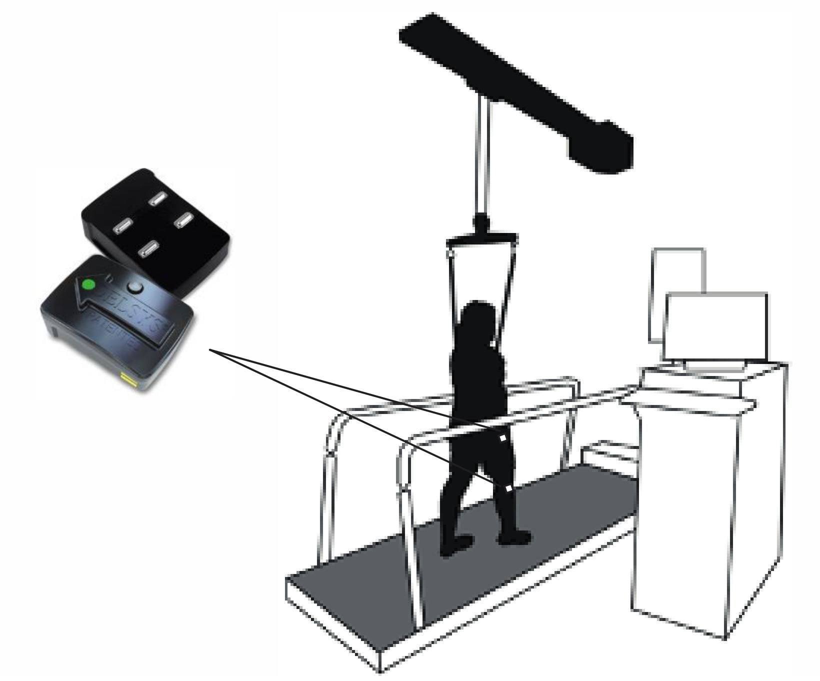
Exploration of Machine Learning to Identify Community Dwelling Older Adults with Balance Dysfunction Using Short Duration Accelerometer Data



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Balance Dysfunction

- Balance dysfunction is one of the most common fall risk factors[1]
- Instrumented test focus on balance dysfunction may provide an opportunity for early fall identification in community dwelling older adults

[1] J. L. O’Loughlin, Y. Robitaille, J.-F. Boivin, and S. Suissa, “Incidence of and risk factors for falls and injurious falls among the community dwelling elderly,” American journal of epidemiology, vol. 137, no. 3, pp. 342–354, 1993.
Image: A2 physical therapy, URL: https://www.a2pt.family/images/thumbs/social/Balance_for_Older_Adults_Main.jpg

Clinical and instrumented tests are sensitive and validated to indicate the decline of balance functions

- The motor control test (**MCT**) provides a quantitative measurement that is a sensitive indicator for the decline of postural control in community dwelling older adults[1].
- Traditional subjective balance tests have also been used to predict balance dysfunction and fall risk.
- However, these tests take time and clinical professionals to administer the test, also with a higher economic cost.

[1] C. C. Harro and C. Garascia, “Reliability and Validity of Computerized Force Platform Measures of Balance Function in Healthy Older Adults,” Journal of geriatric physical therapy (2001), vol. 42, no. 3, pp. E57–E66, 2019.
Image: NeuroCom(R) SMART EquiTest(R) CDP - natus, URL: https://partners.natus.com/asset/resource/file/newborncare/asset/2018-04/015368A_SMART_EquiTest_EN-US_lo-res.pdf

Specific Aims

- Validate the feasibility of wearable sensors to identify older adults who have trouble with balance
- Explore the possibility of using machine learning algorithm on small accelerometer(**ACC**) data set to identify balance dysfunction during walking.
- Explore lower extremity sensor locations for accelerometer sensor.

Image: CNN.com, URL: https://www.cnn.com/2019/01/24/health/married-people-fitter-healthier-study-scli-intl/index.html

