BCI4NAT Seminar Report

Dataset Name: S008_L_vs_R_hand

Course: Brain-Computer Interfaces for Neuroadaptive Technology

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Individual contributions:

Vibhav Vedpathak (5011960) mainly worked on EEG preprocessing and pattern analysis using EEGLAB, while Sandip Chaudhary (5006768) focused on classification and evaluation with BCILAB.

Even though we divided the work based on these tools, we made sure to cross-check and validate each other's parts so that both of us understood the full process and remained consistent in our approach. Through this collaboration, we were able to learn from each other's assignments and gain experience with both BCILAB and EEGLAB. Additionally, we worked together to write and refine the remaining parts of the report.

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1. Introduction

Brain–Computer Interfaces (BCIs) convert brain activity into commands that may be put into action, allowing direct connection between the human brain and external technologies. Motor imagery (MI) is one extensively researched use of BCI technology, where people visualise particular movements without actually performing them. Because MI tasks produce distinctive patterns in the electroencephalogram (EEG), especially in the sensorimotor rhythm (SMR) frequency regions, they can be used for control and classification. Our study uses the EEG Motor Movement/Imagery Dataset (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2022), which provides high-quality EEG recordings for motor imagery research. In this project, we are using EEG data from subject S008 of the EEG Motor Movement/Imagery Dataset to investigate the classification of left vs. right hand motor imagery. The primary objectives are to preprocess EEG data, visualise the two MI conditions, and train a classifier using EEGLAB and BCILAB. The aim is to demonstrate the feasibility of MI-based classification for single-subject EEG data and to provide insights into the neural patterns underlying imagined motor activity.

2. Methods

2.1. Experimental Paradigm

The experiment followed a visually guided motor task design in which participants responded to directional targets presented on a screen by either performing or imagining specific motor movements. In each trial, a target appeared on either the left or right side, indicating which hand the participant should imagine moving. The task required the participant to imagine clenching the indicated fist until the target disappeared, after which they were instructed to relax. Each imagery phase was separated by a rest period to allow a clear distinction between mental activity and baseline. The full dataset includes four types of tasks—two involving actual movements (Tasks 1 and 3) and two involving imagined movements (Tasks 2 and 4). For the purpose of this study, only Task 2 was selected, which focuses on the imagined movement of the left versus the right hand.

2.2. Data Acquisition

EEG data were recorded using the BCI2000 system (http://www.bci2000.org), as part of a motor imagery experiment in which each subject completed 14 runs, including two baseline runs and three runs for each of four task conditions. The EEG signals were captured using 64 electrodes arranged according to the international 10–10 system. This information was confirmed by reviewing the official dataset page on OpenNeuro (ds004362). The EEG was sampled at 160 Hz, and event markers were embedded in the recordings to indicate trial onset and task condition (e.g., left or right-hand imagery). These annotations were used for segmenting the EEG data into task-specific epochs for further analysis.

2.3. Dataset

This study used data from the publicly available EEG Motor Movement/Imagery Dataset (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2022), hosted on OpenNeuro. The dataset includes recordings from 109 participants, each completing 14 runs: two baseline runs (with eyes open and eyes closed) and three runs each for four different motor tasks. For this report, we focus exclusively on data from subject S008 performing Task 2, which involves imagined movement of the left and right hands.

In Task 2, each trial is annotated with one of three event codes: T0, T1, or T2. Here, T0 represents the resting period, T1 marks the onset of imagined movement of the left fist, and T2 marks the onset of imagined movement of the right fist. These event markers were used to segment the EEG data into two distinct classes for preprocessing and classification. Since only Task 2 is used in this analysis, event code meanings from other tasks are not relevant to this report.

