EEG Signal Channel Importance for Motor Imagery Classification

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Abstract

For our semester project we have chosen to help Benjamin H. Rieland continue his research regarding the effect of social situations on electroencephalogram(EEG) classification. Roughly, this correlates to "developing an agent designed to interact intelligently with people in some context, for example, a chatbot or virtual assistant", as the "agent" will be the neural network classifying EEG signals ("interact intelligently with people") to activate or inactivate a simulated robotic arm ("context"). Our project revolved around confirming that the neural network from prior parts of research which was used in the human subject data collection protocol would have been effective with better data, hence we used EEG datasets of motor imagery provided to the public for these exact tasks.With confirmed good data input into the model, we can prove its effectiveness for further data collection tasks planned for future projects by the project lead.

Introduction

It is only fitting to first reflect on the motivation behind this project when it first started and the findings of work done in (Rieland 2023) and (Rieland et al. 2024) carried out prior to this study, as all of that laid the groundwork for the tasks intended in this research.

When people are in social settings, stress levels are heightened, and this can cause excess noise, which could potentially hamper control of any assistive robotic system a person may require. It is well known that EEG signals have a significant amount of noise. If it is possible to remove certain types of noise from an EEG signal with specified machine learning algorithms, then perhaps several layers of machine learning algorithms can effectively mitigate EEG sensor noise to the point where signals become usable for much more sensitive classification algorithms and assistive robotic control. The hypothesis boils down to this: "If a person is in a social situation, then there will be more noise in the EEG signals they produce." And furthermore, "If there is significant noise in EEG signals caused by being in a social situation, then a machine learning algorithm can effectively nullify it." We previously used a StarStim 8 10 electrode sensor array and Necbox for EEG signal LSL streaming, using the Neuroelectric software NIC2. Python & jupyter notebooks were used for the LSL stream capture, data saving, classifier creation, activation value classification and subsequent upload to a UDP socket. MATLAB Simulink was used to create the robotic arm, animate the motion, and read the UDP socket activation value to activate or deactivate the motion accordingly. In (Rieland et al. 2024), the team determined through rolling mean normalization that the data is most likely pre-filtered.

By building on this foundation, we aim to address the classification accuracy of the model previously used and confirm that it is effectively at classifying motor imagery EEG data that is confirmed working and usable by the greater scientific community. This will finally confirm whether the failure of the human subject data collection was on the model side or data collection side, as well as advance our understanding of motor imagery EEG classification as a whole.

Related Work

EEG signal noise and robotic arms controlled via EEG signals is a well-studied topic. However, there is a lack of specific study at the intersection of socially induced stress and its impact on EEG signals for robotics control. One of the original Brain Computer Interface(BCI) papers in the field offers a good baseline for learning how to integrate a BCI with EEG signals, (Wolpaw et al. 2002). Another example from years later is (He et al. 2015), which covers using a Wireless BCI and Brain Machine Interface(BMI) system for wearable robotics. They do not go into noise cancellation, but it is a good starting point for obtaining signals from a BCI and subsequently translating the EEG signals into usable commands. They use noise removal filters on the EEG signal, and further use the filtered signal for wearable robotics, but they do not test for stress-related noise or any type of specified socially induced stress noise.

(Huang et al. 2019) deals with the control of a robotic wheelchair via EEG signals, as well as noise reduction. Although the authors did not include many details in terms of noise reduction and do not indicate they cover stress-induced noise reduction, they do use multiple classifications of EEG signals for an assistive robotic control system and include diagrams for EEG sensors and specific sensor importance. Similarly, (Nandikolla and Medina Portilla 2022) uses EEG signals and an AI-based BCI for the tele-operation of a robotic arm, but the authors do not cover EEG signal noise removal used. Furthermore, (Liu, Habibnezhad, and Jebelli 2021) is also a closely related studyy that deals with covering human-robot collaboration in construction environments via EEG analysis. It uses a simple, wearable, EEG cap to estimate the cognitive load of a working person and adjusts the robot's actions accordingly. Specifically, the authors use wearable EEG cap signals and measure stress levels and cognitive load of the subjects via the signals. However, here also the authors do not cover noise removal. This leads us naturally to the well-studied subject of machine learning algorithms for EEG noise removal.

