Injury Gait Analysis

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Introduction

Worldwide, 35% of adults above 65 years old experience knee pain. This percentage jumps to 50% for adults above 80 years old. Needless to say, low body joint pain is a substantial problem affecting 25% of all adults overall.[1] Our project aims to utilize image analysis of input data from a golf pressure sensing insole, Salted Smart Insoles, and characterize the pressure maps in relation to a normal walking gait and pressure distribution. The program could be trained to recognize various different gaits to identify people with injuries, disabilities, or habitual motions that could be detrimental to joint health.

Problem Statement: To determine how knee pain and overall injury affect the intensity and location of pressure upon the foot while walking.

Solution: Gather gait data from a sample of BMEn students and create a machine learning algorithm to spot the differences between the gaits of those who are injured and those who are not.

Experimental Setup

Data Collection

- To test each subject the pressure insoles were placed in sandals, allowing for each participant to tighten the footwear to their foot size. Subjects were then asked to walk to the rhythm of a metronome at 90 BPM.
- Subject information was recorded including height, weight, age, and any known injuries.
- After data collection, the file was converted and uploaded to MATLAB as a .mp4 file.
- The data was extracted from the videos and classified in the MATLAB code.

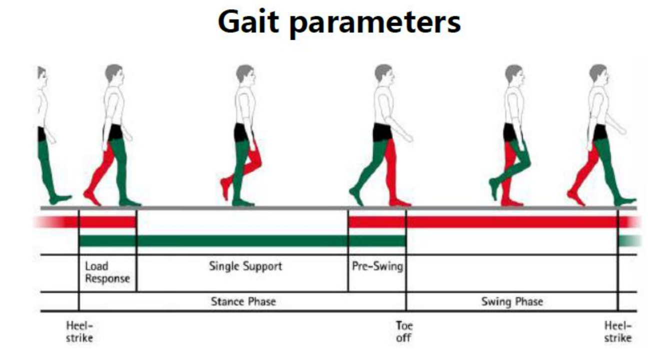


Figure 1: Chart of the walking gait used to collect pressure data

Figure 2: The method used to combine the income and scandal used for data collection

Results

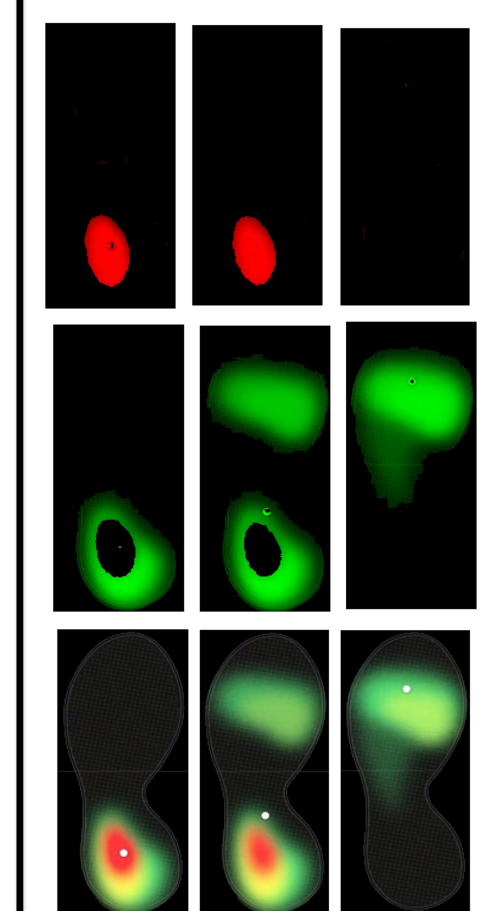


Figure 3: Foot decomposition for a person without injury

Decomposition of the foot map for heel strike, middle phase, and tie strike. There is a different distribution of the load among between each condition.