2.4. EEG Preprocessing

Preprocessing of the EEG dataset was carried out primarily using the EEGLAB GUI in MATLAB 2019a, which provided an interface for filtering, epoching, and referencing. The corresponding commands were retrieved using the eegh history command to extract and compile the underlying script into a reproducible code block. At the start of preprocessing, several filtering strategies were considered to isolate frequency components relevant for motor imagery tasks. Motor imagery is known to induce event-related desynchronization (ERD), particularly in the alpha/mu (8–13 Hz) and beta (12–30 Hz) bands over the sensorimotor cortex. An initial approach was to restrict the analysis to the narrow mu band (8–13 Hz), since this rhythm is strongly associated with sensorimotor activity and is often targeted in motor imagery BCIs. However, since the mu rhythm partly overlaps with the occipital alpha rhythm, a strict focus on 8–13 Hz risked omitting other task-relevant activity. To broaden the captured features, we then considered extending the lower bound to 1 Hz, thereby including delta (1–4 Hz) and theta (4–8 Hz) rhythms, which have been linked to slow cortical potentials and cognitive processes such as attention and motor planning. Ultimately, we applied a 1–30 Hz band-pass filter using the pop_eegfiltnew() function. This range is well-established in BCI practice as it encompasses the key mu and beta rhythms that exhibit ERD/ERS during motor imagery, while at the same time suppressing slow drifts below 1 Hz and high-frequency noise above 30 Hz. This decision is consistent with the feature extraction principles emphasized in the lectures. By preserving both low- and mid-frequency rhythms while reducing irrelevant components, the filter ensured that subsequent classification could draw on a comprehensive set of task-relevant neural features.

The signal was then re-referenced to the common average reference using pop_reref(), a standard step to reduce spatial bias introduced by any individual electrode. Epoching was conducted using pop_epoch(), segmenting the data around event markers 'T1' (left hand) and 'T2' (right hand) within a −1 to +4 second time window. This ensured that both anticipatory and post-stimulus activity were included in the analysis. A baseline correction from −1000 to 0 ms was performed using pop_rmbase() to eliminate DC shifts and inter-trial variability. Each stage of preprocessing was saved using pop_newset to maintain version control.

Although Independent Component Analysis (ICA) was also applied during preprocessing using the GUI and the runica function, the resulting components and associated percentages varied across runs. This inconsistency affected the reproducibility of the pipeline and, as noted in the seminar report instructions, contradicted the requirement for stable and repeatable outputs. While ICA was helpful in visually inspecting components and identifying potential artefacts using the viewprops tool, its outputs were not used in the final report or code to preserve consistency and avoid introducing variability in classification results.

2.5. BCI Approach

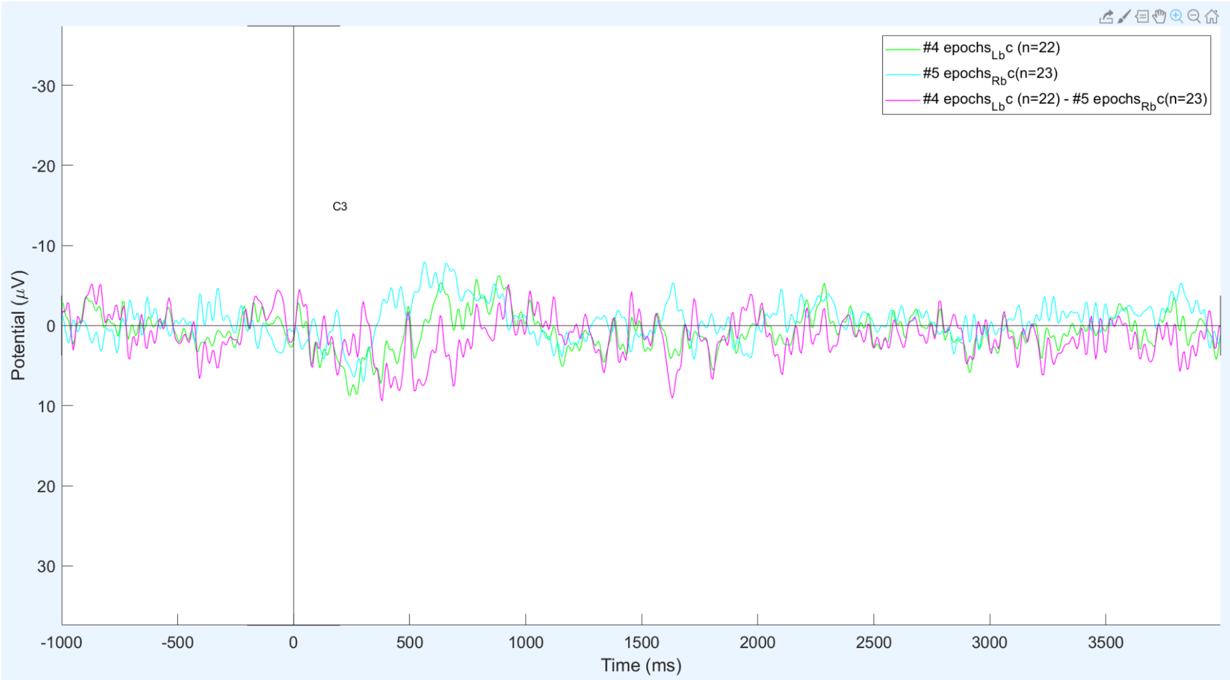
To implement the BCI classification pipeline, we used the Windowed Means paradigm within the BCILAB toolbox, which is suitable for decoding event-related potentials during motor imagery. The EEG dataset (S008_L_vs_R_hand.set) contained trials labelled with the markers T1 (left hand) and T2 (right hand), corresponding to the two classes. In the BCILAB GUI, we selected "Offline Analysis → New approach", choosing "Windowed Means." In the configuration window, we defined a resampling rate of 100 Hz, an epoch range from -1 to 4 seconds, and a frequency band of 8–30 Hz, specifically targeting the motor-related μ (8–13 Hz) and β (13–30 Hz) rhythms. This narrower range was selected to exclude low-frequency components such as delta and theta activity (1–8 Hz), which are less informative for motor imagery and more prone to artifacts, while focusing on the spectral bands known to reflect sensorimotor engagement. Feature extraction was performed over five time intervals from 0 to 2.5 seconds post-stimulus. These windows allowed us to capture the evolving EEG patterns related to motor planning and imagination. The classifier used was Linear Discriminant Analysis (LDA), a standard method for binary EEG classification due to its robustness and interpretability.