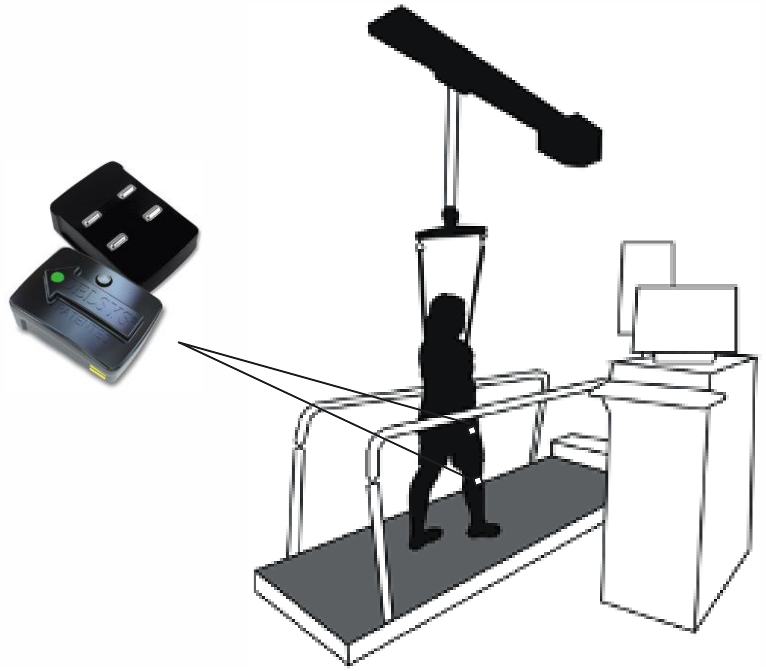
Methods

Participants:

- 21 community dwelling adults have been divided into two balance ability group
  - 12 individuals in high balance group (**HB**, 66.75±4.08 years old, TICS = 25±4.16, MCT = 131.25±4.99ms)
  - 9 individuals in low balance group (**LB**, 66.44±6.31 years old, TICS = 25.89±5.17, MCT = 152.22±3.42ms)
  - MCT cutoff latency: 143.4ms

Procedure:

- Two ACC sensors were placed on right hip and knee
- 120 s comfortable paced walking with predefined self-selected speed performed on the treadmill
- Two independent walking trials were collected from each subject