(Huang and Wang 2021) is a broad review of EEG signal processing methods, including compensating for changes in beta waves due to mental stress. The authors use a Support Vector Machines(SVM) to detect whether a subject is stressed via EEG signal data at only 83 percent accuracy, but the paper does cover some tests where they used a robotic arm with the subjects' EEG signals. They also use other types of machine learning algorithms, and the classification accuracy itself can be improved, albeit 88% accuracy using Linear Discriminant Analysis(LDA) is a fantastic baseline. Here again, they do not go into much detail on removing the noise, let alone removing noise caused by stress.

(Saeed et al. 2020) classified stress via machine learning algorithms over a long-term time frame. The wearable EEG cap had only 5 sensors, demonstrating the effectiveness of a much simpler sensor layout compared to works like the 32 sensors used by (Huang et al. 2019). Following in that vein, (Immanuel and Sangeetha 2022) classified a subject's emotional state from EEG signals using a deep learning system. However, neither (Saeed et al. 2020), nor (Immanuel and Sangeetha 2022) cover using the classified EEG signals for robotic system control. Neither does (Kang and Zhizeng 2013), but they do go into great detail about removing noise from EEG signals using Principal Component Analysis (PCA) and density estimation blind source separation (DEBSS). They removed interference by reconstructing individual EEG signals from their independent signal components after the DEBBS algorithm separated EEG signals into their respective components.

More recent research in the field of stress classification using machine learning is shown in (Phutela et al. 2022), which uses an LSTM model and EEG signals to classify stress. Furthermore, they induce stress in a subject, measure the difference in EEG signals, and classify the stress level of a subject accordingly. However, they do not remove the noise or signal variation caused by the stress, nor do they use the signals for controlling a robotic system.

Furthermore, (Katmah et al. 2021) is a broad review of mental stress assessment methods using EEG signals. The authors use different types of features and classifiers for stress detection results from a subject's EEG signals. The paper offers a great baseline for EEG assessment methods in relation to mental stress as well as other forms of stress, but, as with (Phutela et al. 2022), they do not use the EEG signals for robotic system control.

National Institutes of Health(NIH) has even explored the topic of EEG signals for registering a person's attention to a matter. (Liu, Chiang, and Chu 2013) covered measuring human attention via EEG signals. Although they do not control for noise, the paper does go into detail on how the researchers measured students' attention to a subject with EEG signals and SVM classifiers. They had a good but not great final accuracy of just under 77%, which can definitely be improved upon by more modern classifiers. The important part of this paper is it gives a great introduction to actively measuring a person's attention via EEG signal classification, which we will use as a starting point when creating a new classifier for activating the robotic arm simulated motion. Not only that, in researching the filters used for motor imagery tasks we came across (Wang et al. 2018), which was incredibly helpful for filtering EEG signals for classification by LSTM models (a perfect fit).

All things considered, Some studies do directly align with the objectives of our research, particularly in the area of channel selection for motor imagery classification in EEG-based BCIs. For example (Gaur et al. 2021) propose an automatic, subject-specific channel selection method that enhances motor imagery classification accuracy by using the Pearson correlation coefficient. This method, which focuses on selecting the most relevant EEG channels for each individual, has shown promising results in improving classification performance while reducing the computational complexity of EEG signal processing. Their work is crucial in demonstrating the effectiveness of correlation-based approaches for channel selection, which we also adopt in our study for optimizing the classification of motor imagery tasks.

One of the key datasets frequently used in motor imagery-based BCI research is the (Kaya et al. 2018) dataset, which is among the largest available for EEG motor imagery tasks. This dataset includes extensive EEG recordings from a wide range of subjects, capturing motor imagery tasks such as left and right-hand movement intentions. It is particularly valuable due to its scale and variety, offering a rich source of data for testing and evaluating different BCI techniques, including motor imagery classification. The dataset is designed to facilitate the development and benchmarking of BCI systems, making it an essential resource for researchers aiming to improve the performance and generalizability of motor imagery-based BCIs.

Approach

Given the results of data collection and normalization, we determined the most effective approach is to first confirm the models effectiveness and accuracy before moving forward with human subject data collection. To do this we performed PCA analysis on multiple datasets to determine effective channel locations, and then filter the datasets to only those locations and run the original model from (Rieland 2023) and (Rieland et al. 2024) to determine its effectiveness in classification on confirmed good data.