2.6. Classifier training

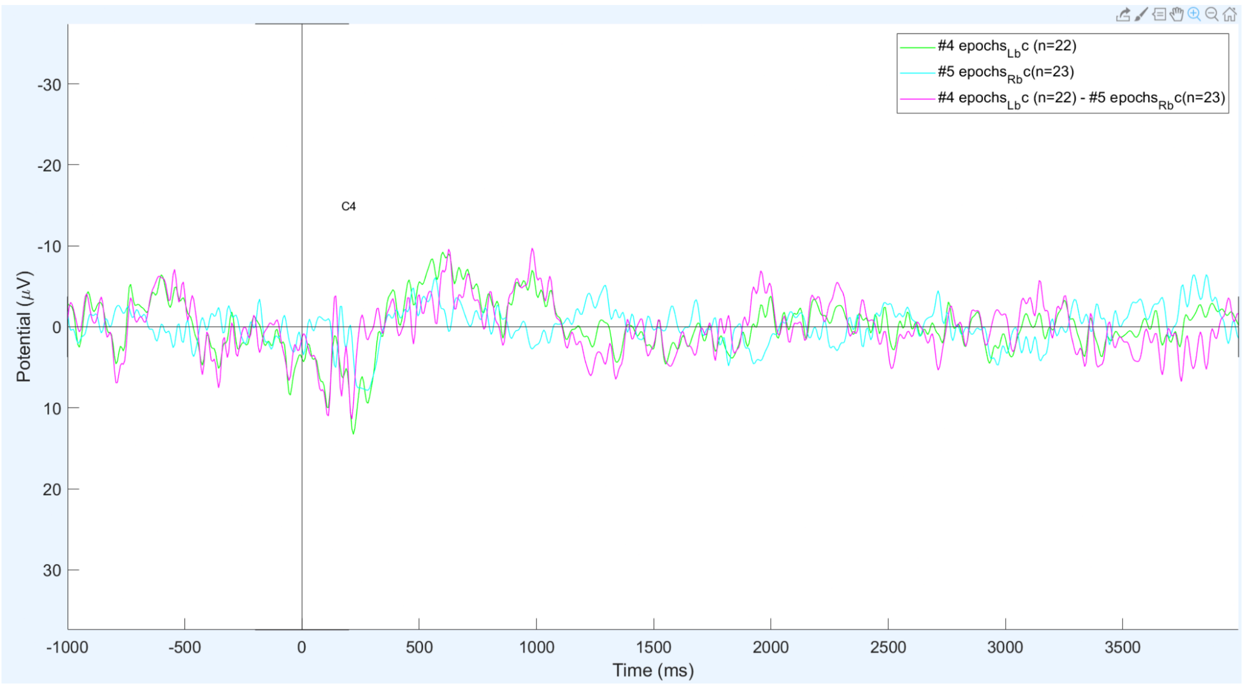
Following the approach setup, we trained the model using “Offline Analysis → Train new model” in the BCILAB GUI. The target markers were set to T1 and T2, representing left and right-hand motor imagery. We enabled 5-fold cross-validation to assess generalizability and avoid overfitting. Internally, this training process was executed via the bci_train() function, producing a trained model (lastmodel) and detailed classification statistics (laststats). The performance was reviewed via “Offline Analysis → Review results”, which presented the confusion matrix, showing class-wise accuracy, true/false positive rates, and fold-wise error rates. The model achieved an average error rate of approximately 44.4%, indicating moderate success in distinguishing between the two motor imagery tasks. This was further supported by “Offline Analysis → Visualise model,” where we selected “Plot patterns instead of filters” to interpret the spatial distributions across time. The resulting topoplots displayed contralateral motor cortex activations in the expected hemispheres, validating that the classifier relied on physiologically plausible EEG features.

