Using Machine Learning and a Wrist-Worn IMU to Detect and Quantify Daily Living Gait in Older Adults and Patients with Neurological Disease

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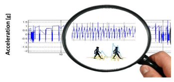
Two Super-Heroes

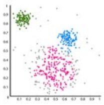
Multiple Roles of Machine Learning in IMUs for Studying Daily Living Gait

Gait Detection: is the person walking (yes or no)?



Finding the "hidden" gait feature in the noise of an IMU
e.g., estimating stride length

"Cluster" analyses:
How to best combine many gait features from an IMU?



Two Super-Heroes

Two Super-Heroes

Two Super-Heroes of Aging Research

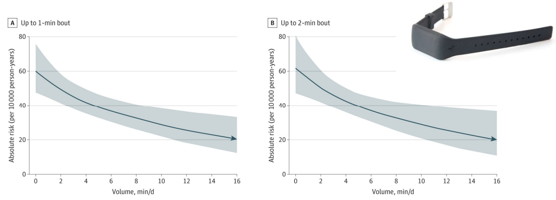
Why is physical activity a super-hero of aging?

Physical activity is a protective factor for:

- Osteoporosis
- Sarcopenia
- Cardiovascular disease
- Stroke
- Diabetes
- Falls
- Mobility disability
- Neurological disease
- Cognitive decline
- Dementia

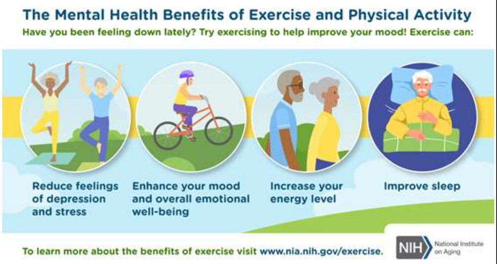
JAMA Network

From: **Vigorous Intermittent Lifestyle Physical Activity and Cancer Incidence Among Nonexercising Adults: The UK Biobank Accelerometry Study**
Emmanuel Stamatakis et al.
JAMA Oncol. 2023;9(9):1255-1259. doi:10.1001/jamaoncol.2023.1830

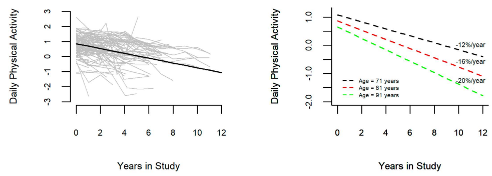


Adjusted Absolute Risk Dose-Response of Vigorous Intermittent Lifestyle Physical Activity (VILPA) Daily Duration, From Bouts of Up to 1 and 2 Minutes, With Physical Activity–Related Cancer Incidence (n = 22 398; 1084 Event). Absolute risk adjusted for **age, sex, body mass index (calculated as weight in kilograms divided by height in meters squared), duration of light-intensity physical activity, duration of moderate-intensity physical activity, smoking status, alcohol consumption, accelerometer-estimated sleep duration, fruit and vegetable consumption, education level, medication use, self-reported parental history of cancer, and prevalent cardiovascular disease**. All analyses were additionally adjusted for vigorous physical activity duration of more than 1 or 2 minutes, as appropriate.

Why is physical activity a super-hero of aging research?



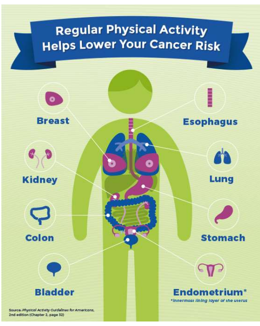
Physical activity a super-hero of aging – super sensitive



- Data from Rush Memory and Aging Project (MAP)
- 1083 older adults (average age 81 years; 76% female)
- Person-specific rates of change varied during a mean follow-up of 5 years, but **1079 of 1083** showed declining daily living physical activity.
- The average decline was 16%/year, with a 4% increased rate of decline for every 10 years of age older at baseline.

AS Buchman et al., 2023

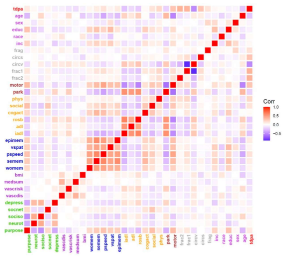
Why is physical activity a super-hero of aging?



