Team BCIPRO: Brain-Computer Interfaces Prosthetics

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Introduction

The goal of our research was to improve the accessibility of current upper-limb prostheses. We aimed to maintain non-invasive aspects of an Electroencephalography (EEG), use affordable material and resources, and match the accuracy and control of conventional prostheses alongside improved training methods. A 3D-printed headset with dry electrodes was used to record brain signal data through EEG software. Brain signals were preprocessed to reduce noise and analyzed with machine learning (ML) models to classify EEG signals with respect to specific actions such as the opening and closing of a hand. A 3D-printed hand actuated by servos through Arduino was used to demonstrate the physical actions interpreted through analysis. Virtual reality (VR) was also leveraged to serve as a tool for prosthetic rehabilitation.

Research Questions

1. Is it possible to generate an end-to-end system using commercially available components to mock up a non-invasive prosthetic device?
2. By combining the use of EEG technology, open-source databases, and 3D-printing, can we offer a cost-efficient, non-invasive method that would not only be effective at interpreting brain waves to generate prosthetic movement, but also made available to those who need it.

Methodology Overview

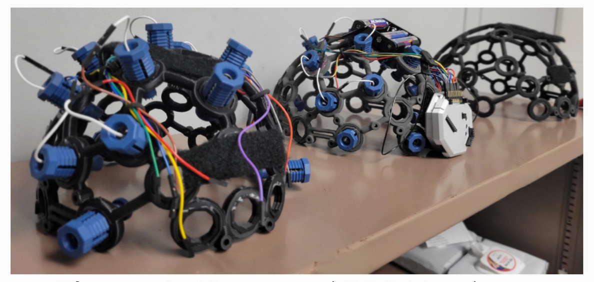


Figure 1. 3D-printed EEG Headsets.

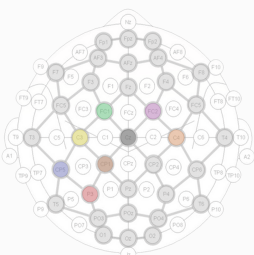


Figure 2. electrode placements.

