ELECOMP CAPSTONE SYMPOSIUM
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THE UNIVERSITY OF RHODE ISLAND

THINK BIG WE DO™

Hand Gesture Classification

Data Labeling of Gesture Based Biosignals

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PISON

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Project Motivation

When collecting gesture-related biosignals for researching, developing, and training gesture classification models, one of the most important preprocessing steps is identifying which regions of the signal correspond to the intentional performance of the gesture (known as "onset detection" or "activity detection"). Purely signal-based onset detection methods exist but are often susceptible to noise such as electromagnetic interference (EMI), and they generally perform poorly with low signal-to-noise ratio (SNR) signals. Further, these methods provide no information about which gesture was performed. Thus, we are leveraging computer vision (CV) methods to perform activity detection of biosignals based on recorded videos of the user's hand while performing the gesture. Onset detection is used to ensure accurate labeling of the samples used to train these models: in particular, it is important to capture as much of the active signal as possible, and even more important to avoid labeling "inactive" or "resting" samples, surrounding the true active region, as "active". **(Fig 1)**

Anticipated Best Outcome

The anticipated best outcome of this project is the development of a fully automated labeling algorithm by April 2022 that can accurately provide classifications of gestures presented by a user through some sort of recording device. Note that this project is funded by a grant from the National Science Foundation (NSF). We are aiming to achieve robust accuracy (99+% overall classification accuracy across all users in the test set), but in terms of the contractual deliverable, this is not strictly necessary.

Key Accomplishments

Key Point generation of previous collected data: In the data collection, the users were given the Pison Device to wear during the collection process which was recording their hand gestures. The task for the keypoint generation was to process every video file collected for the data set, and pass it through an already existing algorithm. This program essentially looked through each video frame by frame looking for certain key points, which were previously defined as cases where gestures were done by the user.

CV Labeling and verification on all data: The DTW algorithm was used to synchronize the EMG data to accurately train and test the machine learning model. Using different confidence thresholds resulted in interesting results. (**Fig. 2**) Finding a compromise between highly accurate data samples and an abundance of data samples was required to train the machine learning model effectively.

LDA Research and Implementation: Doing the LDA research, what was come across was how this predictive model is implemented, was that it divides the data into two classes and draws a line in between the classes, this predictive model can be done multiple times, however the accuracy was bad this time with a 55 percent prediction accuracy, which is not good.

Random Forest Research and Implementation:
Doing the Random Forest research, it was found that the random forest was a decision tree structure that conducted a popularity vote, thus the predictive model took more time, but was very deceiving advertising 99 percent accuracy, but was later found to have around 45-51 percent **(Fig 4)**

Map video Data Offsets and Merge Data: Running through the ALGO-463 script the data was preprocessed and then ran so as to synchronize the time stamps of the device data and the video data so as to correctly map out the video-based offsets. This was useful in testing checking the predictive power considering the data was all synchronized. **(Fig 3)**