Phase 1

Phase 1 included testing our selected EEG datasets for the most impactful features and performing PCA to identify meaningful components for 6 existing corpora of data.

Specifically we started with the BCI Competition IV dataset 1 (Blankertz, Müller et al. 2008) and "largest SCP data of motor imagery" dataset (Kaya et al. 2018). PCA transforms the original features (i.e., EEG channels) into principal components, which are linear combinations of the features. The explained variance ratio reveals how much of the total data variability is captured by each principal component. So, PCA is supposed to give us insight into how well the data can be represented with fewer dimensions and which features contribute to components that explain the most variance.

BCI Competition Dataset 1 This contains 1 single corpus corresponding to one BCI paradigm in which each subject was given a cue for one of the 2 selected Motor Imagery(MI) tasks from the 3 available MI Tasks(move right hand, left hand or either Leg). The two selected MI tasks were assigned target class of 1 and -1 and are represented as such in the marker files. Data was collected at 1000hz and continuous value of amplitudes of EEG signals from the 59 channels are available for each time point in the count files. In this experiment, each cue was displayed for 4 seconds along with a fixation cross, followed by a 2 second blank screen, and then followed by 2 seconds of just a fixation cross. So we expect to see to variation of activation and non activation in intervals of 4 seconds.

Largest SCP data of motor Imagery The largest SCP dataset contains 5 paradigms, each comprising 5 corpora in the original dataset files. The 5 paradigms are:

- CLA: It had 3 states for 3 image action signals on a screen shown for 1 sec each. movement of Right hand, movement of left hand and circle(indicating neutral state).
- HaLT: It had 6 states for 6 image action signals on the screen shown for 1 sec each. Movement of Right leg, left leg and tongue along with the 3 states for CLA.
- FreeForm: It had subject pressing 2 tracked keys on a keyboard with either left or right hand to judge the change in their EEG signals through BCI due to motor planning and execution in the times immediately preceding the key presses.
- NoMT:Similar to HaLT except the subjects were requested to not reacted to actions signals on the screen as a means for consistency check and baseline determination for subsequent BCI interactions.
- 5F: It had 5 states corresponding to the flexions action signals of each finger of one hand on the screen shown for 1 sec each. Used to classify EEG signals for finer movements as compared to CLA, HALT, Freeform or NoMT.

We sanitized each corpus to 0 and 1 for activating versus not activating. Specifically, we changed the labels for hand and/or arm activation to 1 and everything else to 0 (e.g., tongue and leg are mapped as inactive signals). Results of the feature importance and PCA are discussed in the Preprocessing Data subsection below.

Preprocessing Data We had to make a few small adjustments to the design. First, we had to scrap using BCI Competition Dataset 2a and 2b since it was in a specialized file format and there were issues with extracting the information. However, data preprocessing for BCI Competition Dataset 1 and the Largest SCP Dataset went very well, with two small caveats. First, although the BCI Competition Dataset 1 is all at a 1000hz sample rate, only one of the tests within the Largest SCP Dataset is at 1000hz and the rest are sampled at 200hz so our PCA and feature importance datasets are roughly 2/3 at 1000hz sample rate, and 1/3 at 200hz by volumne (since there are 5x the samples in 1000hz datasets). The second is that there is a mismatch on the labels versus samples specifically for the evaluation labels of subject A in the BCI Competition Dataset 1, so that was discarded for simplicity since we have no information on the exact collection process and how the labels match up to the data (e.g., the labels could go from partway through the dataset to the end, or from the start to partway though, we do not know and time constraints forced us to just remove the single dataset).

These results indicate that, moving forward to Phase 2, we had to account for the differences in sample rate. We adjusted the target batch size for classification from 100ms to 20ms to increase the definition of classification (e.g., have the model pick up smaller shifts in the eeg data), and this means that the 1000hz samples will have to be batched in groups of 20 samples (since 1ms = .001 seconds) and the 200hz samples will have to be batched in groups of 1 sample (since 5ms = .02 seconds). We also ran tests with each sample classified individually since the BCI dataset had labels for each input sample. These tests had better results than the grouped samples so both were performed for each subject and test in both the Largest SCP and BCI Competition datasets.