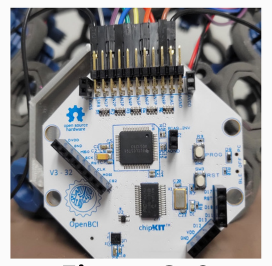
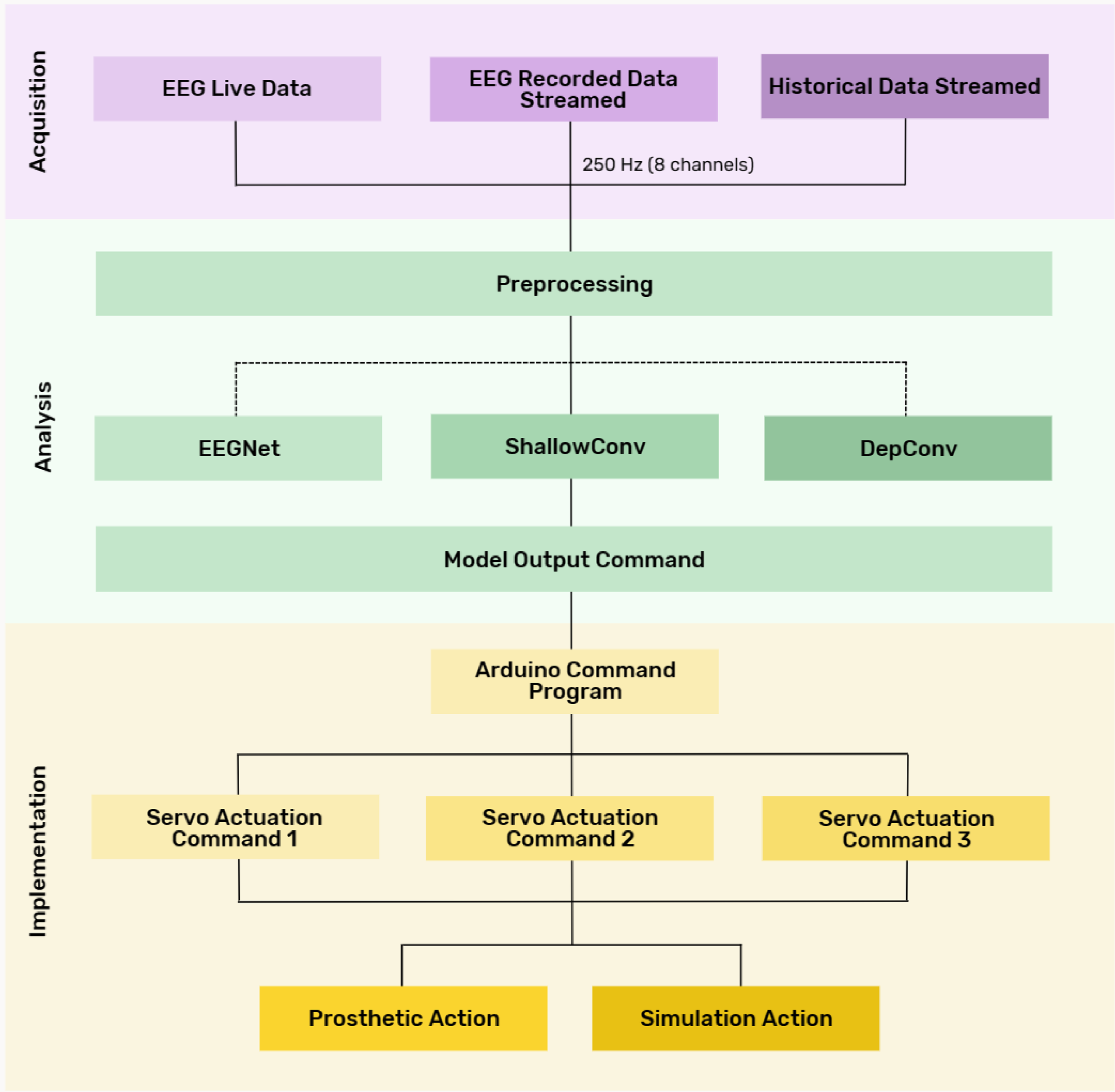


Figure 3. 8 channel ganglion board.



Results

Acquisition

- 3D-printed an EEG headset sourced from OpenBCI and assembled
- An EEG with 8 electrodes was placed on participants to record the execution of hand exercises:
  - open/close right hand
  - open/close thumb and each finger of right hand, one at a time

Analysis

- Four models—xDawn + RG, EEGNet, ShallowConv, and DeepConv—were used to train and test our preprocessed data. ShallowConv did the best with an accuracy of 58.7% followed by EEGNet (55.4%), then DeepConv and xDawn + RG which both had an accuracy of 54.6%.
- Developed a real-time deployment system in two ways: 1) a simulation which uses the prosthetic arm CAD files, and 2) the physical 3D-printed prosthesis actuated by servos through Arduino.
- EEG data recorded from the OpenBCI GUI was translated by the algorithm, via Python, which then predicts an action based on the collected brain signals. Using Pyserial, we transferred instructional movement data in real-time from the prediction to the 3D-printed prosthesis in the form of binary code.