3. Results

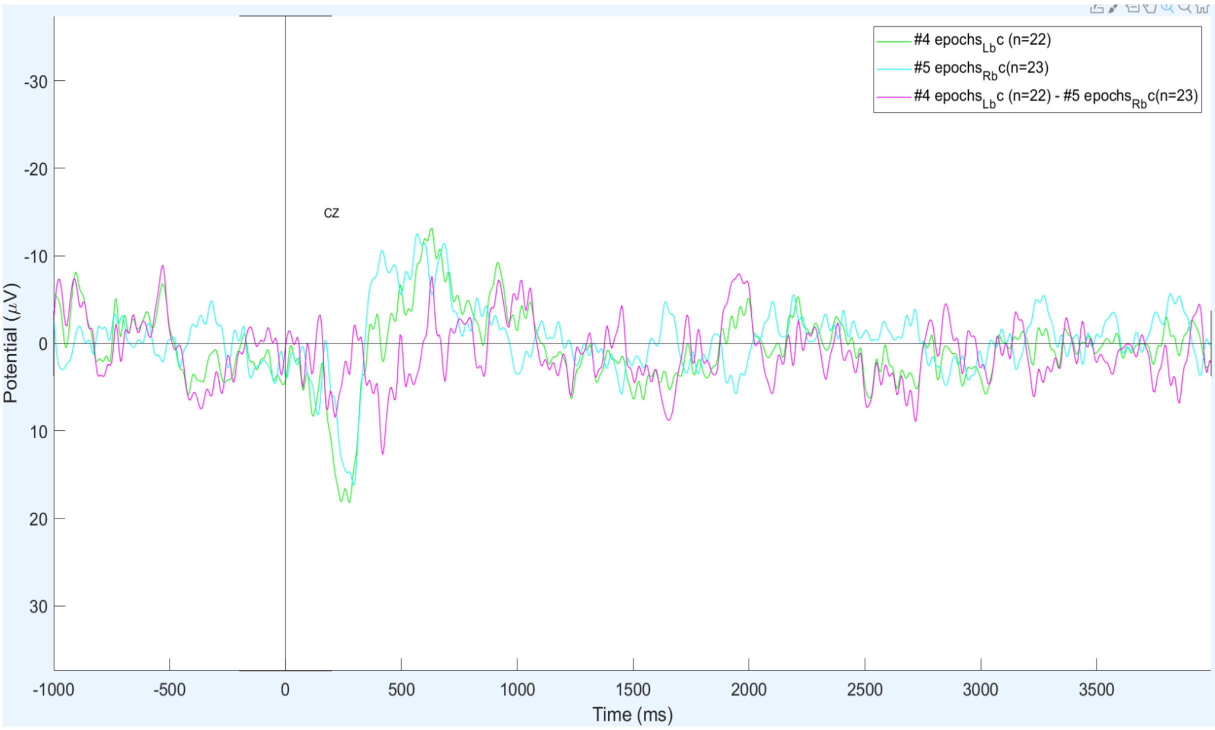
3.1. EEG Patterns of [Mental State]