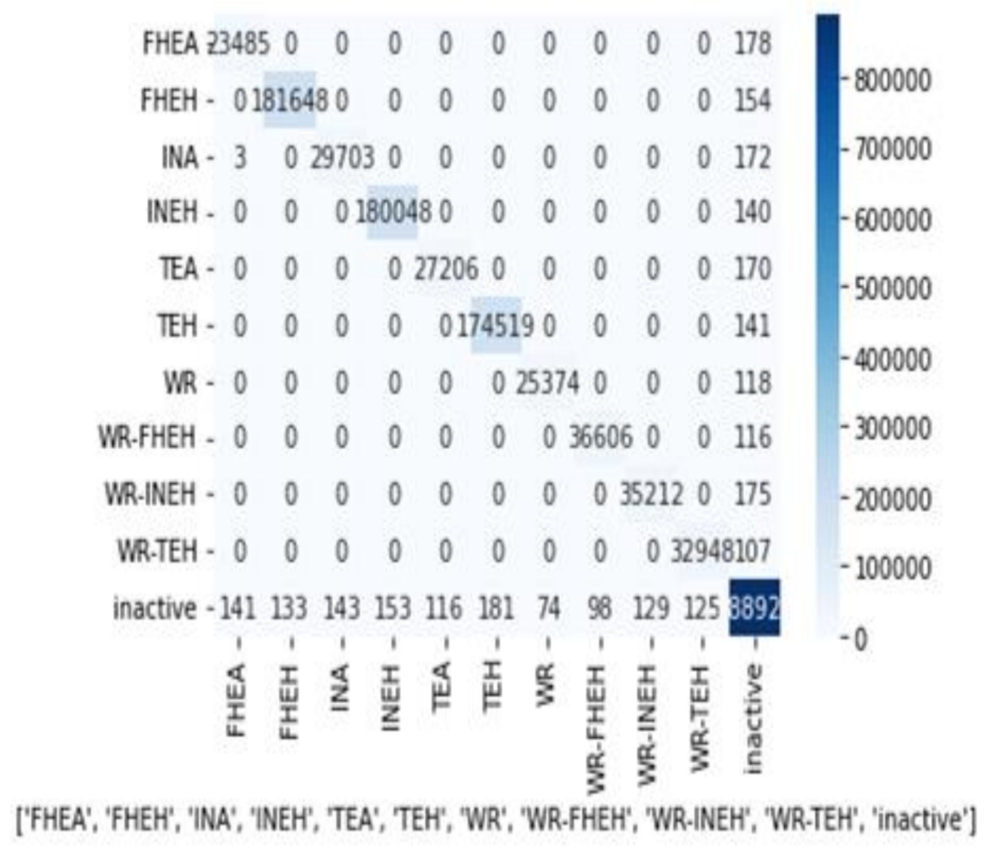

Fig 4: Confusion Matrix of Random Forest

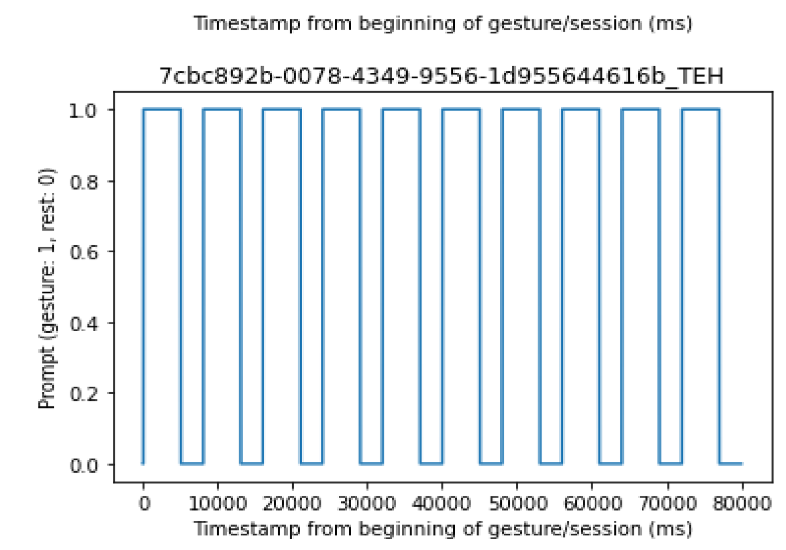

FIg 3: Testing out Merged Timestamps

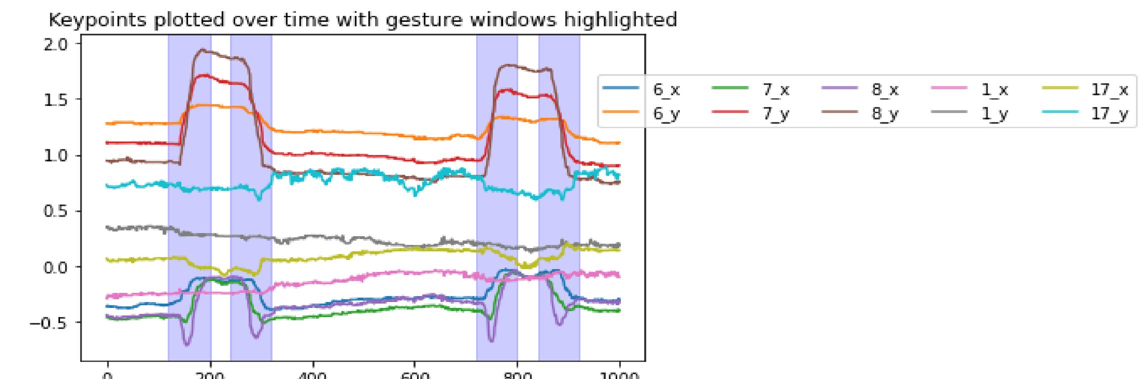

Fig 2: DTW algorithm test for the INA Semi-pronated gesture

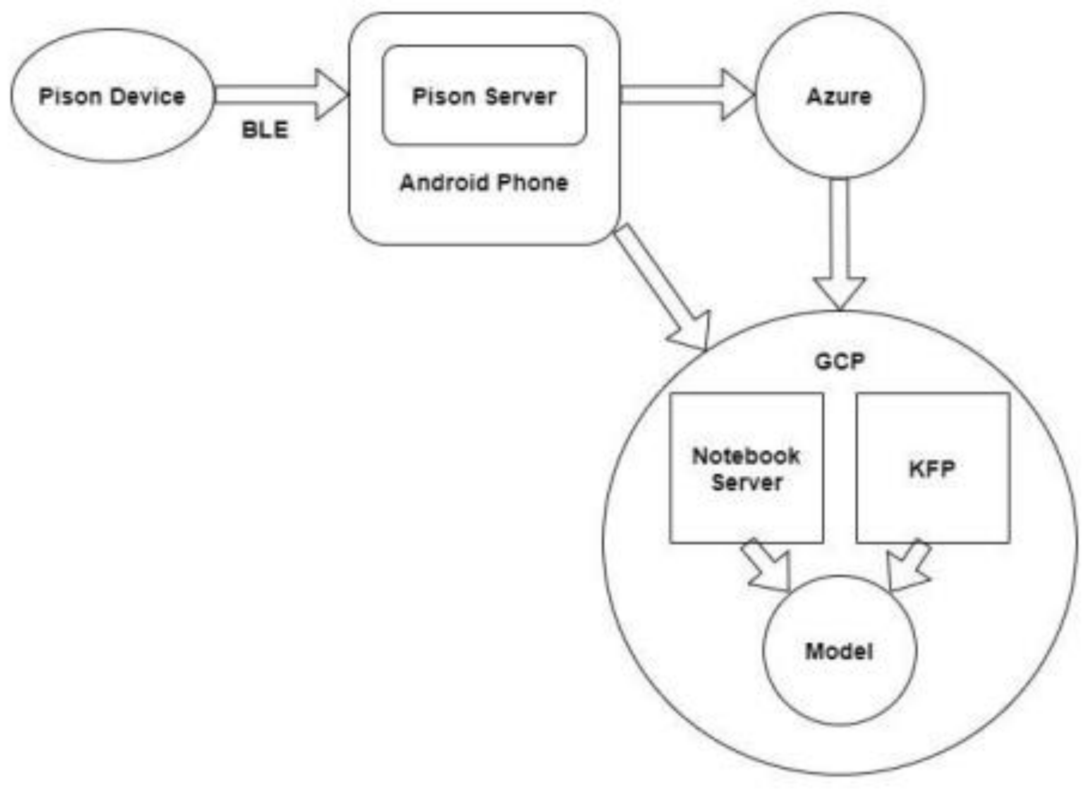

Fig 1: Development Block Diagram

Remaining Technical Challenges

Collective Database: One of the remaining tasks before moving onto the automated algorithm is to generate a data frame which includes each user that has generated data samples, their individual dtw avg and std. Displayed, as well as their KWL onsets and signal to noise ratios. All this combined will allow a comparison between the data samples and to find issues that may need tweaking to more accurately display the data, such as the training confidence threshold. This confidence threshold is a value where a certain amount of data from the entire set of samples is taken as the training set to train the machine learning system. Determining the perfect threshold is a key to a good training set and will lead to more accurate results and better overall performance of the machine learning model.

Fully Automated Pipeline: The process of which we need to follow in order to complete this algorithm is still kind of vague, but we will generally have most of the remaining tasks given to us related to the development of this fully automated data labeling algorithm. In order to reach our goal of creating a fully automated data labeling algorithm, that adjusts seamlessly to each user, instead of virtually having a new session every single time something is adjusted as per what the semi-automated algorithm does. We are still in the research phase of the fully automated data labeling algorithm, but the process will most likely have us understand separate parts of the semi-automated as a reference and aid in the design of the process of the fully automated version. It might need to be re-evaluated how this data-labeling algorithm is reading data. We might need to research ways for the accuracy to be increased based on what was seen with the semi-automated.

Implications for Company & Economic Impact

The best outcome of this project would provide Pison with a first fully automated labeling algorithm to be deployed to future data collection apps. The larger amounts of data streaming in from such low-barrier-to-collection apps would magnify the amount of research, development, and product-market exploration that Pison could perform, thus enabling the company to not only make its technology more robust for existing use cases, but also rapidly expand into new use cases as product-market-fits are identified. This would enable Pison to generate more self-sufficient streams of revenue, and bolster existing ones, allowing the continued growth of the company.