CDC

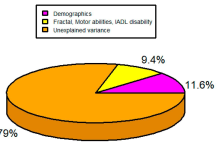
Physical activity a super-hero of aging – sensitive but many open questions

Covariate Groups	Variable at Baseline
Demographics	Age (years)
	Female sex
	Education (years)
	Race
	Income (median level)
Sensor metrics	Sleep fragmentation (0-1)
	Interdaily stability (0-1)
	Intradaily variability (0-2)
	Fractal alpha1
	Fractal alpha2
Motor function	Motor abilities (scaled)
	Parkinsonism (0-100)
Self-report	Physical activities (h/week)
	Social activities (0-5)
	Cognitive activities (0-5)
	Mobility disability (0-3)
	ADL disability (0-6)
	IADL disability (0-8)
Cognitive function	Episodic memory (z-score)
	Visuospatial abilities (z-score)
	Perceptual speed (z-score)
	Semantic memory (z-score)
	Working memory (z-score)
Chronic health	Body mass index
	Chronic medical conditions (0-7)
	Vascular risk factors (0-3)
	Vascular diseases (0-4)
Psychosocial factors	Depressive symptoms (0-10)
	Social network (0-9)
	Social isolation (1-5)
	Neuroticism (0-12)
	Purpose in life average score (1-5)



Low to moderate univariate correlations with physical activity decline.

Physical activity a super-hero of aging – sensitive but with many open questions



- Age, sex, education, and 3 of 27 non-demographic covariates were significantly associated with declining daily living physical activity.
- These three covariates were motor abilities, a fractal metric, and IADL disability.
- These accounted for – ONLY – **21% of the variance** (9% non-demographic and 12% demographics covariates).
- Physical activity declined in **99%** of the cohort and the unexplained variance was **79%**

AS Buchman et al., 2023

Why is gait a super-hero?

Physical activity a super-hero of aging – sensitive but with many open questions

Blocks of covariates	Variance of physical activity decline rate explained by blocks of covariates
Demographic	16% (11%–22%)
Waist sensor-derived mobility metrics - Walking	21% (16%–28%)
Waist sensor-derived mobility metrics - Timed Up & GO	22% (17%–30%)
Waist sensor-derived mobility metrics - Standing	3% (1%–8%)
Wrist sensor-derived other covariates	10% (6%–16%)
Vascular factors	4% (2%–9%)
Cognition	9% (5%–15%)
Psychosocial	6% (3%–12%)
Pulmonary function	5% (2%–10%)
Self-report activities & disabilities	18% (13%–26%)
Conventional motor function	24% (18%–30%)
Blood work and other lab tests	8% (5%–14%)

When covariates from all 12 blocks were included together in a single model, only two measures were independently related to the decline.

Together, they accounted for – ONLY – **30%** of the variance of declining daily physical activity.

S Oveisgharan et al., in prep

Gait speed predicts injurious falls

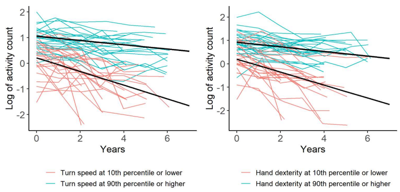
	Model 1	Model 2	Model 3	Model 4
All Population (n = 16 445)				
Linear association (each SD decrease)	0.998 (0.997, 0.998)	0.998 (0.997, 0.998)	0.998 (0.997, 0.999)	0.998 (0.997, 0.999)
Gait speed (m/s) quintiles*				
High (Q5)	Ref	Ref	Ref	Ref
Medium (Q2-Q4)	1.16 (1.00, 1.34)	1.15 (1.00, 1.34)	1.18 (1.01, 1.37)	1.18 (1.01, 1.37)
Low Q1	1.55 (1.31, 1.83)	1.50 (1.27, 1.78)	1.48 (1.24, 1.77)	1.48 (1.24, 1.77)

N=16,45; Mean age at baseline: 75.29 (4.36); Mean follow-up: 4.0±1.3 years

Data presented as hazard ratio [HR, 95% confidence interval (CI)]. Model 1: age and gender. Model 2: age, gender, **physical activity**, BMI and self-reported health status. Model 3: age, gender, **physical activity**, BMI, SF12 (state of health), chronic kidney disease, and polypharmacy. Model 4: **age, gender, physical activity, BMI, SF12 (state of health), chronic kidney disease, polypharmacy and aspirin** (100mg).

T Pham et al., PloS One, 2023

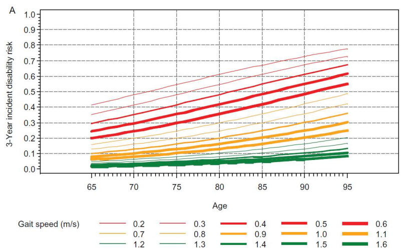
Physical activity a super-hero of aging – sensitive but with many open questions



Left panel illustrates trajectories of physical activity in 25 participants with high (blue) and 25 participants with low (red) levels of **turning speed**. Similarly, right panel illustrates trajectories of physical activity in 50 participants with high and low levels of **hand dexterity**.

