The research has a wide range of practical applications in fields such as home automation and bionics, but the research in the paper is limited to creating a base template model, i.e. MINERVA, for other researchers or projects to use for their specific purposes. Figure 1 shows the system flow chart for representing the hardware and software layers.

At its core, the system can be divided into three component systems: the EEG Module, the Machine Learning model, and the Video Game. The EEG Module takes input signals from the user via non-invasive electrodes, processes them, and passes them onto the Machine Learning model, which then classifies them and provides an accurate output for game control. This setup leverages the unique strengths of BCI while addressing its limitations and working to overcome them. This research foresees a global utility for this project, enhancing entertainment and opening new avenues for both consumers and artists to engage with one another.

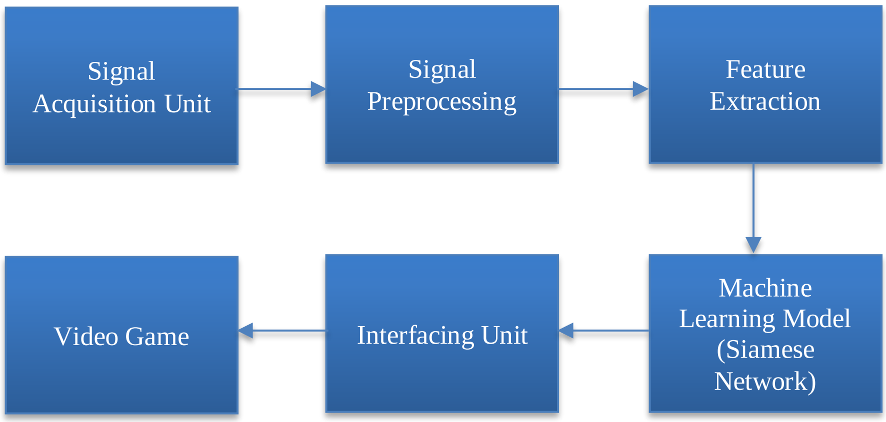


Fig. 1 System flow diagram

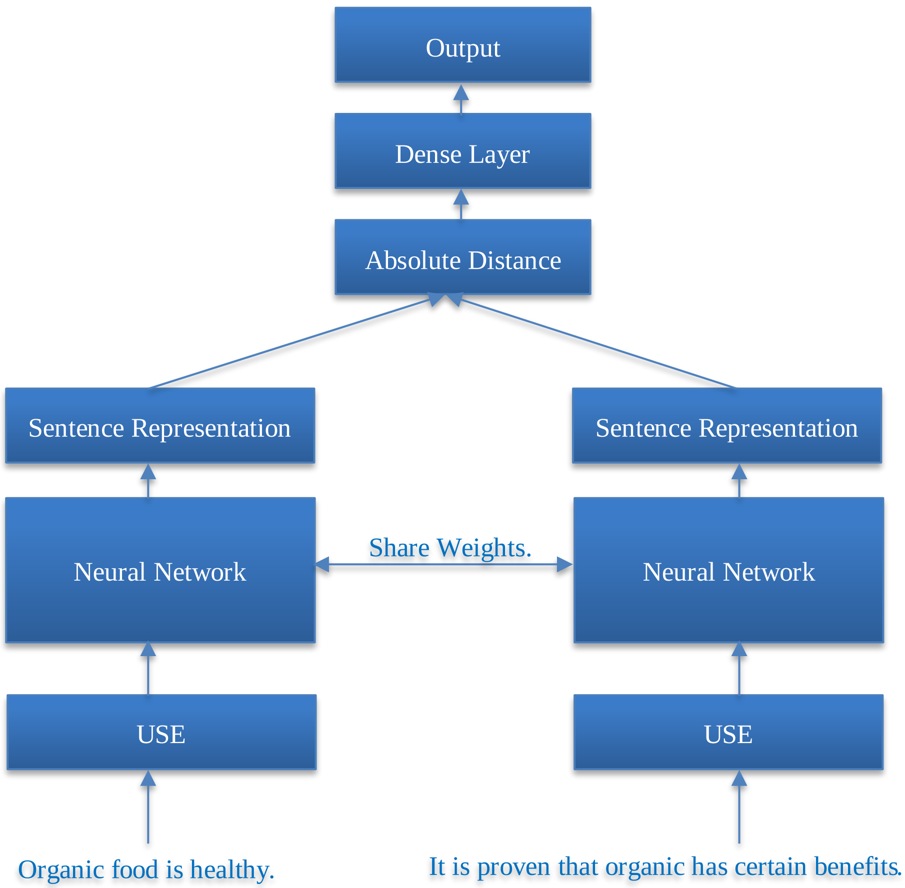


Fig. 2 Siamese network for text classification

The system can be divided into two broad sections: Hardware and Software, as shown in Figure 2, with MINERVA encompassing a section of both. The Hardware layer of the system includes the electrodes and their mounts, the circuitry to acquire the EEG signals, including the adapters, cables, etc., the electronic components to process signals, like the ADS 1299, or the low-pass filter and convert them into digital signals that can be recognized by the computer