Minor adjustments were also made to the labeling criteria as following the application of PCA and the assessment of feature impact on the BCI Competition IV-Dataset 1, it was revealed that a much higher weighted component 1 when the labels were changed to 0 (inactive) for both idle state AND leg motion. Specifically, The BCI labeling system used in SCP dataset assigns specific marker codes to different conditions and tasks. The labeling for legs is denoted by -1, hands is 1, and the idle state is denoted by 0, so these translated to 0, 1, and 0 respectively since we are specifically targetting for arm and hand motor imagery classification.

The original dataset marker codes for the largest SCP tests are as follows:

For CLA, HaLT, FreeForm Interaction Paradigms:

- 1: Left-hand MI
- 2: Right-hand MI
- 3: Passive state
- 4: Left-leg MI
- 5: Tongue MI
- 6: Right-leg MI

For 5F Interaction Paradigms:

- 1: Thumb MI
- 2: Index finger MI

- 3: Middle finger MI
- 4: Ring finger MI
- 5: Pinkie finger MI
- 6: Right-leg MI

For all paradigms, the following marker codes are also used:

- 99: Initial relaxation period (set to 0)
- 91: Inter-session rest break period (ignored)
- 92: Experiment end (ignored)

Findings and Analyses The tasks of phase 1 were successfully accomplished.

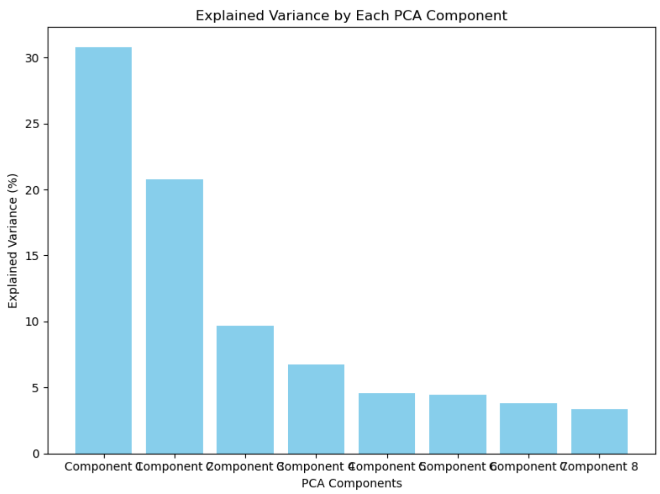

Figure 1: Explained Variance Bar Graph for subject A in single test

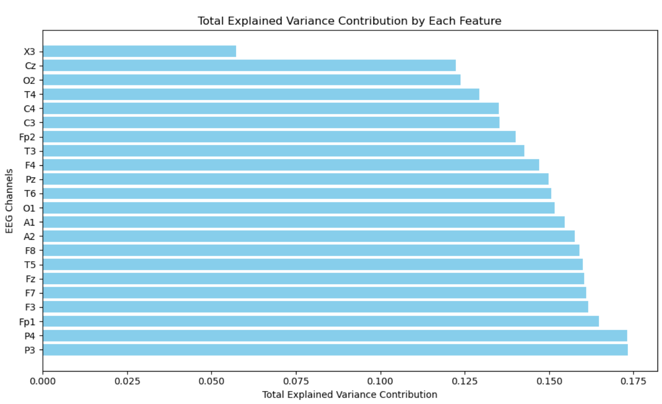

Figure 2: Feature Contribution Bar Graph for subject A in single test

The results of the PCA and feature importance (as seen for a single test of a single subject) in Fig 1 and Fig 2 revealed some very pertinent information.

Fig 1 illustrates the percentage of explained variance for each principal component. The first component accounts for approximately 30% of the variance, significantly higher than the subsequent components. Component 2 contributes around 20%, while components 3 through 8 collectively explain less than 50%. This steep decline indicates that the first two components dominate the data's variability, suggesting the presence of strong underlying patterns captured effectively by these components.

Fig 2 highlights the contributions of individual EEG channels to the total explained variance. Channels P3, P4, Fp1, F3, and F4 exhibit the highest contributions, each exceeding 0.15, with P3 leading slightly above 0.17. These channels, located in the prefrontal and parietal regions, might play a critical role in differentiating EEG patterns relevant to the data labels. Conversely, some intermediary channels, such as Cz and X3, show minimal contributions, suggesting that their inclusion might introduce redundancy rather than meaningful variation.