S Oveisgharan et al., in prep

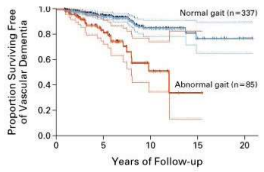
Gait speed predicts disability



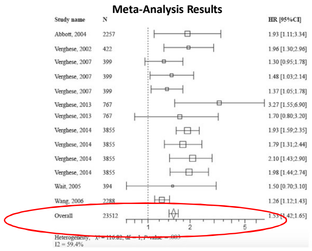
Pooled analysis of 27,220 community-dwelling older adults aged 65 or older with baseline gait speed

Perera et al., JGMS 2016

Gait Changes Predict Dementia: More than Six Years in Advance!!

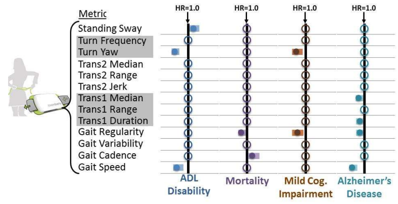


Verghese et al, *NEJM*, 2002



Beauchetet al, *JAMDA, 2016*

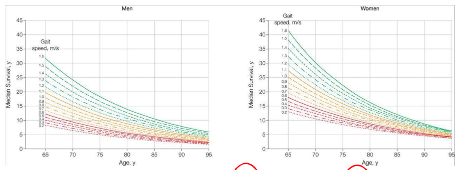
Disparate Gait Profiles Predict Different Adverse Health Outcomes – Using A Wearable Sensor



Mean follow-up of 3.5 years, among 1,249 older adults (mean age 81, 78% female), unique combinations of gait measures predict different adverse outcomes.

A Buchman et al, 2020

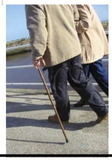
Gait speed predicts death



34,485 community-dwelling older adults aged 65+ years, followed for 6 to 21 yrs.

Mean age: 73.5±5.9 years;
Mean gait speed: 0.92±0.27 m/s

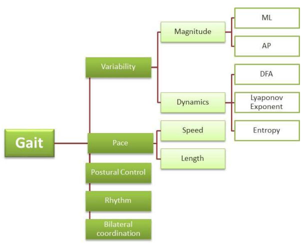
	Men	Women	Men	Women
Walking Speed	1 mph	1 mph	3.5 mph	3/5 mpg
Probability that an 80-year-old will live to age 90	10%	23%	84%	86%
Median life expectancy for an 80-year-old (in years)	84	87	94	97



JAMA. 2011;305(1):50-58. doi:10.1001/jama.2010.1923

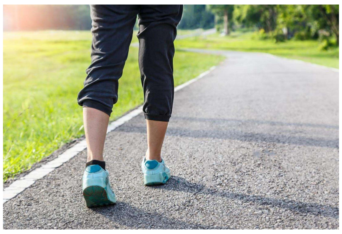
Recommendation of the American Physical Therapy Association

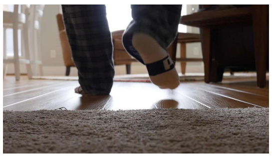
"Gait" is like an ogre / many layers with distinct behaviors, mechanistic, diagnostic, and predictive capacity



The conventional gait lab

The gait lab of the future

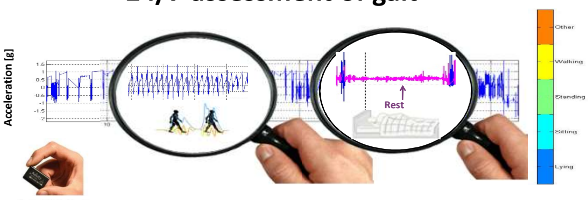




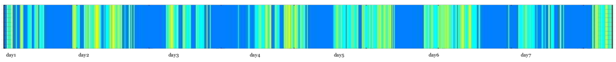
Potential advantages of 24/7 monitoring of gait

	Supervised assessment	Unsupervised assessment
Clinometric properties (e.g., test-retest reliability)	Established	In progress
Setting	Artificial	Ecological
Number of assessments	1 Snapshot	1000's
Sensitive to fatigue, affect and mood	Minimally	Yes
White coat (Hawthorne) effect	Yes	Minimally
Patient centred	Not necessarily	Yes
Real-world challenges	Somewhat	Yes
Real-time feedback for therapy	Questionable	Yes
Interpretation of results	Easy	More challenging
Environmental influences	Minimal	Yes