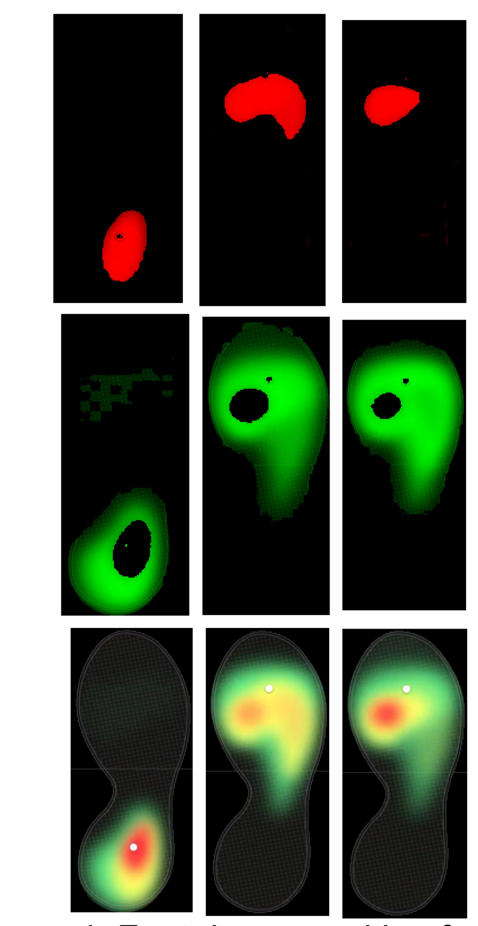


Figure 4: Foot decomposition for a person with injury

System Diagram

- Initially the subject will walk with pressure insoles at an average pace
- After the data was converted and ran through the Pressure Classifier

Pseudocode:

Processing all subject videos:

- Convert to an mp4 file and extract Frames
- Export every 10th Frame to temporary storage folder
- Call the Feature Generation algorithm on each frame
- Add all frame features into single row vector for that subject

Feature Generation for each frame:

- Convert foot imprint to grayscale
- Gray regions of image filled in white
- White image is superimposed onto
- original image to create foot outline