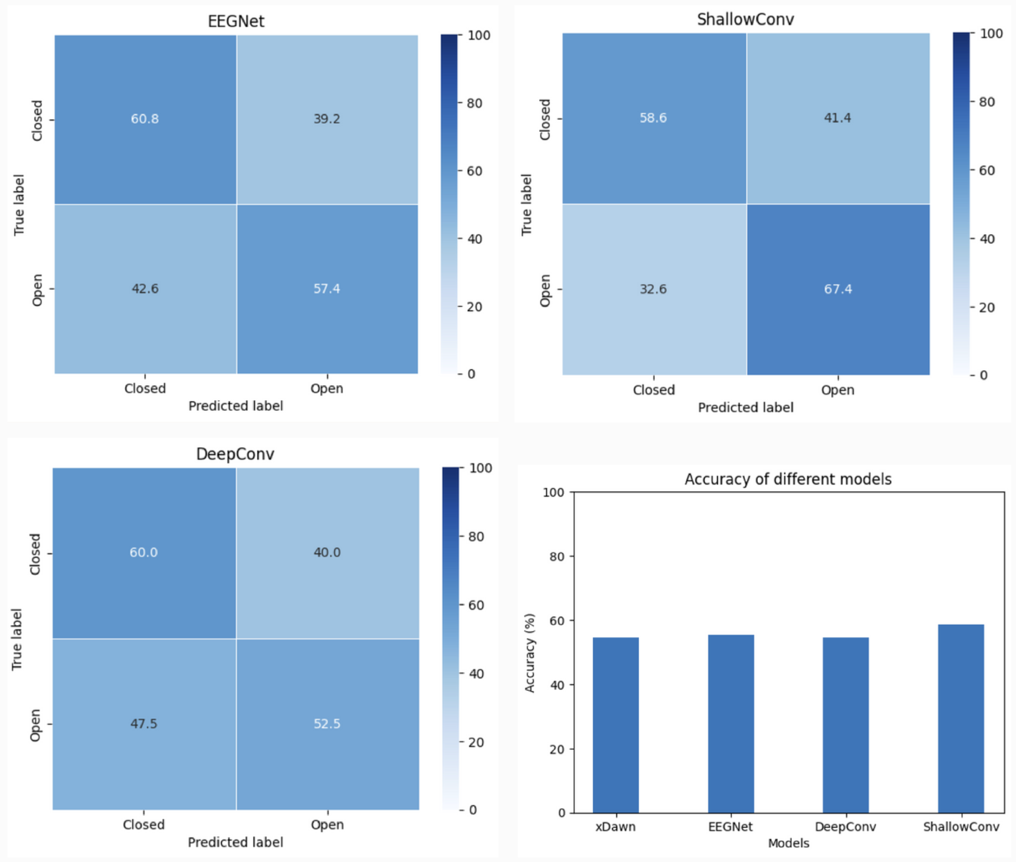


Figure 4. A confusion matrix of our dataset being classified with EEGNet (top left), ShallowConv (top right), and DeepConv (bottom left). A summary of the accuracy of different models (bottom right).

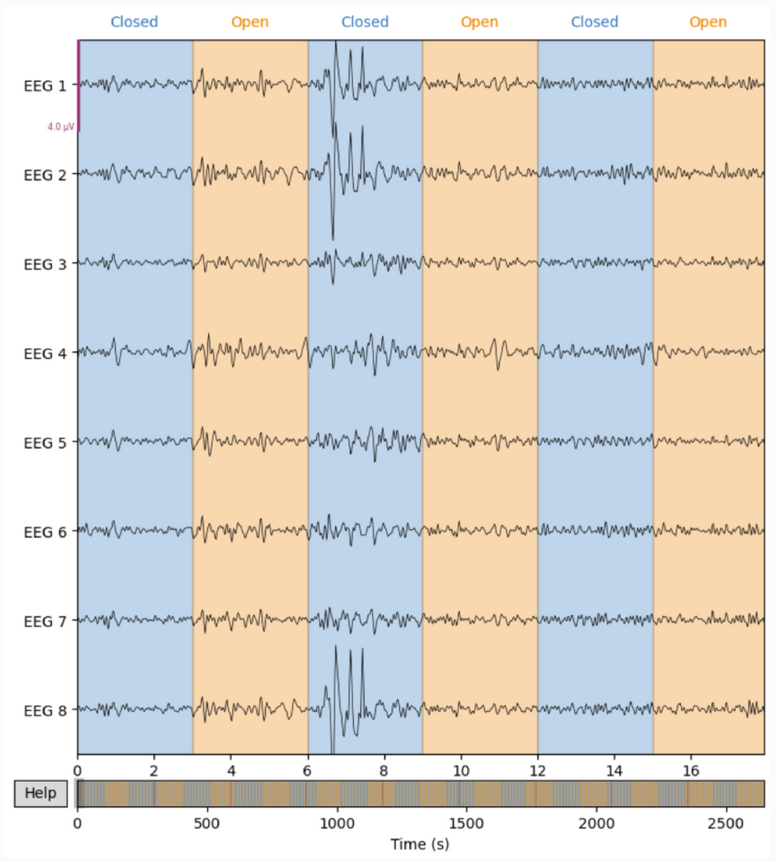


Figure 5. A spectrogram of a sample from our dataset that has been preprocessed and annotated through MNE.