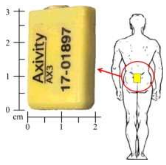
24/7 assessment of gait



Automated activity classification (e.g., lying, sit, stand, walk)

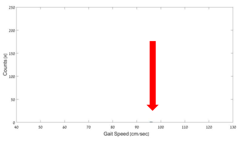


24/7 Findings Using A Lower Back Sensor
Selected Examples

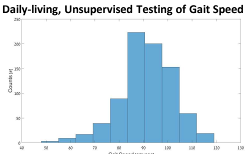


Potential advantages of 24/7 monitoring of gait

Conventional, Supervised Testing of Gait Speed

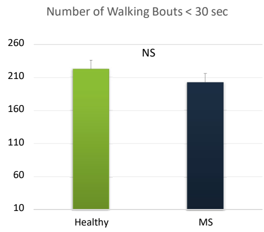


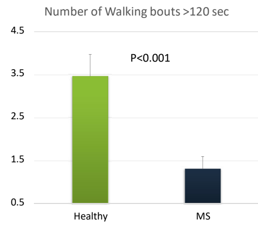
Daily-living, Unsupervised Testing of Gait Speed



E Warmerdam et al., *Lancent Neurology*, 2020

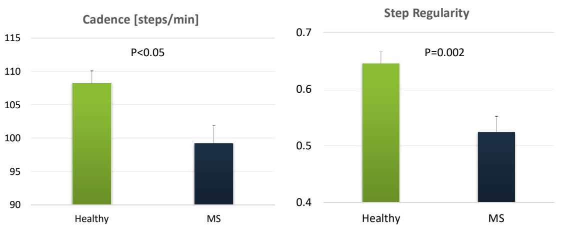
Large walking bouts are reduced in Multiple Sclerosis (MS)



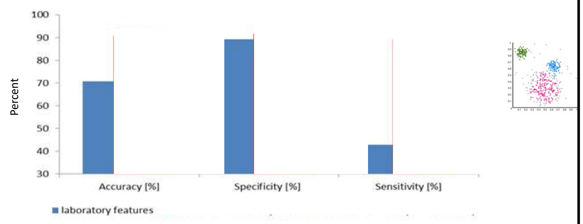


S Shema et al., 2020

Stepping quality reduced in MS

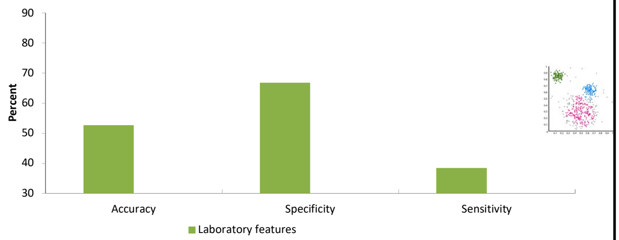


Elderly fallers vs. elderly non-fallers: Conventional vs. continuous monitoring



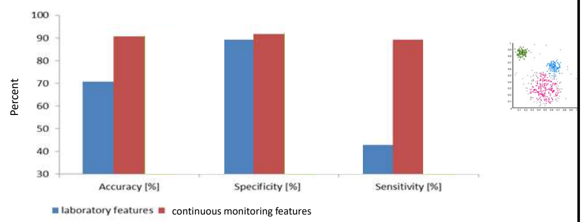
T Iluz et al., 2015

Patients with mild PD vs. older adults: Conventional vs. continuous monitoring



Bernad-Elazari et al. 2016

Elderly fallers vs. elderly non-fallers: Conventional Lab vs. continuous monitoring Machine Learning Selected Cluster Analyses



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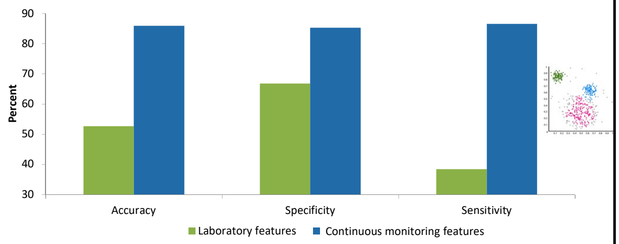
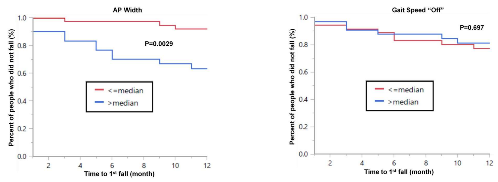


Bernad-Elazari et al. 2016

Prediction of future falls among subjects with PD: 24/7 vs. conventional measures