Phase 2

The PCA done in phase 1 does not assess the individual importance of original features directly; it analyzes the contribution of features to the components that explain the variability. Feature impact analysis carried out in the first part of phase 2 involves evaluating how each original feature(i.e. electrode location/EEG channels) affects the performance of the model and ultimately figuring out which ones are most relevant for achieving our goal of classification of the EEGs'.

We developed and utilized graphs of normalized feature weights and additive scoring derived from the PCA results for each subject. The normalized feature weights provided insights into the relative contributions of each electrode to the principal components, emphasizing their role in explaining variability in the data for individual subjects. On the other hand, the additive scoring aggregated the contributions of each electrode across all principal components, offering a comprehensive measure of their overall importance across the datasets.

After performing these analyses, we combined the results to obtain the total scores for each feature/electrode location. These scores represent the cumulative importance of each feature across both datasets and provide a clear indication of the most significant electrodes for EEG classification. The total scores are visualized using bar graphs for the two datasets, facilitating direct comparison and identifying key electrode locations that consistently contribute to signal classification.

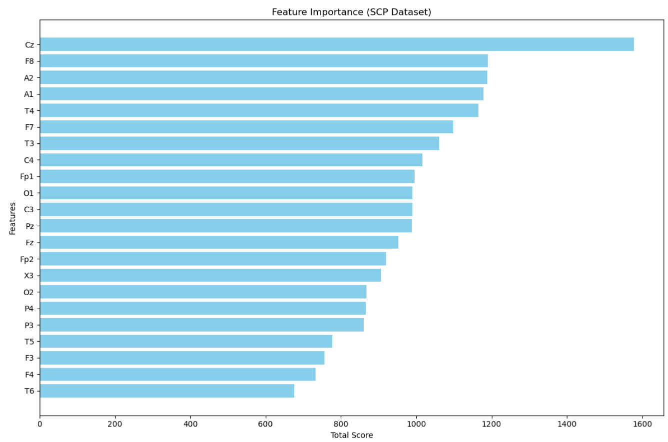

Figure 3: Bar chart depicting feature importance for Largest SCP dataset

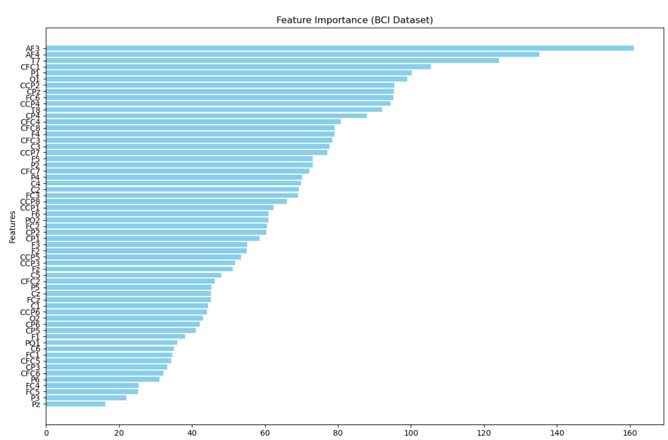

Figure 4: Bar chart depicting feature importance for BCI Competition IV dataset 1

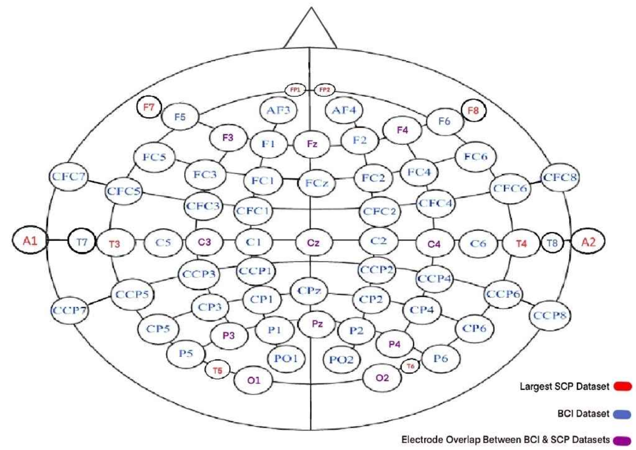

Figure 5: Superimposed EEG Sensor Electrodes Layout for Largest SCP and BCI Competition IV Datasets, derived from (Wang, Chen, and Yao 2020).