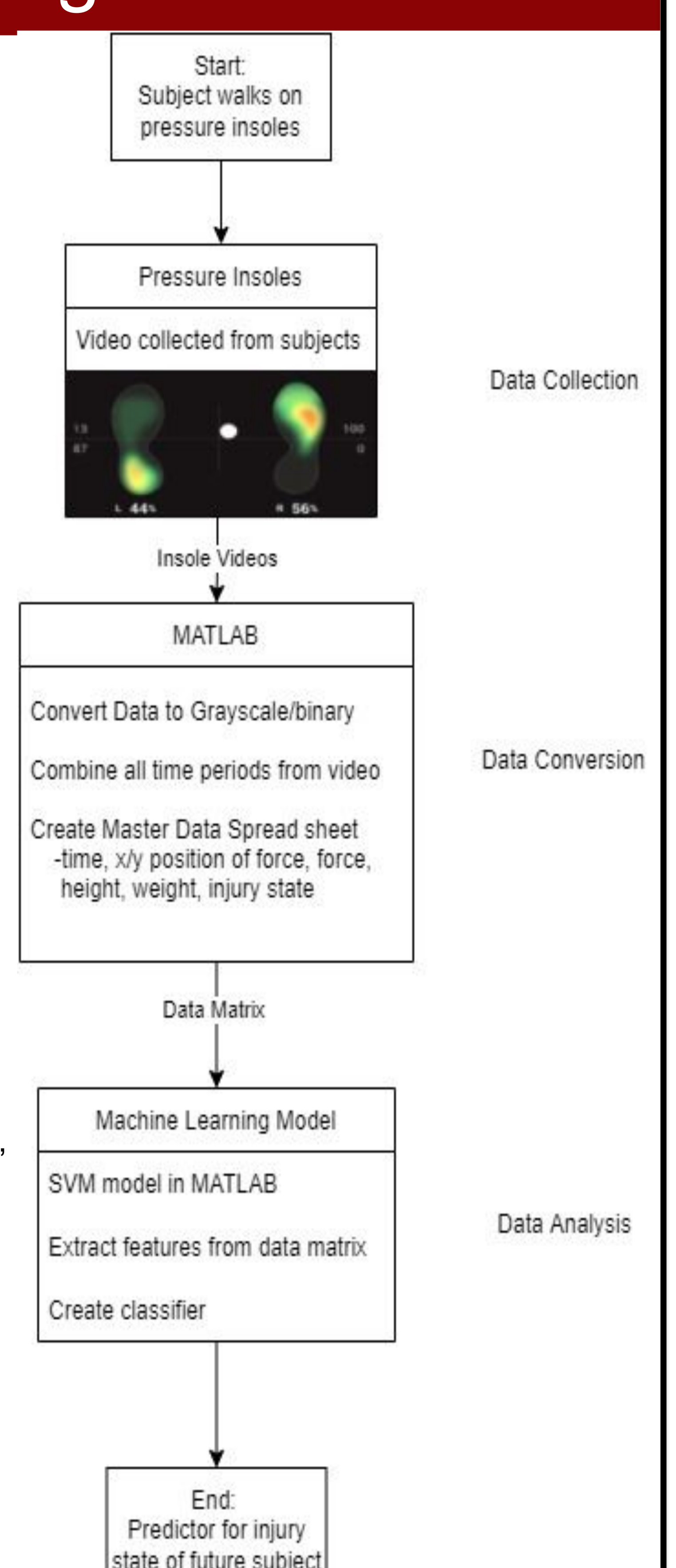
Foot Tracer

For each foot:

- Extract red and green pixel intensities at each pixel
- Compute mean, standard deviation, and median of each color at each sensor location (4 sensors)
- Combine into single vector (12 features total)
- Return combined vector with frame features from each foot

Machine Learning Model:

- Combine Processed data with age, weight, height, gender, and injuries into single matrix
- Chi Square Ranking, fscchi2(), used to rank feature correlation with injury state
- Remove 60 least impactful features (leaving 100)
- Create two cv-partitions, one k-fold with 6 subsamples, one hold-out with 30% withheld
- Fit built in SVM model to both, use bayesian optimization to find best parameters
- Use models to predict test data injury state
- Create confusion matrices to compare models and choose ideal one