Based on 24/7 Measures

Conventional Measures

A Weiss et al., 2014

Relationship between lab and 24/7 metrics in MCI: Mobility function ≠ Mobility capacity

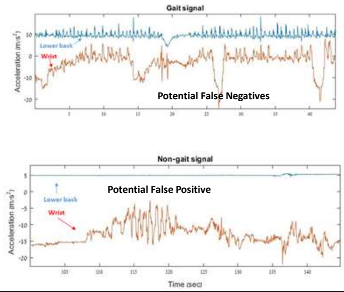
Larger effect sizes for everyday walking

		Controls	MCI	P-value	Cohen's d
Lab Testing	Gait speed (m/sec)	1.06±0.24	0.90±0.29	0.017	0.601
	Stride Length (m)	1.16±0.20	1.02±0.22	0.004	0.666
24/7 Testing					
	SD of stride regularity	0.17±0.01	0.13±0.04	<0.001	1.372
	SD of peak amplitude [g^2/Hz]	0.18±0.01	0.12±0.05	<0.001	1.664

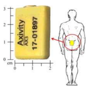
Hausdorff et al., 2017

Challenges of 24/7 monitoring of gait from a wrist-worn IMU: gait detection

- Many degrees of freedom of the wrist and many hand activities not related to gait -> false positives
- The hand is often *not* coordinated with the gait cycle -> false negatives
- This challenge is even more pronounced in **aging** and **neurological disease**, due to reduced arm swing, tremor, other gait disturbances, and the use of walking aids
- Many algorithms *not* validated in these cohorts, e.g., a "one-size-fits-most" (Digital Medicine, 2023)



Let's Move from the Lower Back to the Wrist



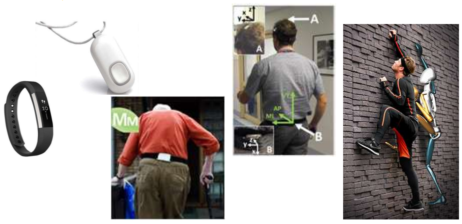
Example of Chorea in Huntington's disease

https://youtu.be/6yZcwfwcMng

Data quality vs. Compliance

Data quality

Acceptance



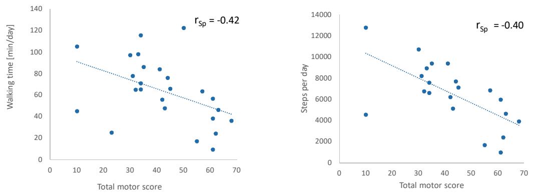
Signal-processing, feature based (FB) algorithm for detecting gait in Huntington's disease from a wrist-worn IMU

Lori Quinn, Columbia U

Karin Keren

K Keren et al., 2021

Association between daily living gait quantity and Total Motor Score (clinical score)



r_{Sp} = Spearman's correlation

K Keren et al., 2021

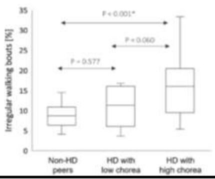
Gait Detection from a Wrist-Worn Sensor Using ML: A Daily Living Study in Older Adults and People with Parkinson's

Yonatan Brand

Dafna Schwartz

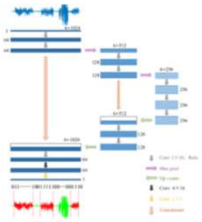
Daily Living Gait in Chorea

Daily-living gait quality		HD participants (n = 28)	Non-HD peers (n = 21)	*P*-value	Effect size
Rhythm	Cadence (step/min)	105.02 ± 8.98	109.76 ± 5.35	0.04	0.62
	Dominant frequency (Hz)	1.81 ± 0.18	1.86 ± 0.12	0.25	0.34
Magnitude	Range (g)	1.74 ± 0.35	1.66 ± 0.24	0.42	0.24
	RMS (g)	0.26 ± 0.05	0.30 ± 0.06	0.015*	0.73
Regularity/ Consistency	Amplitude dominant frequency (unitless)	0.67 ± 0.15	0.87 ± 0.14	<0.001*	1.45
	Width dominant frequency (Hz)	0.83 (0.21)	0.70 (0.02)	<0.001*	0.72
	Step regularity (unitless)	0.40 ± 0.15	0.66 ± 0.07	<0.001*	2.08
	Stride regularity (unitless)	0.33 (0.24)	0.70 (0.08)	<0.001*	0.72
	Step time variability (%)	26.27 ± 5.23	18.63 ± 6.62	<0.001*	1.30

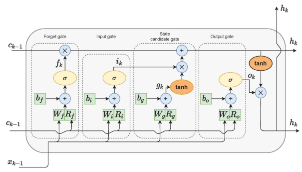


K Keren et al., 2021

Gait Detection from a Wrist-Worn Sensor Using ML: A Daily Living Study in Older Adults and People with Parkinson's