Fig 3 shows the total scores of all 22 features of Largest SCP dataset ranked in decreasing order, it was observed that the electrode locations Cz, F8, A2, A1, T4, F7, T3, and C4 emerged as the top eight features. The decision to focus on the top eight features is guided by the constraints of our physical apparatus, which is equipped with eight channels. This alignment between our analytical findings and the hardware specifications ensures practicality and feasibility for future validation and real-world application. By prioritizing these eight channels, the results can be directly translated into a simplified and efficient experimental setup, facilitating further research and application development.

In similar fashion, Fig 4 shows the total scores for all 59 electrode locations in the BCI Competition IV dataset, ranking them in decreasing order of importance. While this dataset provided some insights, its smaller size and synthetic nature compared to the real-world and larger SCP dataset limit its reliability for identifying impactful features. Consequently, for the purposes of testing the classification accuracy of our original model, we prioritized the Largest SCP dataset's top eight features which were identified as discussed ealier.

Making use of Fig 5 for visualization, when mapping the top eight features of the largest SCP dataset to the BCI Competition IV dataset, only two of these features-specifically, C4 (ranked 23rd) and CZ (ranked 41st)-were present among the 59 features in the BCI dataset. To address this limitation, the remaining six features for BCI Competition IV were selected based on their closest physical proximity in the electrode layout to the other 6 of SCP's top eight features. The final channel use was as follows: Largest SCP dataset channels: Cz, F8, A2, A1, T4, F7, T3, and C4; BCI Competition IV dataset: Cz, F4, T7, T8, CFC4, F3, CFC1, C4. This approach allowed us to align the spatial setup of the SCP dataset with the BCI dataset, making it possible to compare and apply the original classification model, and meaningfully infer areas of the brain which tend to be involved in motor imagery tasks. This allowed us to see how well our findings apply to two different datasets while keeping the feature selection as consistent as possible.

In phase 2 the original neural network proposed in (Rieland 2023) and (Rieland et al. 2024) was utilized to classify the EEG signals. The original model was a simple LSTM architecture with five dense layers arranged in a funnel pattern(starting at 256, then 128, 64, 32, ending at 16 neurons), with Relu activation function, dropout set to .5, and all that filtering into a softmax layer comprising 2 neurons (one for class 0, one for class 1). The model was tested using binary cross-entropy, adam as an optimizer, early stopping based on accuracy, random seed of 42, a sliding window step of 10 samples, and batch size of 1024 samples. Finally, the model was trained for 30 epochs at a learning rate of 0.00001. While these settings were effective for processing all the data for a single test at once, they were unable to classify real-time samples, prompting our approach to identify impactful feature sensor channels.

After identifying and cross referencing for the most impactful features, we trained and tested the original neural network model on the data we previously prepared from the BCI Competition and Largest SCP datasets to ensure it performs correctly. Unfortunately, the results were not good enough to move straight to human subject data collection with Ben Rieland as the subject, but they were more than sufficient to justify further study and tuning (again, with the goal of over 85% accuracy, less than .1 loss, and training and evaluation sets have converged).

Findings and Analyses The tasks of phase 2 were successfully accomplished.

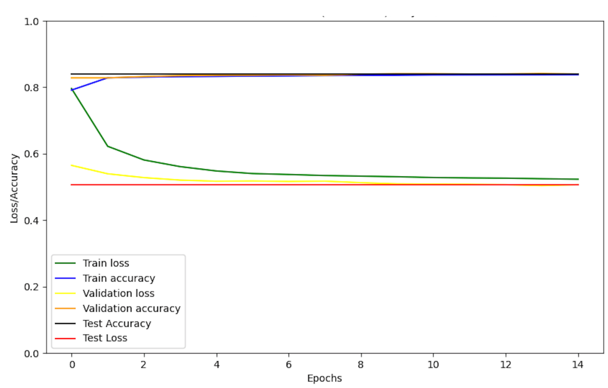

Figure 6: Line Graph showing Loss and accuracy for one instance/subject at 200Hz in Largest SCP dataset