and in turn the machine learning model. The software includes the drivers to interface the processed signals with the computer, the Machine Learning model, the interfacing software between the hardware and the model, and the game itself.

The Signal Acquisition Unit and the Signal Processing Unit are shown in Figure 3. The EEG headset is designed, and it consists of a 3D printed frame based on the 10-20 electrode placement system; spiky electrodes will be used to record the EEG data from the user's head.

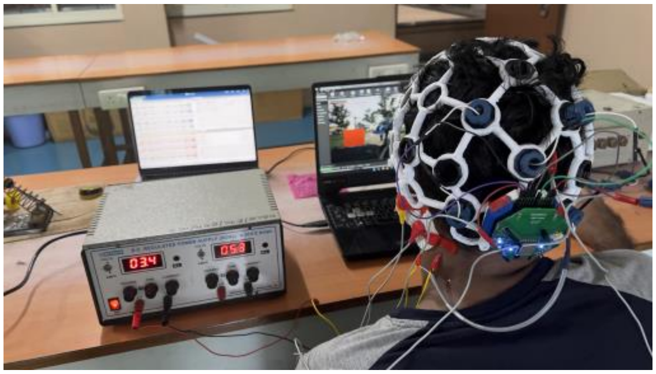


Fig. 3 Experimental setup

For all software designed, there must be a Software Development Life Cycle (SDLC) that is followed for efficient and effective development. A critical part of the SDLC is the development model that is used to build and test the model. There are several popular models, like the Spiral Model, Waterfall Model and V-Model. The Rapid Prototyping Model, which is an enhanced version of the Waterfall Model, is used in the paper. (regex) have long been indispensable tools for developers engaged in text processing, searching, and pattern matching within the realm of computer programming. They provide a concise and powerful way to describe complex patterns in strings, enabling developers to efficiently manipulate and extract information from textual data. Example 1: Consider a common scenario in application development where a developer needs to validate a phone number entered by the user. In this context, a regular expression can be employed to ensure that the entered phone number adheres to a specific pattern.

