# Design and Implementation of a Low-Cost EEG-Based Brain–Computer Interface for Real-Time Video Game Control

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**Abstract**—Brain–Computer Interface (BCI) systems enable communication between human brain and external devices without muscular involvement. This work presents how a game can be controlled using electroencephalography (EEG) signals. In this work, EEG signals are collected with the use of a kit known as DIY Neuroscience kit consisting of an Ardunio Uno R4 Minima and BioAmp EXG pill with gel electrodes. The recorded signals are pre-processed using a band pass filter (1-45 Hz) and a notch filter of 50 Hz to remove unwanted noise and distortions. The signals after pre-processing are distributed into small overlapping segments. From each segments, several time-based and frequency-based features are obtained to record important patterns of brain activity. After completion of Pre-processing, Support vector Machine (SVM) and Linear Discrimination Analysis (LDA) is used to train the model, so it can distinguish between attentive and relaxed state. The result shows EEG Signals can be used to control video games. The Study also shows that low-cost EEG hardware combined with machine learning techniques can be used to make more brain-computer systems.

*Keywords*—Brain–Computer Interface, EEG, LDA, Machine Learning, Neuro-Gaming, SVM

## I. Introduction

Brain-computer Interface (BCI) is a technology that allows direct communication between the human brain and any external hardware device. It works by collecting signals released by human brain and convert them into commands which is further followed by computer or any hardware device. Electroencephalography (EEG) is electrical signals released by brain. It can be collected using electrodes placing on scalp.In recent years, EEG-based BCI system have evolved significantly in many different fields of medical, online gaming etc. These systems can also help human to control computers, prosthetic devices, or other electrical devices using brain signals. BCI technology is very useful for the peoples with any physical impairment who have difficulty using traditional input devices such as keyboard or controllers.One very important use of BCI technology is brain-controlled gaming. As it sounds, it needs no physical equipment to be controlled it can be controlled using brain signals. In this type of gaming, games actions are controlled using brain signals. Instead of using keyboard or any other controlled, the player can interact game using different mental states. This creates a new and innovative way of interacting with digital systems and can improve accessibility in gaming.However, EEG signals are very prone to noise and distractions that are often caused by muscle movements and electrical interference as EEG signals are very weak. Therefore, proper signal processing and machine learning (ML) techniques are required to obtain useful information from these signals.

In this work, an EEG based system that allows user to control video game using brainwaves is presented. EEG signals were collected using a hardware set consist of Ardunio Uno R4 Minima and a BioAmp EXG pill with gel electrodes. The signals were collected and the pre-processed to remove noise and unwanted interferences. After pre-processing, different time domain and frequency domain features are extracted for the EEG signals. Different ML algorithms viz SVM and LDA were utilized to classify the brain signals into two states: attentive and relaxed, which was further used to control video game.

Several researches have been done on EEG signals for making aBCI system. For example, Amin developed an EEG-controlled gaming system that allows users to interact with video game using brain signals[1]. Similarly, Moreno-calderon et al. demonstrated a multiplayer video game controlled using BCI technology[2]. Recent research has also focused on improving wearable EEG devices, making BCI system more efficient and suitable for real-world applications [3]. In addition, studies have showed the importance of use of EEG based BCI system in gaming and other purposes[4].

## II. System Architecture

The complete system architecture is shown in Fig.1. The system uses EEG signals to control a video game. First, EEG signals are collected using an Ardunio Uno R4 Minima and a BioAmp EXG pill with gel electrodes. These signals are the filtered from unwanted noise with the help of filters. After filtration, signals are divided into small parts. From each part, important features are extracted to represent brain activity. These obtained features are given to two ML models, SVM and LDA, to classify between attentive and relaxed state of mind. After classification these two states are used to control the game.