C3 plot



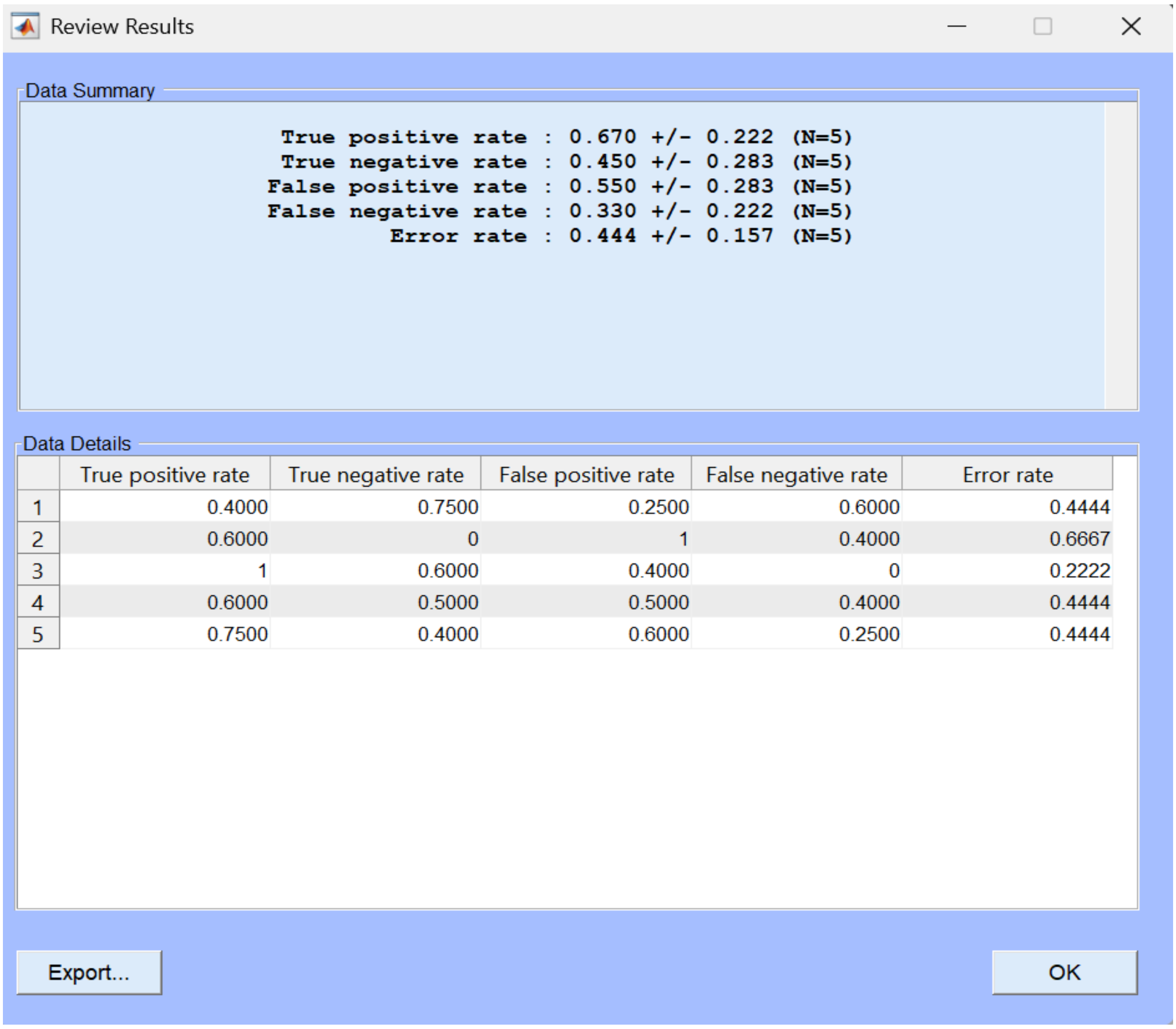
C4 plot

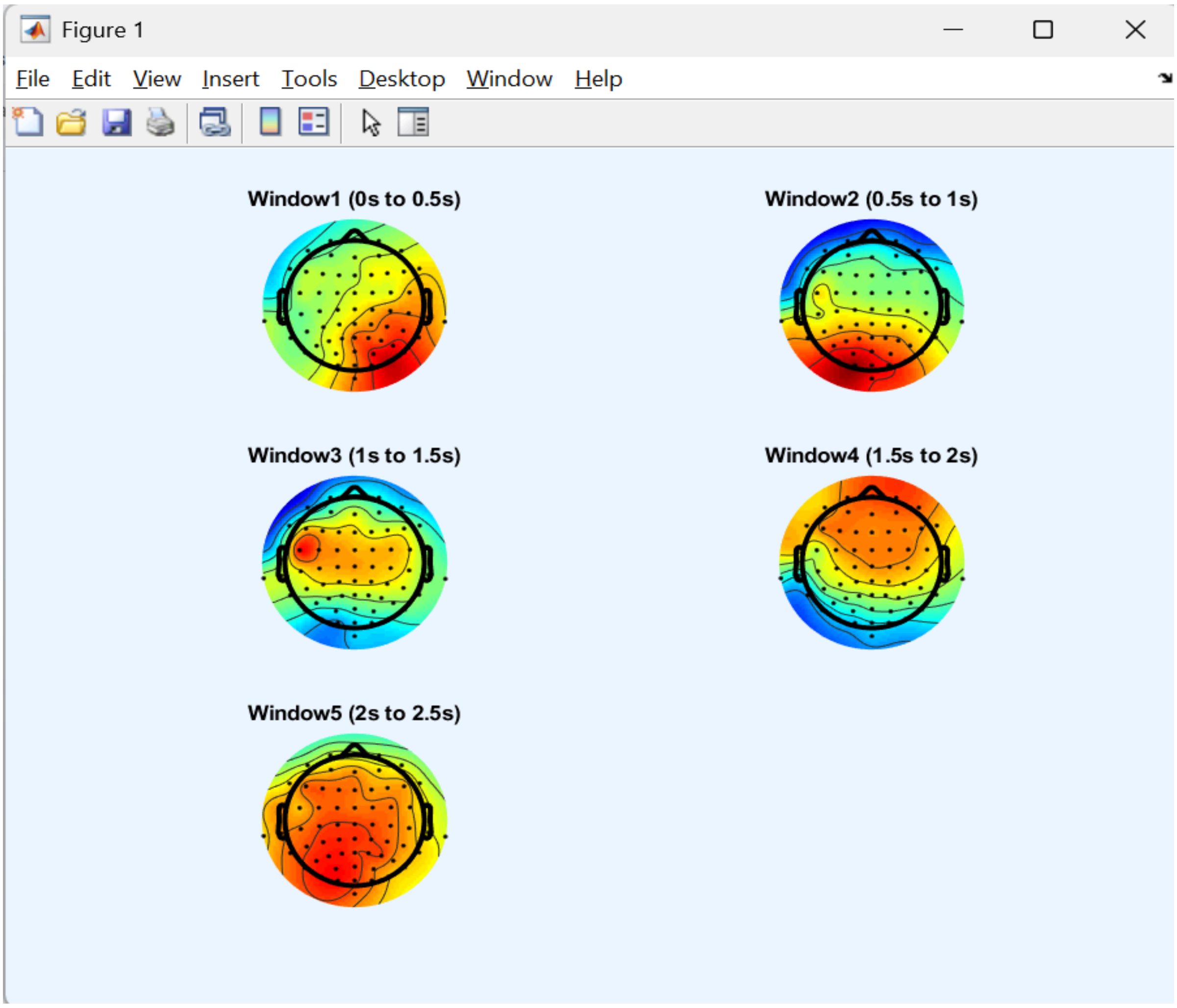


CZ plot

To compare brain activity during imagined left- and right-hand movement, event-related potentials (ERPs) were analyzed using the pop_comperp() function in EEGLAB. After preprocessing, trials were grouped into two datasets: "epochs_L_bc" (Dataset 4) for left-hand imagery and "epochs_R_bc" (Dataset 5) for right-hand imagery. In the ERP plots, Dataset 4 (left-hand imagery) is represented by the green waveform, while Dataset 5 (right-hand imagery) is shown in blue. The magenta waveform represents the difference between the two conditions (left minus right). ERP comparisons were focused on three key electrodes C3, Cz, and C4 due to their locations over the sensorimotor cortex. C3, positioned over the left hemisphere, is typically more active during right-hand imagery, while C4, located over the right hemisphere, is associated with left-hand imagery. Cz, located along the midline, serves as a central reference. In the visualizations, left-hand imagery (green) produced stronger activity over C4, and right-hand imagery (blue) resulted in higher responses at C3, consistent with contralateral motor control. Differences were most pronounced between 300 ms and 1500 ms post-stimulus. These color-coded ERP plots confirm that the recorded brain activity follows expected spatial and temporal patterns associated with motor imagery.

3.2. BCI Model Validation