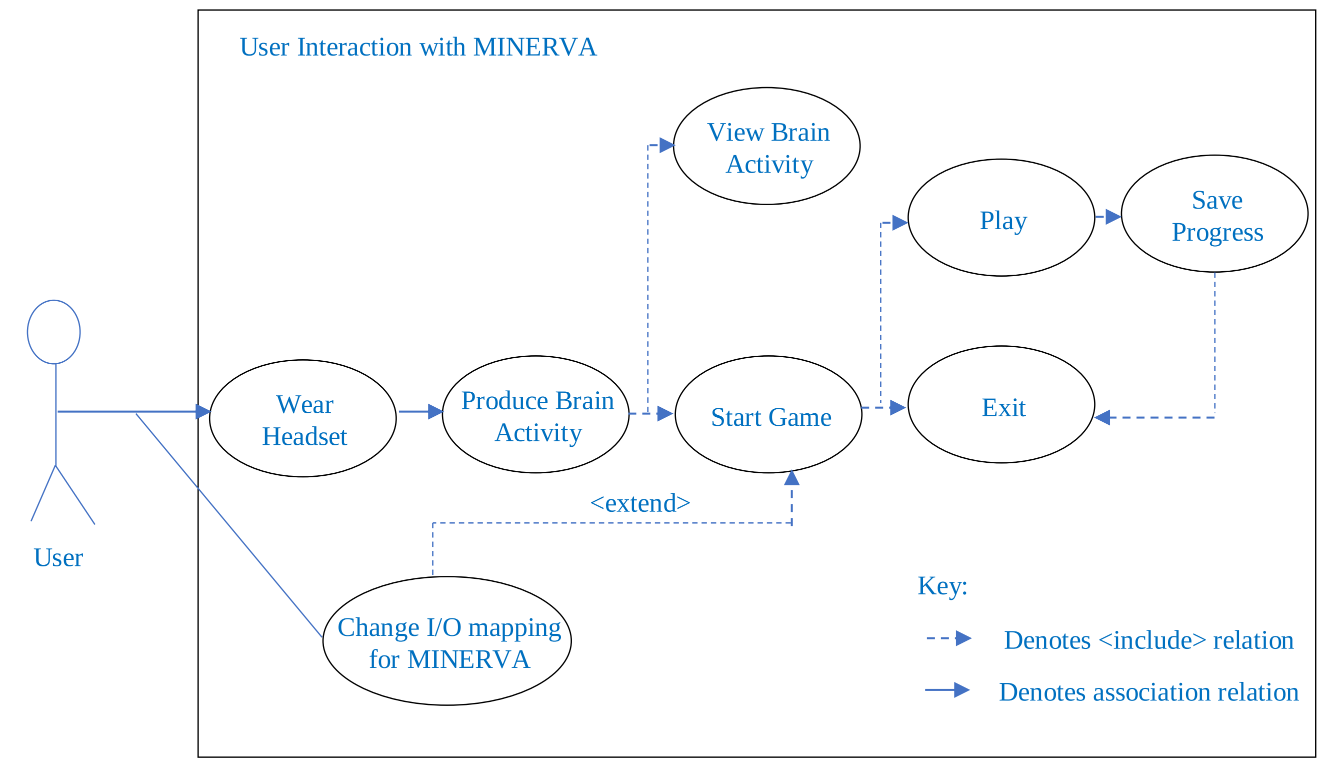


Fig. 4 Use case diagram for the proposed system

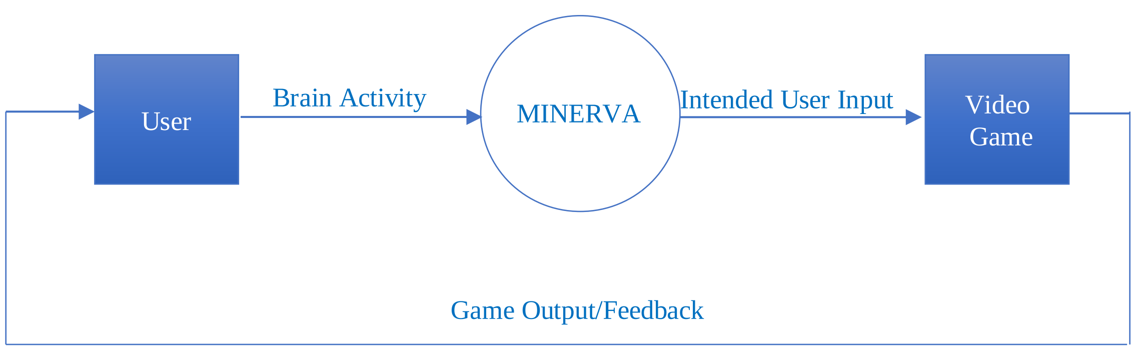


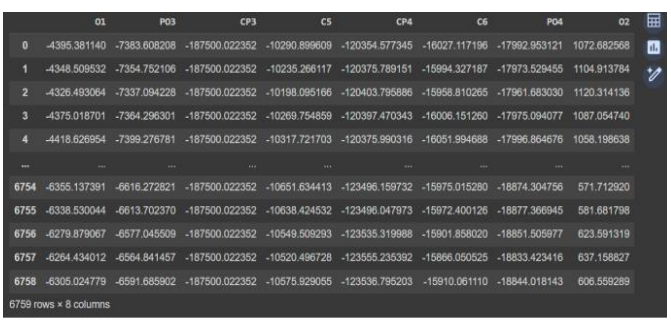
Fig. 5 Dataflow diagram

The use case diagram is shown in Figure 4. The user wears a headset and produces brain signals. Then, the user can start a game and can decide to play or exit the game according to the user's preference.