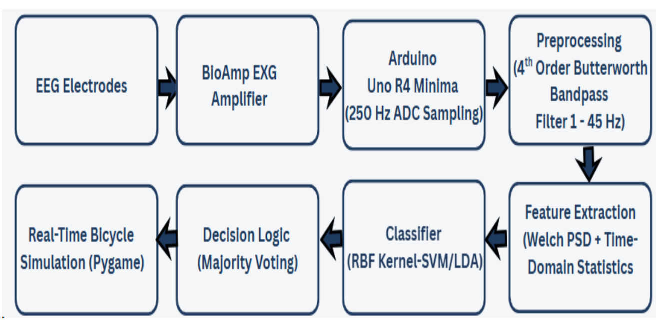


Fig. 1. Overall system architecture of the EEG-based control system

### A. EEG Signal Acquisition

EEG signals are recorded to obtain the electrical activity of the brain. EEG signal were recorded using a low cost hardware setup of an Ardunio Uno R4 Minima and a BioAmp EXG Pill. Gel Electrodes were placed on the scalp to measure the brain signals. These electrodes detect small electrical changes produces by brain activity. The BioAmp EXG pill was used as an amplifier and it amplifies the signal and send the signal to Ardunio Uno R4 Minima for recording. The collected EEG signal is then transferred to a computer for further processing and analysis. As the recorded signal was raw, it contains noise, distortion so it must be pre-processed for further studies. This setup was used to collect EEG signal in simple and cheap way for BCI applications. The signals were recorded from 10 subjects for this study. Data collection is further described in two parts.

1. Hardware setup: EEG signals were collected using a low cost hardware setup which contains an Ardunio Uno R4 Minima and BioAmp EXG pill with gel electrodes. Gel electrodes were placed on scalp using 10-20 electrode placement system. Placements of electrodes were on FP1(Active) and FP2(Reference) points and Ground was placed behind the ear. BioAmp EXG pill was connected to Ardunio Uno R4 Minima to amplify the signal released by brain. Ardunio Uno R4 Minima was connected to computer. Fig. 2 shows acquisition set up.

2. Dataset: 10 subjects were taken to record signals. Each subjects were asked to maintain two states, Attentive and Relaxed. Two chunks of attentive and relaxed states were taken. Subjects were asked to be in Attentive and Relaxed state for 10 minutes each. These recorded signal for 10 minutes was divided into small pieces. The signals were divide into pieces using a 2 second window with 50% overlap, resulting in approximately 11980 EEG segments were obtained from all participants combined as shown in Table 1.
   - Window length: 2 seconds
   - Overlap: 50%
   - Step size: 1 second (because 50% of 2 s = 1 s)
   - Recording time**:** 10 minutes = 600 seconds

Each new EEG segment starts every 1 second.So the number of EEG segments (samples) is given by eq. (1) – (2):

$$\text{Number of segments} = \frac{T-W}{S} + 1 \qquad (1)$$

Where

- $T$= total time (600 s)
- $W$= window length (2 s)
- $S$= step size (1 s)

$$\text{Number of segments} = \frac{600-2}{1} + 1 = 599 \qquad (2)$$

Table 1. EEG Recording Duration and Number of Segments Obtained for Different Cognitive States

| State of mind | Recording Time | EEGSegments Obtained |
|---|---|---|
| Relaxed | 10 minutes | ~599 segments |
| Attentive | 10 minutes | ~599 segments |

Total EEG samples ≈ 1198 segments.

For 10 Subjects: 1198 * 10 = 11980

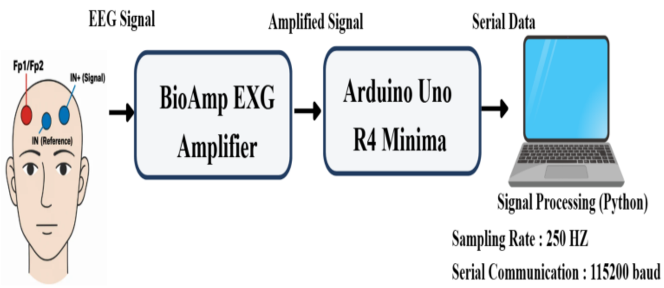


Fig. 2. Single-channel EEG acquisition setup using BioAmp EXG and Arduino

The EEG signals were recorded at a sampling rate of 250 Hz. The EEG data collected is stored in a CSV file. Collected signals are stored in tabular form containing timestamp and voltage. Each row in Table 1 represent to one EEG sample recorded from the BioAmp EXG pill and sent to Arduino Uno R4 Minima.