The architecture of the DCNN, deep convolutional neural network. Adapted from Zou et al. (2020)



LSTM cell diagram, Long Short-Term Memory. Adapted from Zarzycky et al (2021)

Y Brand. D Schwartz et al., 2022

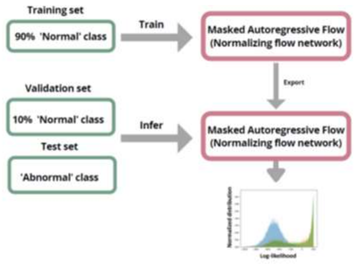
Feature-based algorithm performs poorly when applied to other data sets – overfitting?

		Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
HYAs					
	FB	71.0	36.3	77.8	69.5
OAs					
	FB	76.2 (2.4)	15.4 (5.8)	59.8 (6.3)	77.3 (2.5)
PD					
	FB	77.6 (5.7)	15.2 (11.3)	57.4 (15.6)	57.4 (5.5)

Precision is also referred to as positive predictive value (PPV).

Y Brand. D Schwartz et al., 2022

Gait Detection from a Wrist-Worn Sensor Using ML: A Daily Living Study in Older Adults and People with Parkinson's Anomaly Detection Method



Y Brand. D Schwartz et al., 2022

Gait Detection from a Wrist-Worn Sensor Using Machine Learning Methods: A Daily Living Study in Older Adults and People with Parkinson's Disease

	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
HYAs				
FB	71.0	36.3	77.8	69.5
AR-iHMM	73.2	40.0	94.6	68.4
DCNN	96.0	90.9	83.8	98.4
Bidir-LSTM	90.9	70.6	84.3	92.3
New Anomaly Detection	99.4	79.1	44.6	99.4

	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
OAs				
FB	76.2 (2.4)	15.4 (5.8)	59.8 (6.3)	77.3 (2.5)
AR-iHMM	85.2 (8.1)	27.3 (8.6)	78.7 (17.9)	85 (9.43)
DCNN	96.2 (4.2)	61.4 (3.4)	69.8 (9.8)	97.6 (4.9)
Bidir-LSTM	81.7 (6.6)	38.8 (11.9)	81.7 (5.7)	81.8 (7.4)
New Anomaly Detection	76.2 (0.5)	29.9 (0.5)	67.6 (0.1)	78.1 (0.6)
PD				
FB	77.6 (5.7)	15.2 (11.3)	57.4 (15.6)	57.4 (5.5)
AR-iHMM	92.6 (4.7)	38.1 (24.0)	50 (23.3)	95.1 (5.0)
DCNN	91.7 (7.4)	40.9 (6.0)	72.9 (7.4)	92.9 (9.2)
Bidir-LSTM	76.6 (4.6)	38.3 (7.1)	88.6 (10.9)	76.5 (6.1)
New Anomaly Detection	83.3 (3.8)	20.9 (2.3)	74.7 (8.2)	83.8 (5.4)

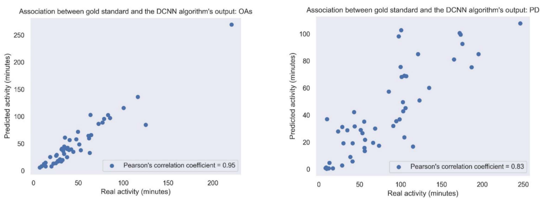
Precision is also referred to as positive predictive value (PPV).

Y Brand. D Schwartz et al., 2022

Limitations and Challenges of these Machine Learning Approaches

- A supervised model requires reliable labels
- Labels derived from the lower-back sensor are not perfect
- In general, ground truth labels are scarce in daily living recordings, especially in clinical populations
- Hence, the potential of "foundation" and self-supervised models

Correlation between the amount of daily walking with the lower-back gold standard and the activity according to the best algorithm (i.e., DCNN)



Daily Living Gait Quality Measure		OAs	PD	p-Value
Rhythm	Dominant Frequency (Hz)	0.86 ± 0.2	1.21 ± 0.45	<0.001 *
Magnitude	RMS (m/s^2)	1.36 ± 0.25	1.16 ± 0.59	0.0293
Regularity/Consistency	Stride Regularity (unitless)	0.13 ± 0.02	0.14 ± 0.05	0.3094
	Amplitude Dominant Frequency (unitless)	0.43 ± 0.07	0.33 ± 0.15	<0.001 *

Self-supervised Learning for Human Activity Recognition Using 700,000 Person-days of Wearable Data - UKBB Wrist-Worn data

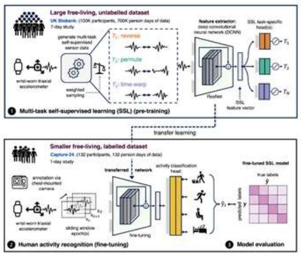


Table 3: Subject-wise F1 and Kappa (κ) for downstream human activity recognition tasks (mean ± SD) using 100,000 participants for pre-training. The relative improvement compares the performance between the model that is trained from scratch and fine-tuning using all the layers.