Implementation

- Built a physical model of prosthetic hand using servo motors with Arduino
  - Printed 3D prosthetic hand
  - Demonstrated how translated EEG signals control physical actions

Virtual Reality

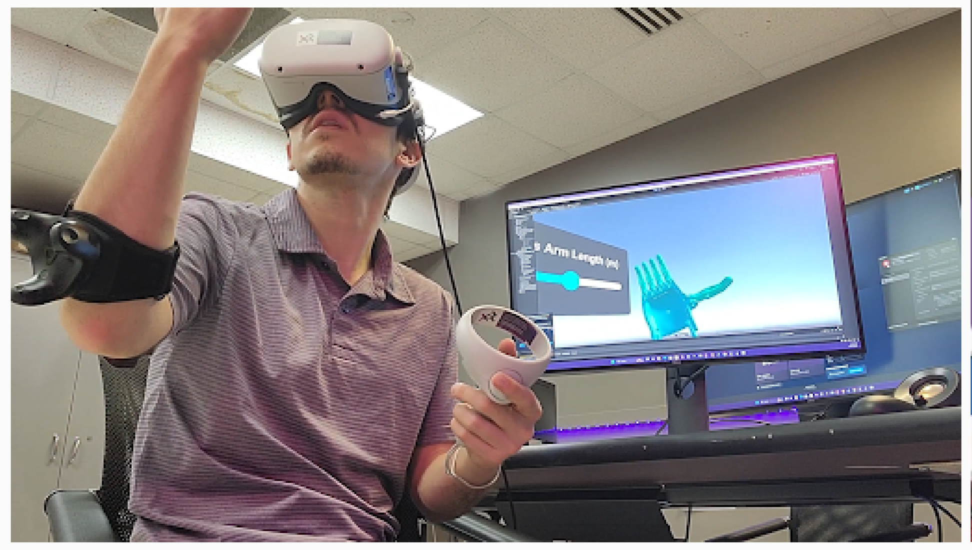


Figure 6. View of VR scene and seated user.

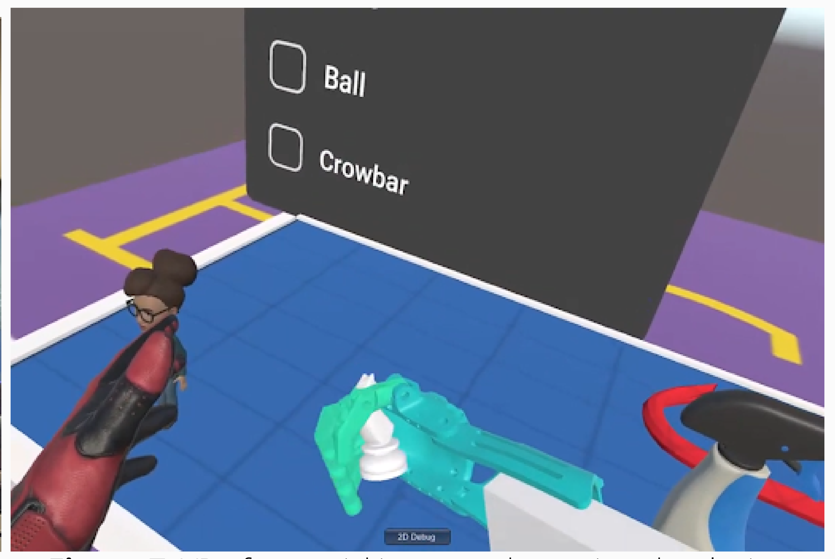


Figure 7. VR of user picking up a chess piece by closing hand.