### B. *Signal Pre-processing*

EEG signal when recorded contains a lot of noise and unwanted signal due to various reasons. Reasons are muscles activity, electrical devices, or other environmental sources. Therefore, pre-processing is important as it is the step in which unwanted noises are removed. It is important to improve the quality of EEG signals before doing any further studies. In this work, a band pass filter (1-45 Hz) is used to keep the required brain signal frequencies and eliminate unwanted low and high frequencies. A 50 Hz notch filter is also used to remove power-line interfaces. After pre-processing, EEG signals are divided into small overlapping segments. This makes it easier to analyse the signals. These signals after filtration are used for feature extraction and ML classification as shown in Fig. 3.

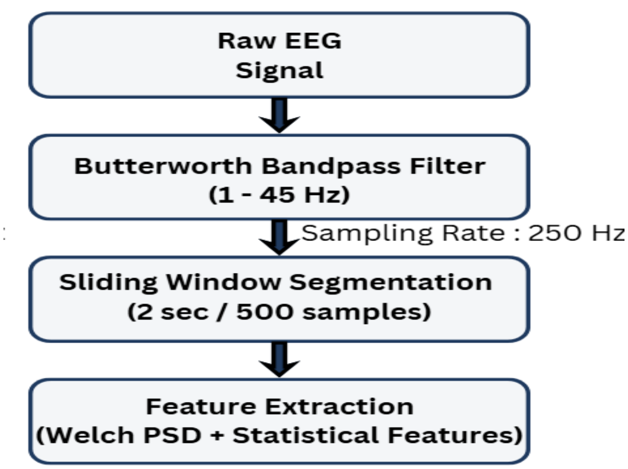


Fig. 3. EEG signal pre-processing pipeline

### C. *Feature Extraction*

Feature extraction converts raw EEG signal into numerical value that can be used by ML algorithm. In this study, both time-domain and frequency-domain features are obtained from each EEG segment.Time-domain features describe the basic features of the signal over time. These include mean, variance, standard deviation, root mean square, skewness, and kurtosis. These values are used in studying the strength, variation, and distribution of the EEG signal within each part.Frequency-domain features are used to study the how the signal energy is distributed across different brainwave frequencies.

Table 2. Different Frequency Ranges

| Frequency Bands | Frequency Range (Hz) | Associated Brain State |
|---|---|---|
| Delta | 0.5 – 4 Hz | Deep sleep |
| Theta | 4 – 8 Hz | Meditation |
| Alpha | 8 – 13 Hz | Relaxed |
| Beta | 13 – 30 Hz | Active |
| Gamma | 30 – 45 Hz | High-level cognition |

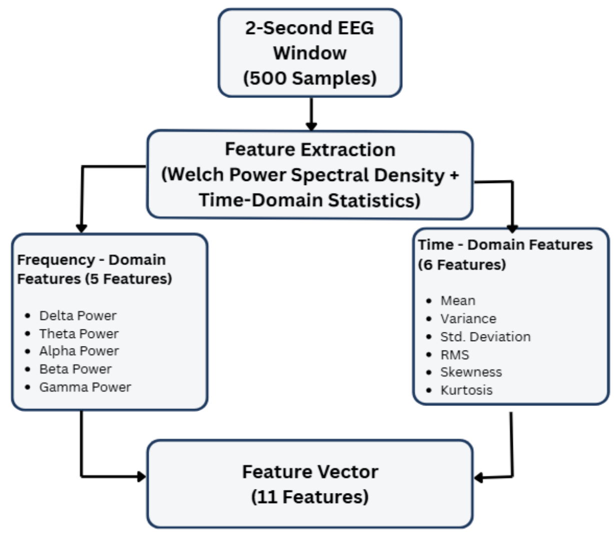


Fig. 4. Extracted EEG feature representation

Spectral analysis is used to calculate the power of the main EEG frequency bands, including delta, theta, alpha, beta, gamma. These frequency bands are related to different brain states such as attention and relaxation. All the frequency bands have different frequency ranges. Table 2 shows the different range of the frequency bands. According to these frequency ranges EEG signals are classified into different states, either attentive or relaxed.In Fig 4. We can see; after pre-processing important time domain and frequency domain features are extracted from parts which were divided into smaller ones. These features are used to represent the important patterns in EEG signals and are used as input for ML classifier. Table 3 shows all 11 extracted features used in this study. Out of 11 features 6 are time domain features and 5 are frequency domain features.

