Greetings, my name is Hayden Cressman and I will be showing you my project on how machine learning can be used to help with the early diagnosis of autism using postural control features.

Autism Spectrum Disorder not only causes communication deficiencies but also deficiencies in motor control a well. These deficiencies can cause instability and loss of balance in an individual that we can measure through a persons Center of Pressure.

Center of pressure in this case refers to the point on which the pressure of your body over the bottoms of your feet would be if it were averaged into one spot. The movement of your center of pressure can be used to see how unstable you are by way of your base of support. At quiet rest, this center of pressure should average out to be directly under you, and if it deviates greatly this can be a sign of postural instability.

Stability and balance stem from certain systems in the human body. Specifically, they include the visual system, the inner ear, and our sense of touch. Issues with processing information can cause children with autism to have a harder time maintaining their balance during quiet standing than their typical development counterparts.

As of now there does not happen to be any direct clinical test for diagnosing autism. However, using machine learning and center of pressure data we can come up with a way to help medical professionals with their diagnosis of autism at an early age. This data is gathered from children aged 6 -15, however the goal is to aid those ages 3 and younger since these motor deficiencies can be found and improved through intervention.

For collecting COP data in our case, a small force plate was used to measure subjects center of pressure for 30 seconds trials over the course of 4 total trials. All trials are with the subject at quiet standing, so hands at their sides, looking forward, trying not to move as best they can. Two of the trials are done with eyes open, and two with eyes closed. [gesture to the beautiful picture]

We collect the data as best we can and use only trials that provide usable data without the child essentially leaving quiet rest stance and or opening their eyes during the closed eyed trial. From this data we derived and used 7 total attributes.

The displacement in the mediolateral (side to side) and anteroposterior (front to back) directions, the area of your postural sway, the multiscale entropy in the side to side and front to back directions, and the complexity index based off these entropies.

I am showing the COP data acquired from a test subject on the board for both an eyes open and an eyes closed trial. From these you can see how a child with ASD can perform at quiet rest with their eyes open versus their eyes closed, along with their sway area which was made into an ellipse so as to avoid obvious outliers in their sway.

From this data we can collect their entropy over time. Entropy in this case is used to determine the randomness and predictability of the system over multiple time scales.

In a basic sense, the sample entropy determines the difference between consecutive data points and determines if there is a mathematical pattern that can be seen. Studies have shown that lower entropy can be indicative of lower stability and has been used in other studies along with the complexity index to determine whether a subject is at risk of falling.

The complexity index is essentially a summation of all the entropy points to give an overall value to the level that the entropy is found to be. Again, a lower complexity is indicative of lower postural stability.

All seven of these attributes were used to train and test seven supervised machine learning algorithms. The use of supervised learning is since supervised algorithms take in labelled data and use those in order to predict and classify other, unknown labelled data.

The tests were run using 20 seconds of the center of pressure data, so 2000 data points, the 7 attributes, and trained and tested on a 70-30 split. What this means is that 70 percent of the trials were used for training the classifiers, and 30 percent of the trials were used for testing whether the classifiers were able to predict accurately.

The method of deploying these classifiers was through a python environment using the SciKit learn package. This package made it extremely easy to apply our data to the classifiers and obtain results in a short time.

As for the effectiveness of each classification model, the decision tree and random forest performed equally as best, with logistic regression and discriminant analysis being the next best two respectively. These values are the F1 score for each classification model, and the equation to calculate the F1 score can be seen below. Since the dataset was on the smaller side, the F1 score and the overall accuracy for each classification model was around the same.

To calculate the F1 score, we can look at the confusion matrices generate by each model. As the model performs their algorithms on the test data, we can see what the algorithm got correct and what it got wrong. The reason for the F1 score is because some algorithms are better at predicting one case than it is another, which can give a skewed accuracy that can be corrected by viewing the F1 score. As we can see none of them got a perfect accuracy for predicting ASD or TD, but overall, they had a better rate of predicting ASD than they did at predicting TD.

From these findings we can see that certain classifiers outperform others, with Naïve Bayes coming in very low on the F1 score surprisingly, however overall, they are able to predict ASD based on center of pressure data well.

Going forward with these finding and methods we hope to see higher accuracy with the inclusion of more data both for the control group and the test group.

One component of machine learning that was not explored due to time constraints was attribute weights. With attribute weights we are able to make one attribute more deterministic of the data than others. This can be useful if one attribute, say entropy or complexity, is found to be of greater importance to postural sway than others, but for this project all attributes were weighted the same importance to the classification models.

One problem that was found in the data was just how the data was calculated. Going forward some of the data will need to be cleaned up before using, because in the case of certain children who go through typical development in the control group, their data was taken at 60 hz whereas for our group with ASD, their data was taken at 100 hz. This disparity of data caused issues when calculating entropy since entropy’s prime function is to determine the distance between consecutive groups of points.

And finally including a wider range of classification models into this work will help determine which models are best when examining center of pressure data. Some with always outperform others, and more data will help with determining which ones should move forward into further research.

Thank you to NSF and Texas State for this research opportunity and thank you Dr. Li for letting me work alongside you on this. Now I will take questions.