Figure 5 shows a data flow diagram. The user's brain activity is processed by Minerva, and the output is given to the video game. The design process involves three stages: component research, PCB layout, and fabrication. The electrodes are connected to header pins on the board, by which the signal first passes through the low-pass Filter. To achieve precision standards in the research, the ADS1299 is used. This device is an advanced eight-channel Analog-to-Digital Converter (ADC) featuring simultaneous-sampling delta-sigma technology. It operates at 24 bits and is renowned for its low noise characteristics. Additionally, the ADS1299 integrates a Programmable Gain Amplifier (PGA), internal reference voltage, and an on-board oscillator, making it highly versatile for high-precision. Each of these components is carefully selected and integrated according to the specific requirements of the PCB design, ensuring reliable operation and functionality of the entire system.

4. Results and Discussion

The OpenBCI GUI stores the raw data collected by the electrodes in the form of a text file in the GUI directory. First, MINERVA finds the latest subdirectory of the GUI directory and then finds the latest file within this directory. This is the file being used to record the current session. This file is then imported into Python and cleaned. OpenBCI uses a recording format that stores a lot of information other than the raw data itself, including timestamps, accelerometer readings and session metadata applications. Using its suite of custom-written functions, MINERVA cleans up the file and stores only the relevant signal information.



	O1	PO3	CP3	C5	CP4	C6	PO4	O2
0	-4395.381140	-7383.608208	-187500.022352	-10290.899609	-120354.577345	-16027.117196	-17992.953121	1072.682568
1	-4348.509532	-7354.752106	-187500.022352	-10235.266117	-120375.789151	-15994.327187	-17973.529455	1104.913784
2	-4326.493064	-7337.094228	-187500.022352	-10198.095166	-120403.795886	-15958.810265	-17961.683030	1120.314136
3	-4375.018701	-7364.296301	-187500.022352	-10269.754859	-120397.470343	-16006.151260	-17975.094077	1087.054740
4	-4418.626954	-7399.276781	-187500.022352	-10317.721703	-120375.990316	-16051.994688	-17996.864676	1058.198638
...	...	...	...	...	...	...	...	...
6754	-6355.137391	-6616.272821	-187500.022352	-10651.634413	-123496.159732	-15975.015280	-18874.304756	571.712920
6755	-6338.530044	-6613.702370	-187500.022352	-10638.424532	-123496.047973	-15972.400126	-18877.366945	581.681798
6756	-6279.879067	-6577.045509	-187500.022352	-10549.509293	-123535.319988	-15901.858020	-18851.505977	623.591319
6757	-6264.434012	-6564.841457	-187500.022352	-10520.496728	-123555.235392	-15866.050525	-18833.423416	637.158827
6758	-6305.024779	-6591.685902	-187500.022352	-10575.929055	-123536.795203	-15910.061110	-18844.018143	606.559289

6759 rows × 8 columns

Fig. 6 Processed and cleaned data by MINERVA

Figure 6 shows the processed and cleaned data by Minerva. Minerva is designed for high-performance data processing and supports huge networks. The size of data and performance is no issue in Minerva.

Once data has been stored, using the pandas' library, MINERVA converts the data into a data frame data structure for easier and faster processing. The advantages of filters are that they can really help increase the SNR of signals, especially in situations where the target EEG signals are in a limited band.

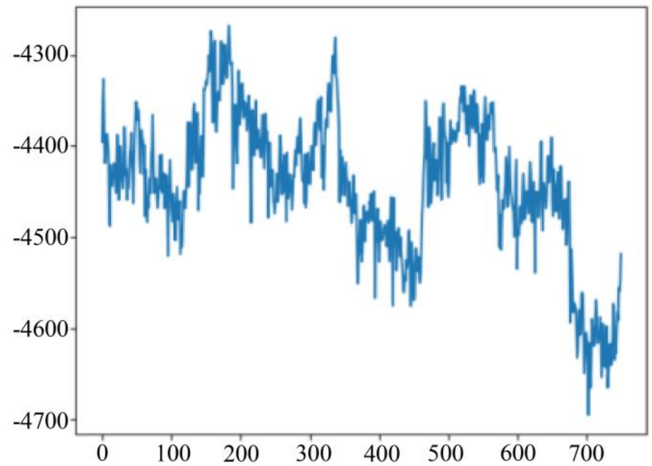


Fig. 7 Raw SSVEP signal using Matplotlib

From here, this data frame is passed onto MINERVA's pre-processing suite. The plot of the raw SSVEP signal is shown in Figure 7. In this paper, the PCA is used, as it is a relatively simple and common algorithm that can give results that rival other methods. On implementing PCA, it can be seen how many features correlate to the amount of variance in the data. After PCA is applied, a total of 27 features out of the original 160 remain, which encapsulate 95% of the variance in the data, as shown in Figure 8. MINERVA proceeds to label the dataset and exports it as an Excel file.