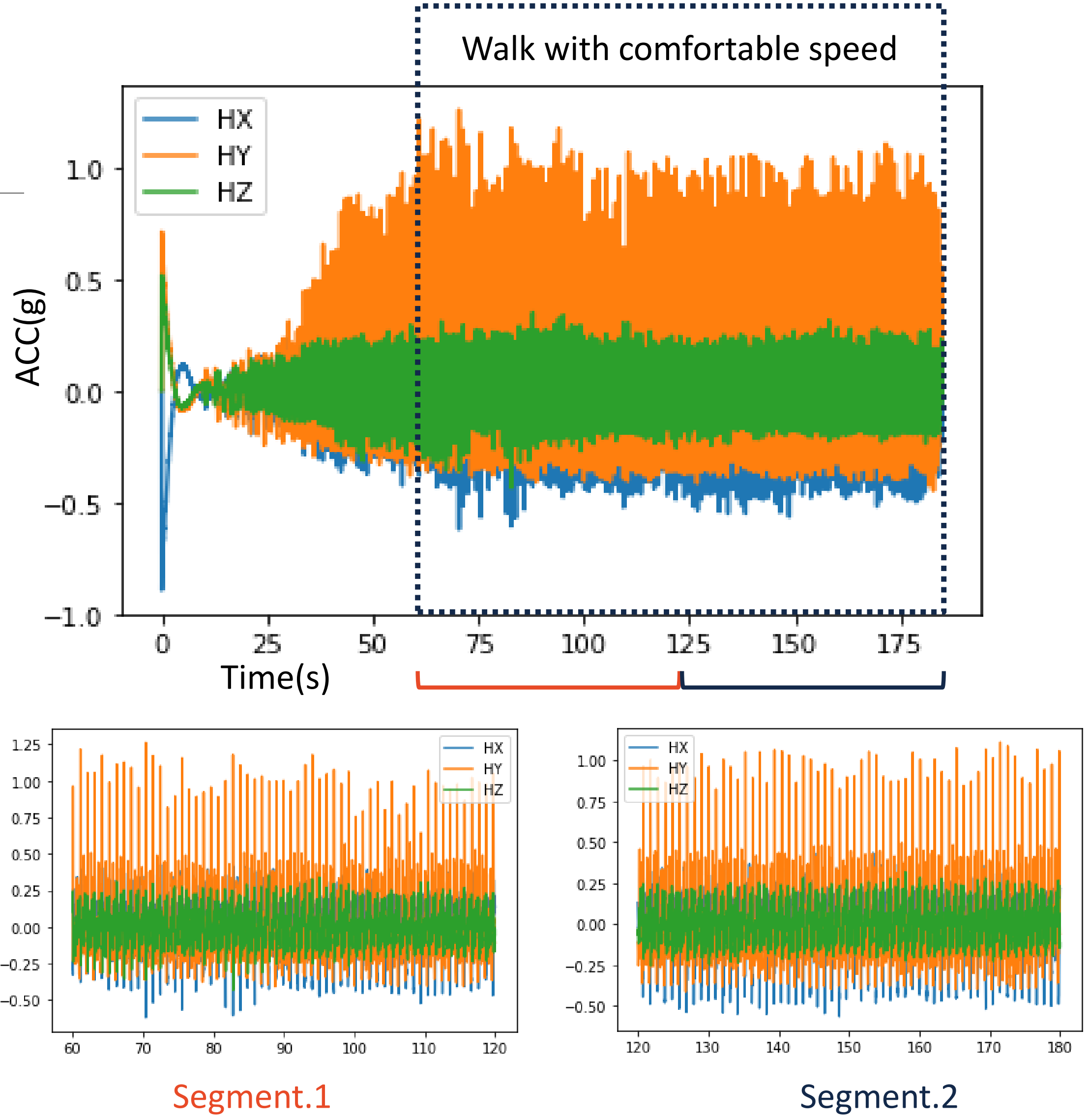
Methods

Data Analysis:

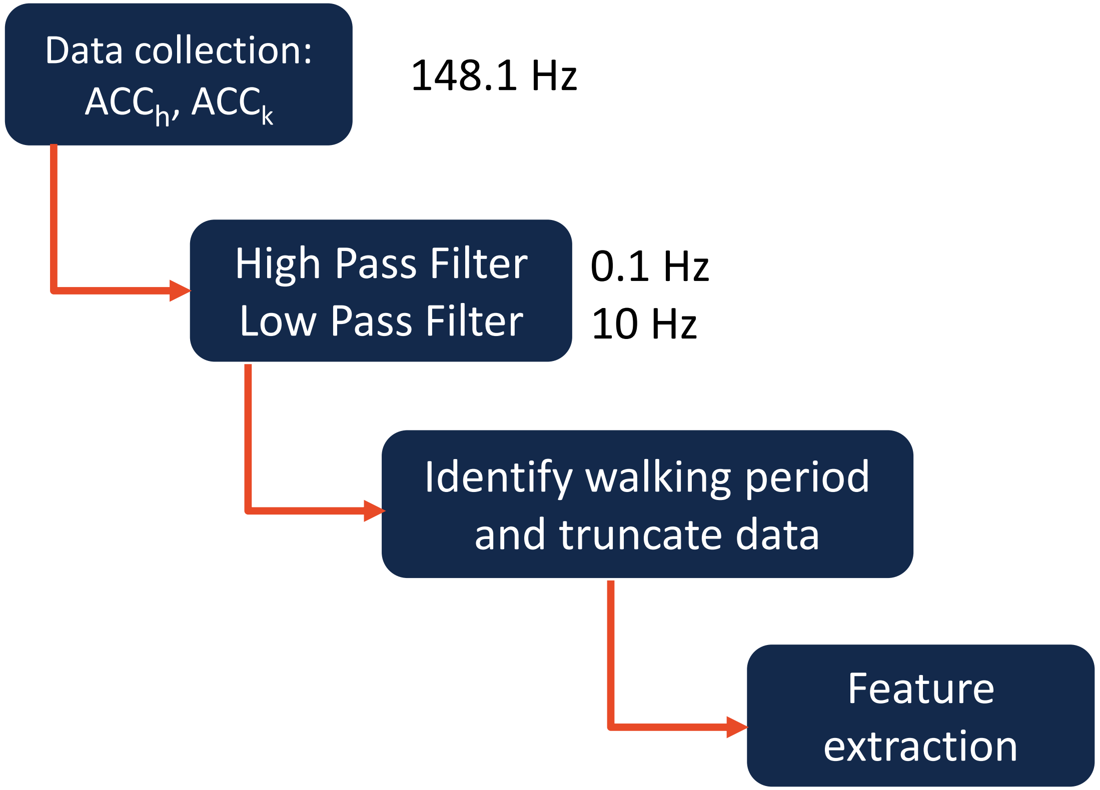
- ACC date was truncate to 60s independent segments for features extraction

Statistical Analysis:

- ACC features examined for cohort differences using t-test (p value = 0.05 set for significance)