We tested our prosthetic hand model in a VR environment, using a variety of hardware and software which included a simulation built in Unity. Hardware tested included the HTC Vive and Tracker and Base Stations, as well as the Oculus Quest 2 Head Mounted Display (HMD) and Controller. We modeled a variety of activities, which involved tasks such as gripping and interacting with objects. We also tested using various headsets and hand controllers to investigate a variety of VR options.

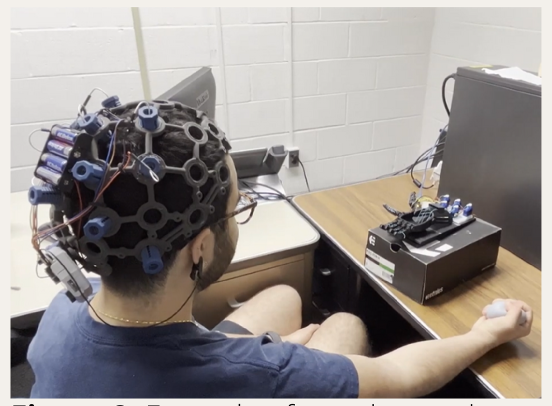


Figure 8. Example of a end-to-end system in which live data is converted into action within the prosthesis.

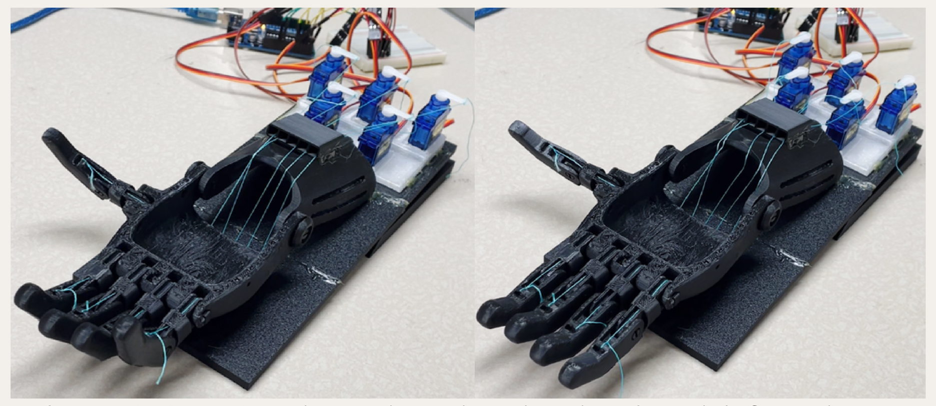


Figure 9. 3D-printed prosthetic hand in the closed (left) and open (right) positions.

Conclusions

We successfully met the goals set for data collection and prosthetic arm actuation. Additionally, we have created a functional algorithm for action prediction but were not able to achieve the desired accuracy. Overall, we achieved our primary goal of collecting brain signal data, analyzing that data through an algorithm, and actuating a prosthetic arm with actions interpreted from the brain signals all in real-time. Moving forward, there is room to increase accessibility and quality of prostheses through further development of non-invasive brain-computer interface (BCI) based technology for 3D-printed prostheses and VR environment prosthetic models.

Future Research

1. Modifying an existing commercial prosthetic arm, or modifying our own existing prosthetic arm to add innovative features such as additional degrees of freedom.
2. Improving aesthetics or functionality to make a prosthetic arm look and feel more realistic, which could help a user be more comfortable with the device.
3. Speak with healthcare industry professionals, especially occupational therapists who have dealt with upper-arm prosthetic training and discuss their desires for customization options for a VR environment.
4. Focus on testing and identifying the optimal placement for these reference and ground electrodes.
5. Explore other deep learning models, such as transformers.
6. Collecting data from participants with limb loss and adjusting our model accordingly.
7. Look into targeted instance tests that try to isolate a singular action, so that a corresponding EEG signal can be more confidently associated with that action.

Acknowledgements & References

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