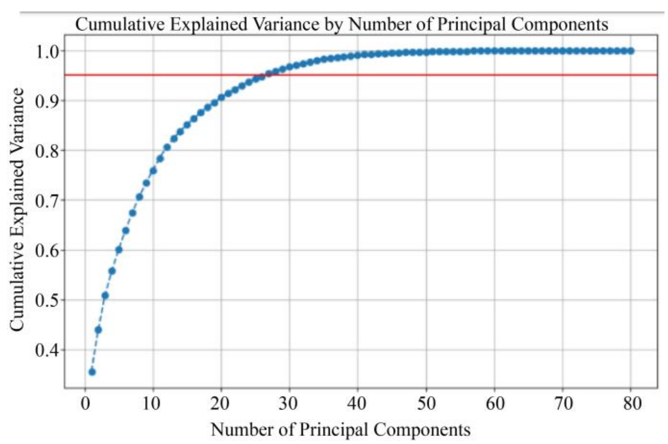


Fig. 8 Cumulative variance graph for 160 feature dataset

This game is built as a demonstration project in order to showcase the capabilities and applications of the BCI system. It allows the user to control a playable character in a virtual environment. The player is spawned in a cave, which they have to navigate in order to get teleported to the next level, where they fight the main boss of the game. The game features a basic melee combat system, allowing the player to partake in combat. It also makes use of flashing buttons on the HUD

(Head Up Display) in order to stimulate the user and generate P300 signals. The initial level is set in a dimly lit cave, designed to create an atmosphere of mystery and anticipation. The layout encourages exploration, with the teleporter being a key element that transports the player to the second map. The User Interface (UI) is kept minimalistic to avoid distractions and enhance the focus on BCI control. Key UI elements include health bars for the player and the boss enemy, as well as simple prompts that are flashing buttons on the screen to act as novel stimuli to invoke SSVEPs. As the connecting point between the game and hardware, MINERVA shoulders the responsibility of facilitating communications and data transfer between them. The algorithm is as follows:

- Initialize: Initialize MINERVA and the recording session. Finds the file for the current session and reads the metadata and initial readings.
- File Clear: Clears the contents of the file after reading data to ensure faster access and accurate current readings.
- Data Read/Write: Reads the current data epoch from the file and writes it to memory.
- Processing: Processes the data and passes it to the model for predictions.
- Output Write: Writes the prediction of the model to an output file, which is being constantly read by the game. Once an output is written, the file will be cleared before another output is written to avoid ambiguity.
- Repeat steps 2-5 for as many iterations as desired.

The data is processed as input and written as output in the form of .txt files and .csv files, respectively, requiring the read csv() function in the Pandas library.

Fig. 9 Game interface output

The GUI, as shown in Figure 9, successfully received the streamed data via WiFi and displayed it in real-time. This allowed for immediate assessment of the signal quality and enabled quick adjustments to the setup if necessary. The GUI also provides intuitive controls for adjusting the gain settings of each channel. Proper gain adjustments are essential for optimizing the signal amplitude and achieving a high signal-to-noise ratio.

The GUI's band-pass filter functionality allowed users to isolate the EEG frequency range of interest, typically between 0.5 Hz and 50 Hz. The notch filter effectively removed the 50/60 Hz power line interference, a common issue in EEG signal acquisition. By eliminating this specific frequency component, the notch filter improved the overall signal quality and made the data more reliable for subsequent analysis.

The signal acquired by the headset is stored in a text file, whereupon it is retrieved and processed into features, which are then fed to the classifier. Using MATLAB's Classification Learner App, we can test the accuracy of the data on a variety of models. Among all the models, Boosted Trees and Subspace Discriminant models give the best accuracy, above 50%. However, we also have to be careful of overfitting and giving positive results on the training data while completely failing on the test set.