Data		Random forest	ResNet: Trained from scratch	ResNet: Fine-tune self-supervised, After ConV layers	ResNet: Fine-tune self-supervised, All layers	Improvement
Capture-24	F1	.694 ± .099	.708 ± .094	.723 ± .097	**.726 ± .093**	2.5 %
	κ	.683 ± .101	.703 ± .092	.718 ± .090	**.737 ± .087**	4.8%
Rowlands	F1	.700 ± .090	.696 ± .106	.724 ± .081	**.796 ± .093**	14.4%
	κ	.830 ± .086	.810 ± .098	.850 ± .062	**.874 ± .073**	7.9%
WISDM	F1	.711 ± .149	.684 ± .123	.759 ± .121	**.810 ± .127**	18.4%
	κ	.715 ± .153	.685 ± .124	.758 ± .121	**.809 ± .126**	18.1%
REALWORLD	F1	.731 ± .119	.705 ± .062	.764 ± .052	**.792 ± .075**	12.3%
	κ	.680 ± .142	.638 ± .079	.703 ± .063	**.739 ± .086**	15.8%
Opportunity	F1	.416 ± .185	.383 ± .124	.570 ± .078	**.595 ± .085**	55.4%
	κ	.318 ± .206	.238 ± .154	.435 ± .092	**.471 ± .104**	97.9%
PAMAP2	F1	.753 ± .093	.605 ± .086	.725 ± .054	**.789 ± .054**	30.4%
	κ	.744 ± .101	.596 ± .086	.717 ± .057	**.769 ± .059**	29.0 %
ADL	F1	.764 ± .180	.414 ± .179	.645 ± .107	**.829 ± .101**	100.0 %
	κ	.720 ± .199	.368 ± .198	.654 ± .123	**.849 ± .113**	130.7%

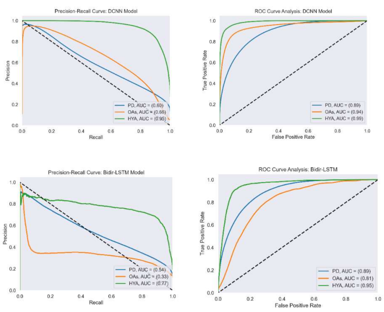
Yuan et al. 2022 – preprint archive

A Closer Look

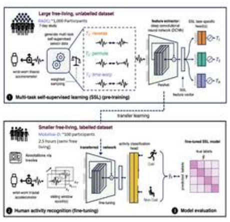
- Good accuracy (ROC curves)
- However, lots of room for improvement, even for the DCNN model, when looking at Precision-Recall Curves

Recall in the ML context is also referred to as the true positive rate or *sensitivity*.

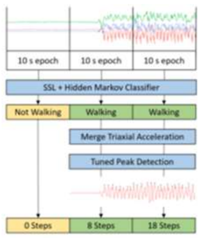
Precision is also referred to as positive predictive value (PPV).



Development and Validation of a ML Wrist-worn Step Detection Algorithm with Deployment in the UKBB (OxWalk)

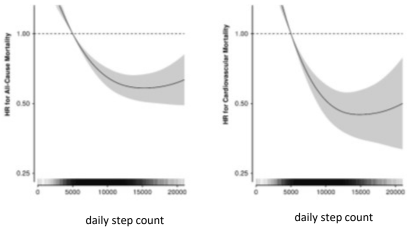


Adapted from Yuan et al. (2022)



SR Small et al. preprint archive

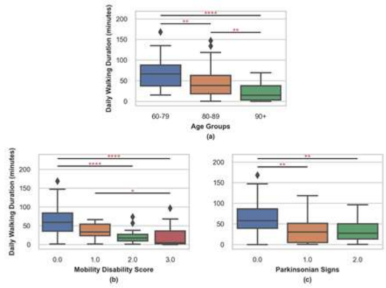
Clinical Utility- UKBB Wrist-Worn data



Spline plot of hazard ratio and 95% confidence interval of the association of continuously modelled median daily step count.