Data Preprocessing & Feature Extraction

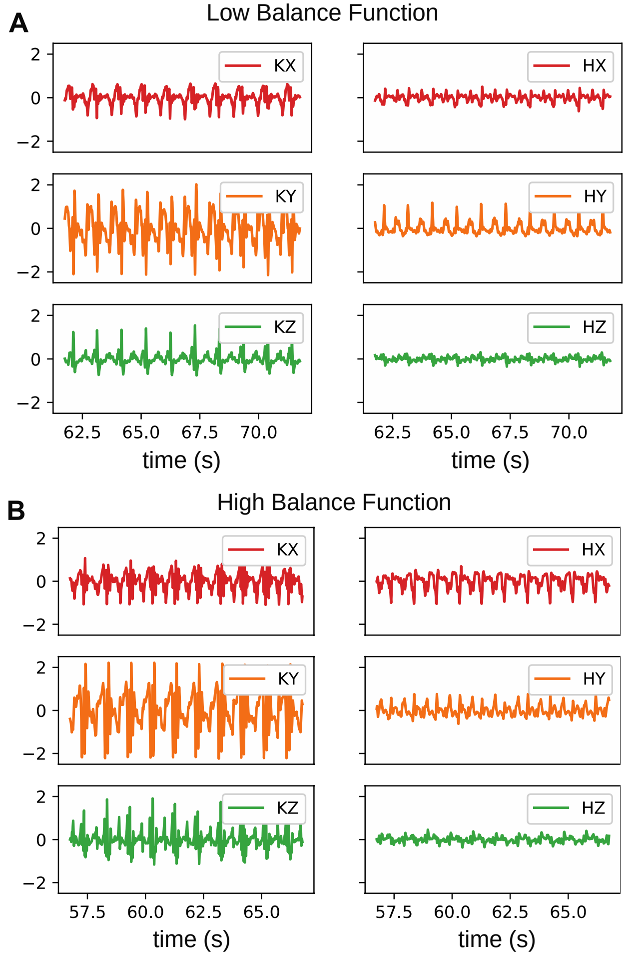


Features Extracted	
Mean	μ_h, μ_k
Standard Deviation	σ_h, σ_k
Coefficient Of Variance	CVh, CVk
Root Mean Square	$RMSh, RMSk$
Auto Correlation	A_h, Ak
Mean Amplitude Deviation	$MADh, MADk$
Signal Magnitude Area	$SMAh, SMAk$
Signal Energy	SEh, SEk
Paired Correlation Coefficient	$r_{xy}^h, r_{yz}^h, r_{xz}^h, r_{xy}^k, r_{yz}^k, r_{xz}^k$
Peak-to-peak Mean	μ_h^{P2P}, μ_k^{P2P}
Peak-to-peak Standard Deviation	$\sigma_h^{P2P}, \sigma_k^{P2P}$
Peak-to-peak Maximum	$\gamma_h^{P2P}, \gamma_k^{P2P}$

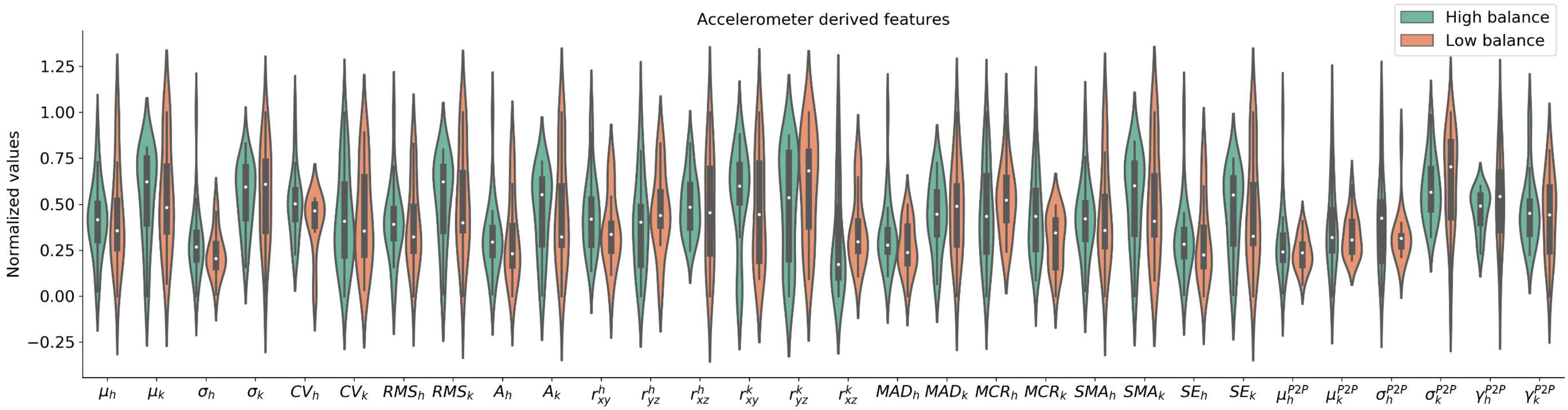
HB and LB have very similar ACC frequency profile

