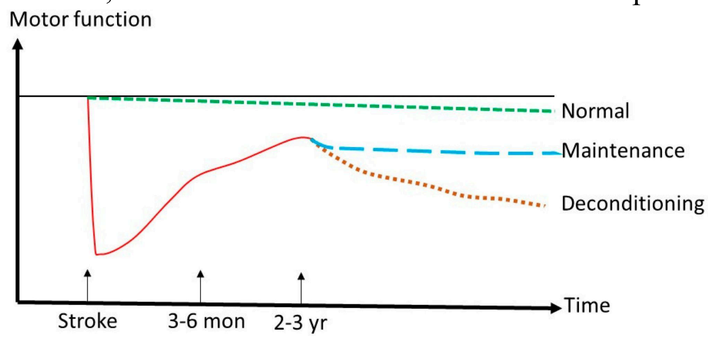
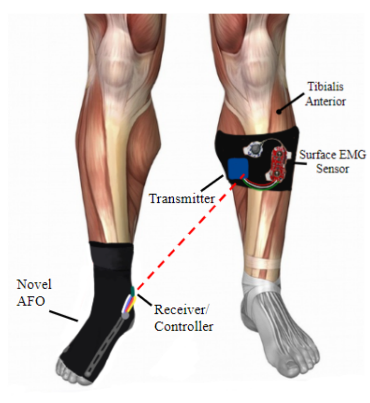
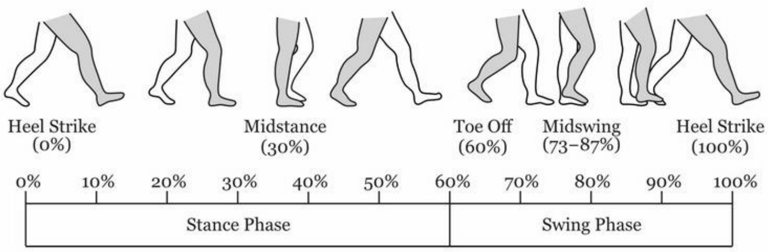
Impacts of Strokes on Gait: Over 12 million people worldwide suffer from a stroke yearly with more than 90% of stroke survivors suffering from some form of functional disabilities, and 80% having an unstable gait that improves to a certain extent within the first three to six months after a stroke, otherwise known as the late subacute phase as shown below. The lasting effects of a stroke on the movement of the ankle joint can cause stroke patients to adopt a sedentary lifestyle and be at risk of falling and seriously injuring themselves. Once the first six to twelve months post-stroke pass, recovery and mobility gain plateaus. However, there are few assistive technologies for gait stability for stroke survivors after the initial 6 to 12-month recovery period, as gait abnormalities continue to be present. The most common of these is foot drop, which impedes the dorsiflexion, or upward lifting of an individual's foot which is vital to gait stability. Foot drop causes excessive plantarflexion, or downward flexing of the ankle resulting in the patient dragging their toes. This inability to make the foot clear the ground often causes patients to develop a gait in which they hoist their leg from the hip to provide the extra clearance necessary for their foot to swing forward unimpeded. This dragging of the foot also causes a serious risk of falls for the patient.

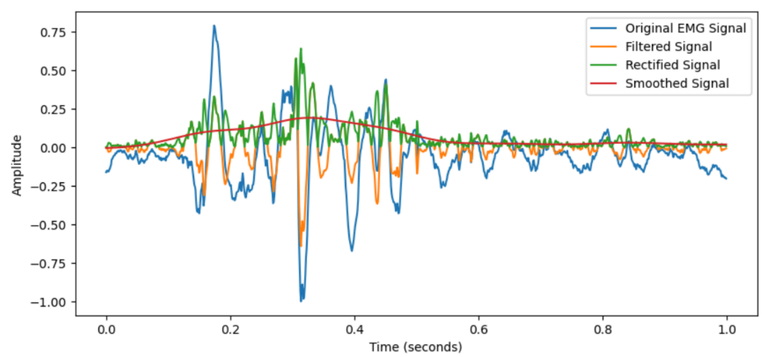


Goals and Innovation of This Project: Ankle-foot orthoses (AFOs) are the technology most commonly used to combat foot drop. These devices generally hold the ankle immobile to prevent prevent the dragging of the toe to a certain extent. This cannot, however, facilitate the same level of dexterity and inherently shock-absorbant properties of natural ankle movement. Thus, in this project I aimed to develop a novel active orthosis that utilizes real-time EMG (muscle activity) data from the contralateral (non-impacted) side to predict gait cycle phase in the impacted side. This information would then be used to control the orthosis to assist dorsiflexion, the upward flexion of the foot, accordingly. This concept greatly improves on the accuracy of previous designs which used force-sensing resistors, which used the force exerted by the foot on the ground to determine where in the gait cycle an individual was, as mechanically intrinsic signals such as this introduce delay into the system. In order to create my AFO, I created a deep neural network which could process windows of EMG data to determine where in the gait cycle the individual's other foot would be in a healthy gait. This replicates the process that would occur in my final design (shown to the right) as the strong and consistent EMG signals measured in the tibialis anterior (it maintains a consistent pattern through the phases of the gait cycle) of the healthy leg are processed and used to control the AFO accordingly. I also created a physical prototype of my AFO which emulated its envisioned functionality.