Table 3. Extracted EEG Features

| Feature Type | Feature Name |
|---|---|
| Time Domain | Mean |
| Time Domain | Variance |
| Time Domain | Standard Deviation |
| Time Domain | Root Mean Square (RMS) |
| Time Domain | Skewness |
| Time Domain | Kurtosis |
| Frequency Domain | Delta Power |
| Frequency Domain | Theta Power |
| Frequency Domain | Alpha Power |
| Frequency Domain | Beta Power |
| Frequency Domain | Gamma Power |

### *D. Classification*

After feature extraction, the numerical features obtained from the EEG signals are used for differentiating using ML models. Two ML algorithms were used: Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA). The algorithms are used to differentiate between attentive and relaxed states. It identifies patterns in the EEG data and classify the brain signals into different states of mind. The features obtained after pre-processing were used as an input to both classifier. In this phase, a model is being trained for identifying different states of mind and read the different patterns that matches to different brain states. The main importance of training the model is to correctly identify the Attentive and Relaxed state of the human mind.

SVM is a one of the ML model used to train the model. It separates data into different classes by finding the best boundary between them. In this work, it acts as a line between attentive and relaxed state. It is widely used in EEG signal classification as it works well with complex data. In this work, RBF kernel is used to improve the efficiency of the classification. Another ML used to train the model is LDA. It differentiates the classes by maximizing the difference between them while minimizing the difference between minimizing the variation within each class. After training, classifier was tested using new EEG data. The prediction steps take place next. Mental state was predicted and used to control video game.

### *E. Cross-Validation Strategy*

Cross validation is used to check how proper the ML model perform with new data set. In this work, the Leave One Subject Out (LOSO) cross validation technique is used. This method helps test the data if multiple subjects are available. In LOSO cross validation, the EEG data from one subject is kept for testing and other subjects are used in training the model. The model is first trained so it can learn patterns on brain wave by using training data. After successful training of the model that one subject used for testing is used for test the model. This process is repeated for each subject in the dataset as shown in Fig. 5. Every time a new subject is selected for testing and the remaining are used for training.

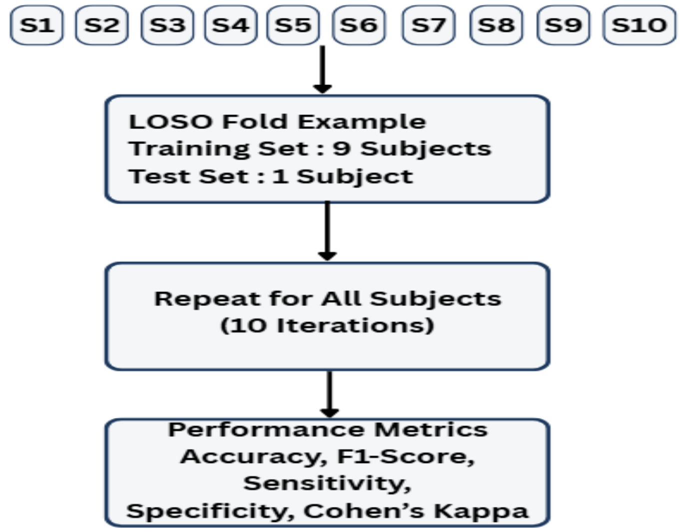


Fig. 5. Leave-One-Subject-Out cross validation strategy

Finally, the result from all the tests is combined to calculate the efficiency and overall performance of if the model. This method provides more efficient performance because the model is always tested on data it has not seen before.

## III. Results and Discussion

EEG signal acquisition was carried out by attaching electrodes to the frontal scalp at positions Fp1/Fp2 to measure the signals generated during the acquisition process. The electrodes detected the signals produced by the neural activity. The signals were then sent to the acquisition system for recording. The EEG signals were then pre-processed to extract features for classification and control purposes in real-time applications.The EEG signal acquisition setup employed for collecting brain wave signals is shown in Fig. 6. 10 subjects were considered for signal acquisition, among which 6 are male and 4 are female of age 20-30 years.