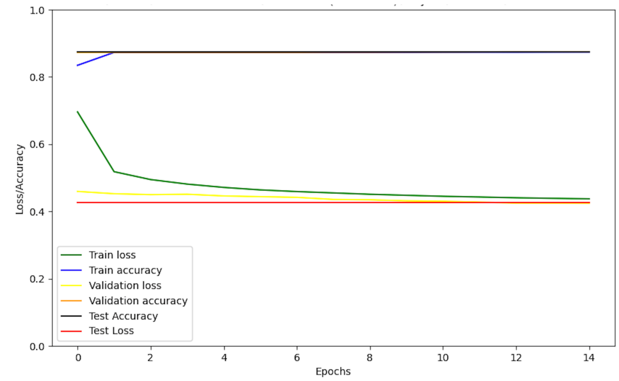

Figure 7: Line Graph showing Loss and accuracy for one instance/subject at 200Hz in Largest SCP dataset

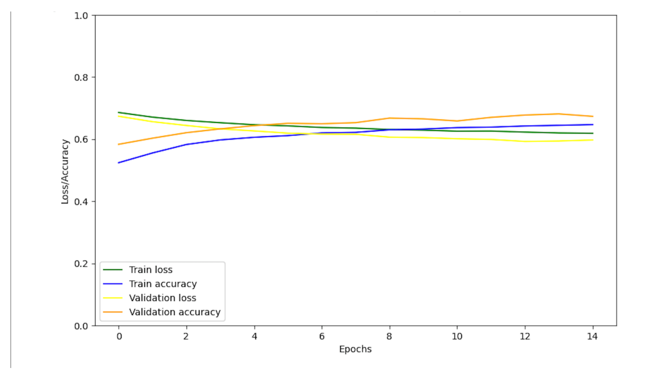

Figure 8: Line Graph showing Loss and accuracy for an instance/subject at 1000Hz in BCI Competition IV dataset

To present and discuss a few examples that help explain the overall trend, we look at Fig 6 and Fig 7 which show the accuracy and loss for 2 separate 200 Hz samples from Largest SCP dataset. It is evident that accuracy increases to around 85% and loss decreases to around 50% after a few training epoches which shows that our identified top features work pretty well for classification using our Model. But on the other hand there are a few outliers like the the example in Fig 8 which shows accuracy and loss for a 1000hz sample from BCI Competition IV dataset. It only shows increase in accuracy to about 60% and reduction in loss also to about 60% which is not a great result for the purposes of classification of EEG signals.

Hence, The overall results of the machine learning training were not very clear cut. Some of the tests and subjects were easily classified with high accuracy and low loss. However, other tests showed results barely better than random guessing. This is most clear with the difference in accuracy and loss when classifying the 200hz datasets versus the 1000hz datasets, and specifically with a certain few subjects as discussed above. This was brought up in the corresponding dataset papers, and tracks with some of their results regarding low BCI proficiency and its effect on classification.

Results

Phase 1 Evaluation was to confirm that there are impactful features which clearly have a higher weight for the classification, and to this extent it was a resounding success as several subject test datasets have an impact of component 1 over .8 which is almost a 1 to 1 correlation with classification. The tabulation was also a resounding success as there are clear front-running features which are used almost across the board for motor imagery tasks.

The evaluation of EEG signal datasets has been completed successfully. Next step, to prove feature feasibility prior to testing the original neural network, we used the original neural network model for classifying the data. Although some subjects and tests got amazing accuracy and some did poorly, even the poorly performing ones showed signs of capturing trends, so more research should be done regarding model effectiveness and hyperparameter tuning.

Overall the results indicate that not only are there areas of the brain which effectively produce classifiable motor imagery EEG data, but that the original model from (Rieland 2023) and (Rieland et al. 2024) produced for on-the-fly classification should have at least been partially effective for the subject testing, and further shows that the data collection itself was the main culprit for the previous failure.

Conclusion

This work has clearly demonstrated that classifying EEG signals for motor imagery tasks is not only possible, but there are some clear winners in terms of channel placement location for this purpose, such as C4 and T4-T8 (T4 was swapped with T8 between the datasets).

Unfortunately, time constraints precluded us from using a small random forest classifier to test different feature permutations and this is a target for future short term work. Future long term work will be to establish effective channels for the random forest classifier, cross reference those results with the top performing features from this experiment, publish those fully tabulated results, and then continue to human subject data collection.

Future work includes further training the models for more epochs to confirm accuracy and loss results, run further testing on more motor imagery datasets to confirm the results, and performing human subject data collection with an updated model according to the same protocol used previously in our prior research work.

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