Groups	All subjects	HB	LB	P-value
MCT	140.24 ± 11.36	131.25 ± 4.99	152.22 ± 3.42	$< \mathbf{0.01}$
Hx	2.05 ± 0.47	2.19 ± 0.57	1.88 ± 0.15	0.19
Hy	2.15 ± 0.47	2.35 ± 1.21	1.88 ± 0.15	0.72
Hz	1.76 ± 1.34	1.90 ± 1.58	1.58 ± 0.95	0.91
Kx	1.75 ± 0.40	1.85 ± 0.31	1.62 ± 0.47	0.16
Ky	2.00 ± 1.29	2.21 ± 1.66	1.70 ± 0.33	0.66
Kz	2.43 ± 1.74	2.67 ± 1.95	2.11 ± 1.41	0.19

- Although different pattern can be observed in x, y, z-acceleration coordinates



Subtle changes in ACC derived features in **LB**

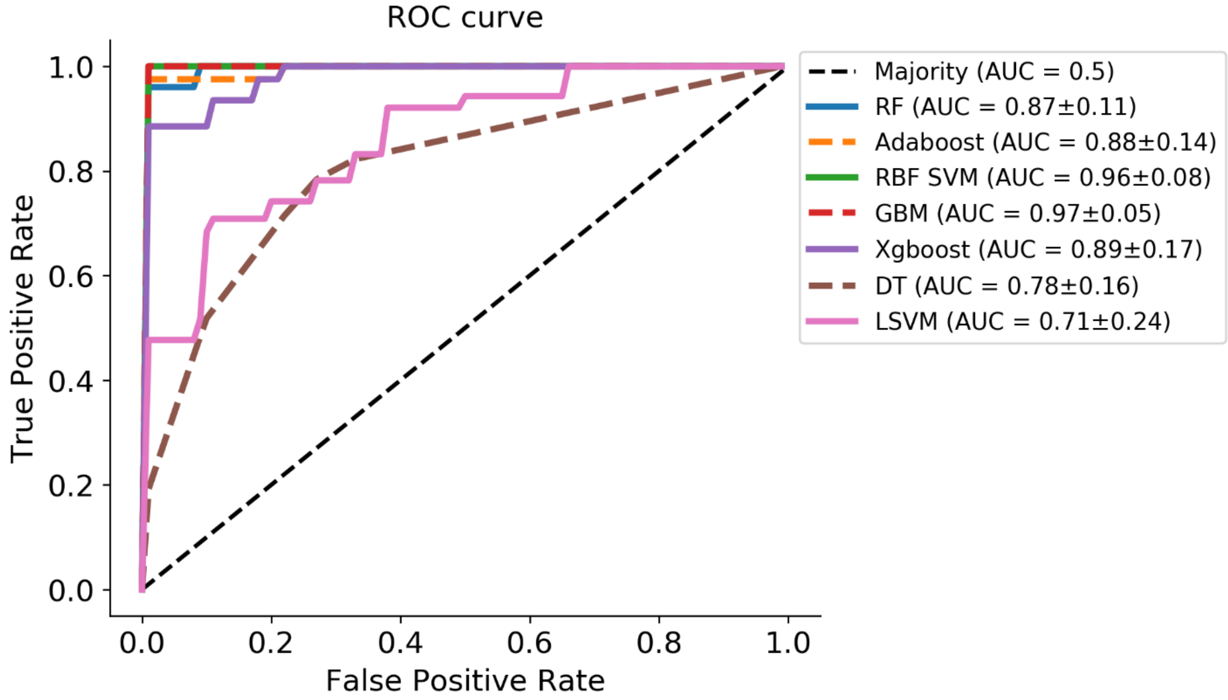


Findings:

- No pattern distinguishing subjects with low or high balance function are evident in the exploratory plots.
- No statistically significant differences between subject groups in all features, were found from independent t-tests

ML model explorations and results

- All features were normalized between 0 and 1
- Total seven ML algorithms were compared.
  - Decision tree(DT), ensemble random forest(RF), support vector machine (SVM) with linear (LSVM) and radial basis function (RBF SVM) kernels, gradient boosting machine (GBM), adaptive boosting (Adaboost) and eXtreme gradient boosting (XGBoost)