Fig. 6. Real time signal acquisition from 1 subject

The proposed EEG-based system was successfully integrated with a bicycle PyGame simulation for real-time control. Brain signals acquired from the subjects were continuously processed to control the bicycle movement within the simulation environment. In the developed system, increased attention accelerated the bicycle, while a relaxed state deaccelerated its movement. The system demonstrated smooth and responsive interaction between the subject's brain activity and the simulation. Experimental modelling was done using different ML models viz. SVM and LDA. Their performance is compared in Table 4. Statistical features such as mean, variance, RMS, skewness, and kurtosis were obtained from each EEG pieces we got from the EEG signals to describe the shape and variation of the EEG signals. These features describe how EEG signal changes over time. They help the ML model to find pattern in brain signals and distinguish them more perfectly. The experiment modelling achieves an accuracy of 62.40 % using SVM. The same methodology is implemented for real time demonstration. Fig. 7. shows the real-time demonstration of the EEG-based bicycle PyGame simulation.

Table 4.Model Performance Study

| Parameter | SVM | LDA |
|---|---|---|
| Classification Type | Non-linear | Linear |
| Kernel Used | RBF Kernel | Not required |
| Training Speed | Moderate | Fast |
| Complexity Handling | Better for complex EEG patterns | Works well for simple patterns |
| Overall Performance | Better | Slightly lower |

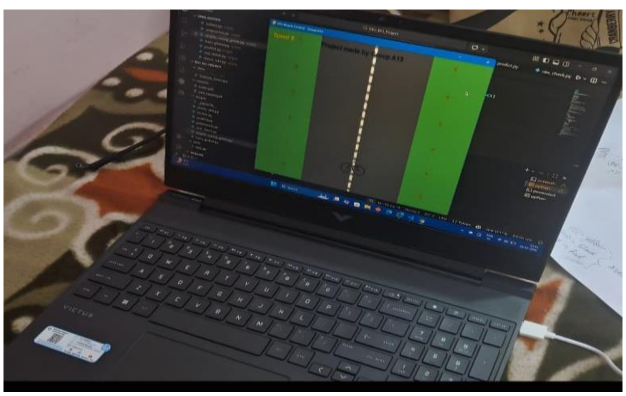

Fig. 7. Real time demonstration of video game control

Experimental evaluation proves that SVM provides slightly better classification performance compared to LDA due to its ability to model nonlinear relationships within the feature as shown in Table 5. However, LDA offers faster calculation and lower complexity. Kappa coefficient of SVM is 0.248 and for LDA is 0.1813.

Table 5. Classification Performance Comparison

| Classifier | Accuracy (%) | Specificity (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| SVM | 62.40 | 53.34 | 71.43 | 64.00 |
| LDA | 59.07 | 38.00 | 79.00 | 66.00 |

The moderate classification accuracy of 62.40% can be attributed to several factors, including inter-subject variability among participants, the use of a single channel EEG, noise contamination during acquisition and the limitations associated with the low-cost EEG hardware. Despite these challenges, the system successfully demonstrated real-time EEG-based game control and validated the feasibility of low-cost brain-computer interface implementations.

## IV. Conclusion

In this paper, an EEG based BCI system for playing a video game is presented. EEG signals were collected using a low cost hardware setup consisting of an Ardunio Uno R4 Minima and BioAmp EXG pill is used with gel electrodes. First, the signal was collected using gel electrodes. BioAmp EXG pill was used to amplify the small brain signals which were sent to Arduino Uno. Ardunio Uno R4 Minima sent the signal to computer. The recorded signals consist of noise. The raw EEG data set were pre-processed to remove all unwanted noise. Filters were used for this purpose. After pre-processing models were trained using SVM and LDA. These helps model to differentiate between attentive and relaxed state of the mind. After training, the model prediction takes place to control the video game. This work shows the low cost EEG device combined with ML methods can be used to develop simple and practical BCI application.

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