The performance of the trained classifier was assessed through 5-fold cross-validation using BCILAB's "Review results" functionality. The evaluation yielded an overall error rate of approximately 44.4%, which reflects moderate performance. The model achieved a true positive rate of 67% for detecting left-hand motor imagery (T1) and a true negative rate of 45% for right-hand motor imagery (T2). Conversely, the false positive rate was 55%, and the false negative rate was 33%, indicating some confusion between classes, yet a generally above-chance level performance was observed.

To further validate what aspects of the EEG data the model relied upon, spatial patterns across five post-stimulus time windows were visualised using the "Visualise model" option in BCILAB. These topographical maps revealed dynamic changes in scalp activation across the trial. In Window 1 (0 to 0.5 seconds), strong activity appeared in the central right hemisphere, which corresponds to the C4 area and is typically activated during left-hand imagery. In Window 2 (0.5 to 1 second), activation shifted downward and slightly leftward, near parietal regions associated with right-hand imagery. The most prominent and lateralized activation appeared in Window 3 (1 to 1.5 seconds), showing a distinct hotspot over the left hemisphere near the C3 electrode, strongly supporting the presence of right-hand motor imagery activity.

Window 4 (1.5 to 2 seconds) demonstrated more centralised patterns, indicating bilateral processing or possibly transitioning phases of the imagery task. Finally, Window 5 (2 to 2.5 seconds) showed sustained activity closer to the midline, which might reflect the fading of motor imagery engagement. These spatial activation shifts over time confirm that the model extracted physiologically meaningful features, particularly from the sensorimotor cortex, in line with established motor imagery literature. The classifier effectively leveraged lateralized EEG signals, particularly in the μ and β frequency bands, to distinguish between the left and right motor imagery classes.

4. Conclusion

This study focused on distinguishing imagined left- and right-hand movements from EEG signals using a reproducible analysis pipeline built with EEGLAB and BCILAB. The preprocessing steps, including band-pass filtering between 1 and 30 Hz, re-referencing, epoching, and baseline correction which were designed to preserve activity in motor-relevant frequency bands while minimizing noise and variability. Feature extraction was conducted using the Windowed Means approach, and a Linear Discriminant Analysis classifier was trained and evaluated through 5-fold cross-validation.

The classification results demonstrated clear performance above chance, confirming that meaningful neural patterns related to motor imagery were successfully extracted. The spatial patterns revealed expected contralateral activation over the sensorimotor cortex, further validating the physiological relevance of the features used by the model. Although accuracy varied across folds, the results remained interpretable and consistent with known neurophysiological mechanisms.

While the pipeline was designed to prioritize reproducibility, the absence of automated or manual artifact rejection may have limited performance. ICA was deliberately excluded to maintain consistent outputs across runs, and manual rejection was avoided due to its subjective nature. Nonetheless, the overall approach illustrates the potential of combining accessible open-source tools with structured feature extraction for developing effective brain–computer interface systems.