Findings:

- GBM and RBF SVM algorithms shows consistent low false positive rates and high true positive rates

ML model explorations and results

Algorithm	Accuracy	F1 score	AUC
DT	0.780 ± 0.16	0.709 ± 0.24	0.782 ± 0.16
RF	0.890 ± 0.09	0.860 ± 0.12	0.865 ± 0.11
LSVM	0.646 ± 0.12	0.60 ± 0.06	0.705 ± 0.24
RBF SVM	$\mathbf{0.915 \pm 0.07}$	$\mathbf{0.889 \pm 0.09}$	$\mathbf{0.957 \pm 0.08}$
Adaboost	0.866 ± 0.12	0.858 ± 0.12	0.875 ± 0.14
GBM	$\mathbf{0.915 \pm 0.09}$	$\mathbf{0.893 \pm 0.11}$	$\mathbf{0.965 \pm 0.05}$
XGBoost	0.902 ± 0.13	0.899 ± 0.12	0.893 ± 0.17

Findings:

- GBM algorithm provided the best average CV performance
- Followed by RBF SVM by a slight margin.

Discussion

- Results of this study suggests that accelerometer data can be used to classify balance dysfunction within community dwelling adults, which demonstrate consistency with similar ML studies predicts fall risks[1][2][3][4].
- GBM provide improvements in overall classification performance in classifying balance dysfunction compare to random forest algorithm which was used in past ML approaches to predict fall risk[1][5].
- In comparison to prior one sensor system[6], the two-sensor approach provide a potential opportunity for the tracking of additional lower extremity motion.
- Compare to traditional instrumented balance tests, ACC based ML techniques can be used by a non-clinical professional in any setting, which relieves the time and economic burden on both patient and clinical professionals.

[1] Drover et al., 2017; [2] Aicha et al., 2018; [3] Howcroft et al., 2018; [4] Montensinos., et al., 2015; [5] Hua et al., 2018; [6] howcroft et al., 2013

Conclusions

- In this study, we established the feasibility of using 60s of accelerometer data from wearable sensors, when walking, to identify older adults who have low or high balance function
- GBM algorithm in classifying older women with low or high balance function provides promise for the use of wearable sensor data.
- **Next steps:**
  1. explore the optimal trial duration and data features to best classify balance dysfunction.
  2. investigate the optimal sensor location by comparing the corresponding sensitivity of sensor locations in the lower extremity with other commonly used locations such as the shoulder
  3. design novel classification architectures best suited for this task

Image: Healthline.com, URL: https://www.healthline.com/hlcmsresource/images/topic_centers/3895-older_Man_with_Walking_Stick_Outdoors-732x549-thumbnail.jpg

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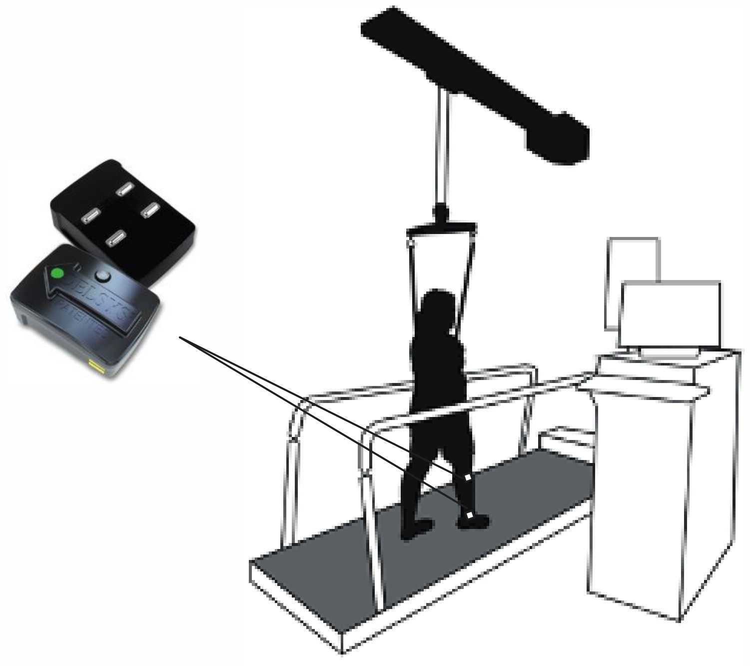

Instrumented Treadmill

Thank you!