Results

System Performance

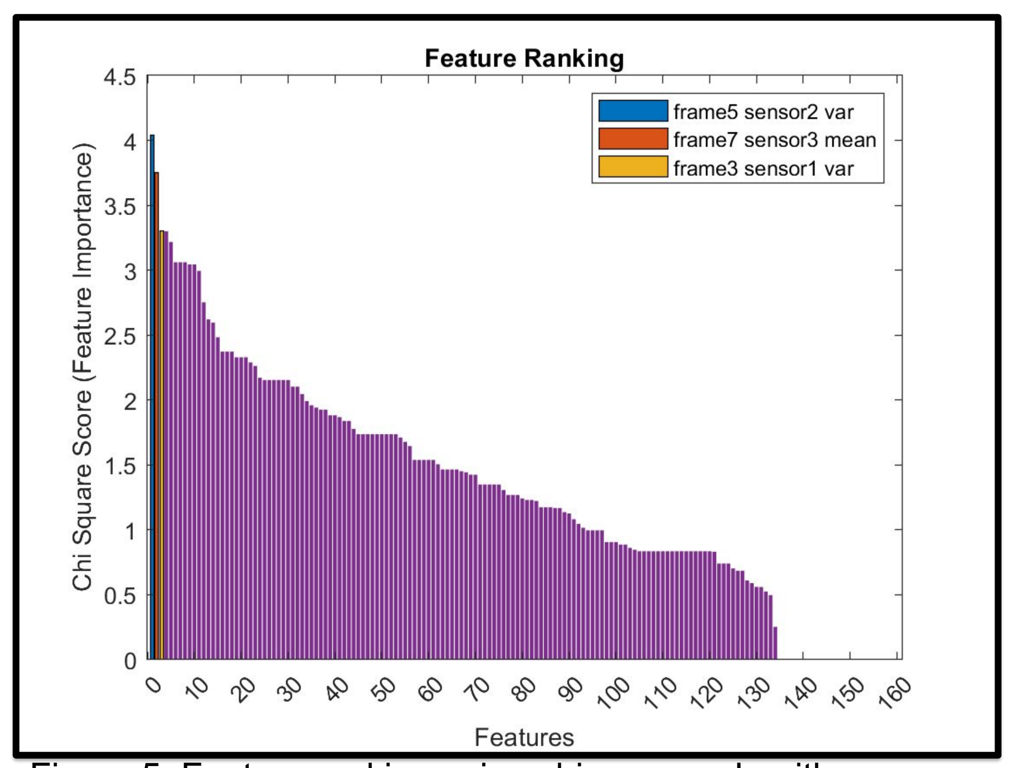


Figure 5: Feature ranking using chi-square algorithm

K-Fold CV Model

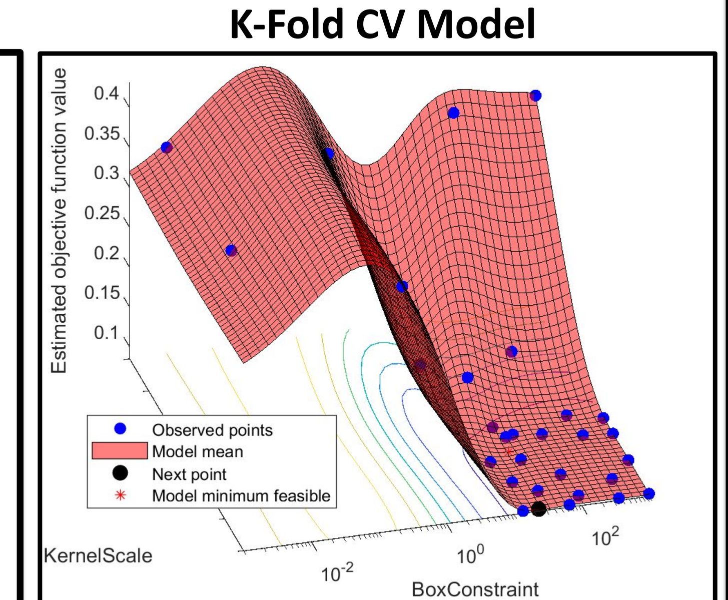


Figure 6: SVM Model 1 parameter tuning
Model 1 is over fit with an testing accuracy of 100%, note extra folds in parameter tuning.

Partitioned CV Model

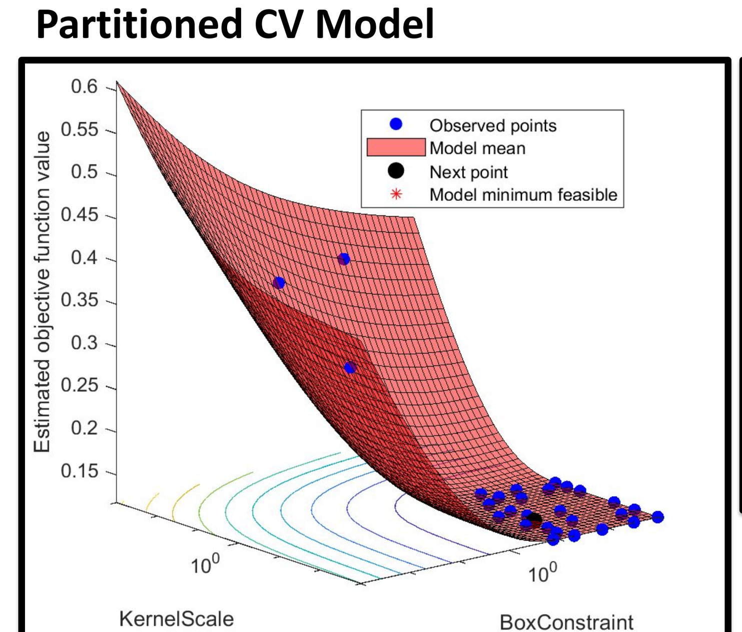


Figure 7: Model 2 Parameter Tuning

partitioned cv (model 2)

True Class \ Predicted Class	0	1
0	4	
1	1	1

Figure 8: Model 2 confusion matrix using test data

Model 2 Statistics
Raw Training Accuracy
100%
CV Training Accuracy
88.2%
Testing Accuracy
82.3%

The partitioned CV Model predictor is the final product of this project. 0 and 1 denotes non-injured and injured gaits respectively; only one type II error made. Overall SVM model predicts injuries with 82.3% accuracy primarily using features shown in Figure 5.

Summary and Future Directions

Summary

- Data collected through the Salted Smart Insoles was processed through Pressure Classifier to obtain useful frames for analysis.
- Pressure Classifier then used an SVM model to classify the data as injured vs. healthy based on the best feature rankings such as mean intensity and variance
- SVM model allows for accurate injury predictions without significant overfitting

Future Directions

- Pressure Classifier could be more accessible if it was built into an app, allowing the user to have instantaneous feedback.
- A potential expansion upon this project would be to collect additional data on subjects with a variety of injuries. This would provide the ability to determine the type of injury a subject is experiencing based upon their pressure map.
- Access to raw voltage data and a greater number of sensors per sensor pad, as well as different sizes of sensor pads for different test subjects.

Acknowledgements

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References

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