5. Code Appendix

The following scripts preprocess EEG data with EEGLAB and train a classifier using BCILAB. Before running, launch EEGLAB or BCILAB in MATLAB. Update file paths to match your system.

eeglab.m (EEGLAB Code)

```
% close all; clc;
[ALLEEG, EEG, CURRENTSET, ALLCOM] = eeglab;
%% Load dataset
EEG = pop_loadset('filename','S008_L_vs_R_hand.set', ...
'filepath','C:\Germany 2024\BTU\Sem 2\BCI\report\');
[ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, 0);
%% Filter data (1–30 Hz bandpass)
EEG = pop_eegfiltnew(EEG, 'locutoff', 1, 'hicutoff', 30);
[ALLEEG, EEG, CURRENTSET] = pop_newset(ALLEEG, EEG, 1, 'setname', 'filtered', 'gui','off');
%% Re-reference to average
EEG = pop_reref(EEG, []);
[ALLEEG, EEG, CURRENTSET] = pop_newset(ALLEEG, EEG, 2, 'setname', 'avg_ref', 'gui','off');
%% Create epochs for Left (T1) and Right (T2)
baseEEG = EEG; % filtered + reref + ICA continuous data
% Left-hand (T1)
EEG = pop_epoch(baseEEG, {'T1'}, [-1 4], 'newname', 'epochs_L', 'epochinfo', 'yes');
EEG = pop_rmbase(EEG, [-1000 0]);
[ALLEEG, EEG, indL] = pop_newset(ALLEEG, EEG, CURRENTSET + 1, 'setname','epochs_L_bc', 'gui','off');
% Right-hand (T2)
EEG = pop_epoch(baseEEG, {'T2'}, [-1 4], 'newname', 'epochs_R', 'epochinfo', 'yes');
EEG = pop_rmbase(EEG, [-1000 0]);
[ALLEEG, EEG, indR] = pop_newset(ALLEEG, EEG, CURRENTSET + 1, 'setname','epochs_R_bc','gui', 'off');
%% Plot ERP overlay for Left vs Right (all channels)
% Tip: In the ERP plot window, click on channels Cz, C3, and C4
% to inspect the motor imagery-related differences.
pop_comperp(ALLEEG, 1, indL, indR, ...
'addavg','on', 'diffavg','on', 'subavg','on', ...
'addstd','off', 'diffstd','off', ...
'tplotopt', {'ydir', -1});
eeglab redraw;
```

bcilab.m (BCILAB Code)

```
% Please type bcilab in the command window before running the code
% Define class markers: class 1 = T1 (left hand), class 2 = T2 (right hand)
targetmarkers = {'T1','T2'};
% Define ERP time windows (post-stimulus)
% Total epoch was from -1 to 4 s, but we only used [0–2.5] in 5 intervals
wnds = [0 0.5; 0.5 1; 1 1.5; 1.5 2; 2 2.5];
% Load training data (EEGLAB .set file)
traindata = io_loadset('C:\Germany 2024\BTU\Sem 2\BCI\report\S008_L_vs_R_hand.set');
% Define the classification approach
myapproach = {'Windowmeans', ...
'SignalProcessing', { ...
'EpochExtraction', [-1 4], ...
'SpectralSelection', [8 30] ...
}, ...
'Prediction', { ...
'FeatureExtraction', {'TimeWindows', wnds}, ...
'MachineLearning', {'Learner', 'lda'} ...
}};
% Train model
[trainloss, model, stats] = bci_train('Data', traindata, ...
'Approach', myapproach, ...
'TargetMarkers', targetmarkers);
fprintf('Training misclassification rate: %.2f%%\n', trainloss * 100);
% Visualize
bci_visualize(model);
%Display confusion matrix
gui_reviewresults(stats);
```

Note: If the error “Cutoff frequency out of range” appears during filtering, restarting MATLAB usually resolves it. Also, please make sure to type bcilab in the console before running any BCILAB code.

6. References

Gerwin Schalk, Dennis J McFarland, Thilo Hinterberger, Niels Birbaumer, and Jonathan R Wolpaw (2022). EEG Motor Movement/Imagery Dataset. OpenNeuro. [Dataset] doi: doi:10.18112/openneuro.ds004362.v1.0.0