Comparative Results Analysis with existing methods is done below:

- CROWN: Neurosity's CROWN is a consumer EEG device that helps users focus and be productive. It can also be used for applications such as gaming and BCI. Compared to the CROWN, MINERVA is not only more multipurpose, allowing users to control whatever they want and interact with any device through the Wifi-Shield, but it is also cheaper.
- UltraCortex Mark IV: OpenBCI's Cyton board is the design architecture that MINERVA is based upon. However, MINERVA emerges as the clear winner, with all the same functionality, and produced at 1/5th of the cost. MINERVA is light, durable, and easy to use, unlike the Ultracortex.

5. Conclusion

As a BCI system, MINERVA is extremely easy to set up and use for a person who even has little knowledge of Python and EEG Signals. In the future, this may be improved even further by adding documentation to the code. Commercial BCI systems' costs are sky-high, and thus, BCI is not a technology that has taken off in the same way AI has. The benefits are not obvious yet. MINERVA is produced at 1/4th the cost of ANY other commercial BCI system. Using machine learning and basic signal processing, MINERVA has managed to bring down the latency between input and output from up to half a minute to anywhere from 5-10s, up to a 3x improvement. As it is reflected on the journey of the design and implementation of the research, it is clear that the pursuit of this paper has been a testament to interdisciplinary collaboration and the relentless pursuit of pushing the boundaries of what is conceivable.

References

[1] J.J. Vidal, "Toward Direct Brain-Computer Communication," *Annual Review of Biophysics and Bioengineering*, vol. 2, pp. 157-180, 1973. [CrossRef] [Google Scholar] [Publisher Link]

[2] Christoph Guger et al., "Prosthetic Control by an EEG-based Brain-Computer Interface (BCI)," *Proceeding AAATE 5th European Conference for the Advancement of Assistive Technology*, pp. 3-6, 1999. [Google Scholar]

[3] Elizabeth Winter Wolpaw, and Jonathan Wolpaw, *Brain-Computer Interfaces: Principles and Practice*, Oxford University Press, pp. 1-400, 2012. [CrossRef] [Publisher Link]

[4] Mohd Zaizu Ilyas, Puteh Saad, and Muhammad Imran Ahmad, "A Survey of Analysis and Classification of EEG Signals for Brain-Computer Interfaces," *2015 2nd International Conference on Biomedical Engineering (ICoBE)*, Penang, Malaysia, pp. 1-6, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[5] Reza Abiri, "A Comprehensive Review of EEG-Based Brain-Computer Interface Paradigms," *Journal of Neural Engineering*, vol. 16, no. 1, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[6] Jesus Minguillon, M. Angel Lopez-Gordo, and Francisco Pelayo, "Trends in EEG-BCI for Daily-Life: Requirements for Artifact Removal," *Biomedical Signal Processing and Control*, vol. 31, pp. 407-418, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[7] M. Fabiani et al., "Definition, Identification, and Reliability of Measurement of the P300 Component of the Event-Related Brain Potential," *Advances in Psychophysiology*, vol. 2, no. 3, pp. 1-78, 1987. [Google Scholar] [Publisher Link]

[8] Th. Mulder, "Motor Imagery and Action Observation: Cognitive Tools for Rehabilitation," *Journal of Neural Transmission*, vol. 114, no. 10, pp. 1265-1278, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[9] R. Ortner et al., *A Motor Imagery Based Brain-Computer Interface for Stroke Rehabilitation*, Annual Review of Cybertherapy and Telemedicine, Studies in Health Technology and Informatics, vol. 181, pp. 319-323, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[10] Nataliya Kosmyna, and Anatole Lécuyer, "Designing Guiding Systems for Brain-Computer Interfaces," *Frontiers in Human Neuroscience*, vol. 11, pp. 1-15, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Jerry J. Shih et al., "Brain-Computer Interfaces in Medicine," *Mayo Clinic Proceedings*, vol. 87, no. 3, pp. 268-279, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[12] Danny Plass-Oude Bos et al., *Brain-Computer Interfacing and Games*, Brain-Computer Interfaces, pp. 149-178, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[13] Minkyu Ahn et al., "A Review of Brain-Computer Interface Games and an Opinion Survey from Researchers, Developers and Users," *Sensors*, vol. 14, no. 8, pp. 14601-14633, 2014. [CrossRef] [Google Scholar] [Publisher Link]