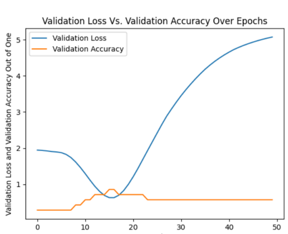


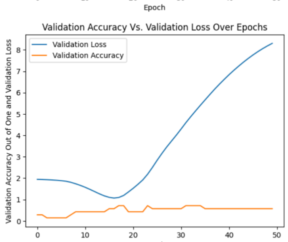
The Gait Cycle and Data Preparation: My project relies on the symmetry of the gait cycle (shown below) as the EMG data from one leg must be used to determine where in the gait cycle the other leg should be. As shown in the diagram, the gait cycle has two main phases, generally divided into seven subphases and can also be measured in percentage. At every point during the gait cycle, the other leg will be at a very specific corresponding part of the gait cycle. The data (from the MyPredict database) used for my initial machine learning model was split into one-second windows and labeled based on which of these seven subphases the window ended in. This data (shown to the right) was peak-normalized and filtered to eliminate the natural differences between the peaks in the EMG data of different gait cycles. In the first phase of the ML model, thirty samples from one individual were used whereas the second phase used 1500 individually labeled pieces of data which were labeled based on the percentage of the gait cycle they ended in, allowing for a greater degree of accuracy in my predictions and thus, the eventual motion of the AFO.

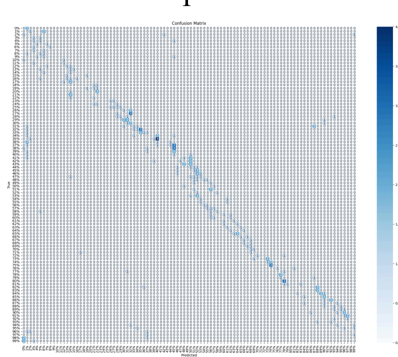




ML Model Testing and Phases: In the first phase of machine learning models I trained and tested, I used 30 samples of data, which, though a very low number, allowed me to identify if the model was more accurate with filtered or unfiltered data. The model achieved a maximum accuracy of 85.71% with the unfiltered data (only peak-normalized) and 71.43% with the filtered data. Additionally, the accuracy over the 50 epochs for which the model was trained remained far more consistent with the model's confidence in its predictions with the unfiltered data (shown left) than the filtered data (below unfiltered). The model's confidence is represented by loss; a lower loss means the model is more confident in its predictions. In the second phase of machine learning models, I labeled 1500 one-second windows of gait data from five different individuals (300 from

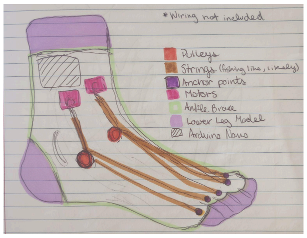




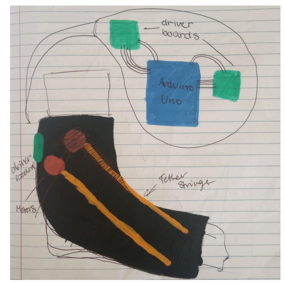


each), using four individuals for training and the other for my testing set. In this phase I trained two much larger models with this data. The larger of these two performed better, as shown in the confusion matrix above comparing the actual percentage and percentage predicted by the model, as its predicted values had a standard deviation of ±10.8% of a gait cycle.

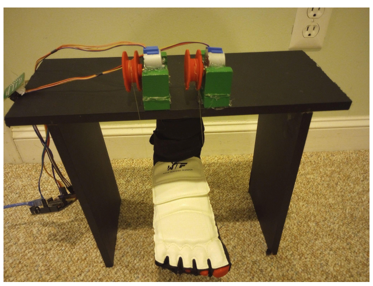
Prototype Iterations and Improvements: Design version 1.0 (below) was tested by pulling the strings anchored to the front of the AFO toward the ankle of the foot brace used in the designs which was worn on a 3D-printed foot with a moblise ankle joint.



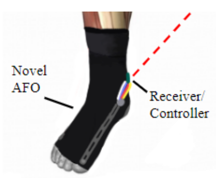
This hoever, did not result in the desired upward movement of the device. Version 2.0 (below) was designed to have the pulleys placed above the ankle. While the mpre upward motion of the strings caused the desired motion, the motors (with the pulleys attached to them) could not be securely anchored. Version 2.0 also placed the electronics behind the brace.



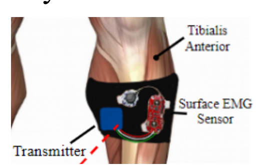
Version 3.0 (below) had the 3D-printed foot anchored to the small stool I made for that purpose and had the motors placed above the stool to ensure they were secure and the electronics placed similarly.



Version 3.1 saw this design programmed to emulate normal foot movement over the gait cycle at 20% speed while version 3.2 was programmed to mave the AFO to a specific angle based on manually inputted gait percentages. Version 3.3 will see the machine learning model interfaced with the AFO such that that the Arduino moves the AFO based on the model's predictions for a running input of EMG data. In order to get closer to a fully functional design, version 4.0 (below) will have a much stronger motor situated at the ankle connected to a rigid frame which prevents the tether strings from impeding activity and allows the device to move only the distance the patient has not, preventing muscle deterioration.



Version 5.0 will include the EMG activity measuring array on the unimpacted leg (right), using surface EMG to minimize intrusivity.



This will allow the system to respond to actual inputs from the patient, making it a fully functional device.

Future Research: As creating, designing, and improving a piece of assistive technology, especially wearable technology, such as my novel AFO require working with actual patients to ensure the device is comfortable and effective. Thus I hope to work with stroke patients, such as my grandfather, to iterate on my designs in the future. I am also very interested in soft robotics and would like to explore its potential applications in my AFO. I truly believe that through my research, I can create a device that will allow people like my grandfather to walk confidently without fear.