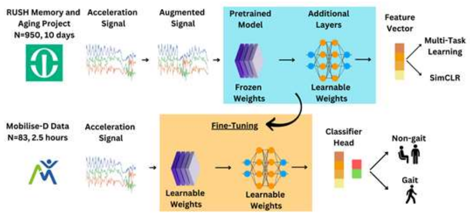
SR Small et al. preprint

ElderNet: Initial Clinical Application



Y Brand et al., in prep

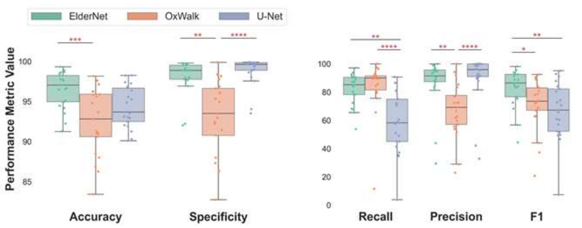
ElderNet Pipeline: Extending a self-supervised pipeline via fine-tuning to unlabeled and labeled data from older adults



Y Brand et al., in prep

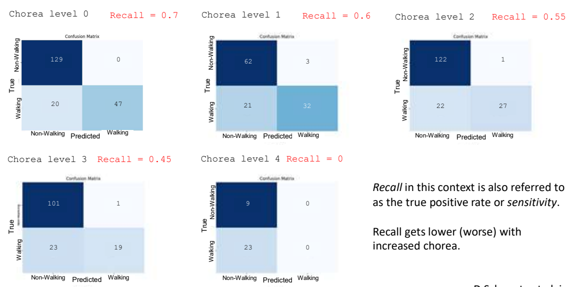
Can State-of-the-Art Gait Detection Algorithms Accurately detect Gait – from a wrist-worn IMU – in the presence of Chorea among patients with Huntington's disease?

The benefits of fine-tuning to the cohort of interest: ElderNet vs OxWalk (Small et al.) and U-Net (DCNN)



Y Brand et al., in prep

Classification for gait/non-gait applying the Yuan et al. model to HD - without any adjustments

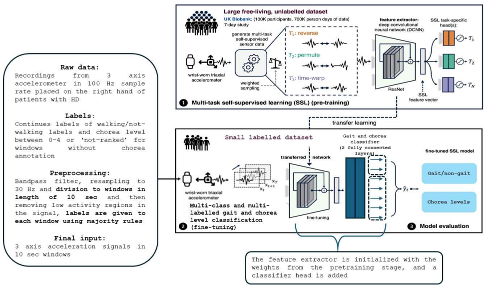


Recall in this context is also referred to as the true positive rate or *sensitivity*.

Recall gets lower (worse) with increased chorea.

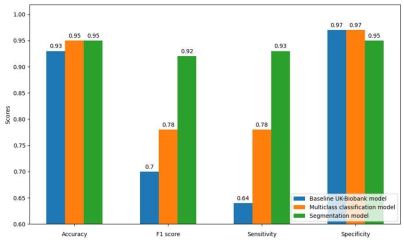
D Schwartz et al. in prep

Classification for gait/non-gait applying the Yuan et al. model to HD – fine tuning to HD



D Schwartz et al. in prep

Benefits of Fine-Tuning UKBioBank Model (Yuan et al) when Assessing Patients with HD



Sensitivity = Recall = True positive rate

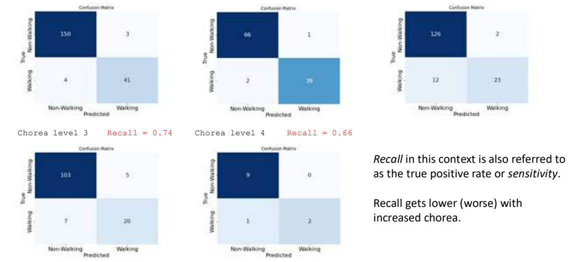
Specificity = True negative rate

Precision = PPV (Positive Predictive Value).

F1 score combines precision and recall using their harmonic mean

D Schwartz et al. in prep

Classification of gait with fine tuning: initial results in HD



Recall in this context is also referred to as the true positive rate or *sensitivity*.

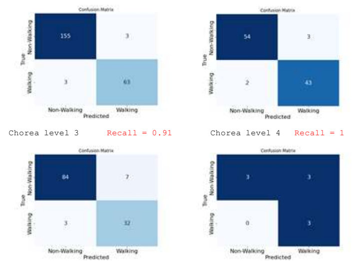
Recall gets lower (worse) with increased chorea.

D Schwartz et al. in prep

Two Super-Heroes: Maybe it's time to bring them together?



SSL, Fine tuning to HD with Segmentation: results

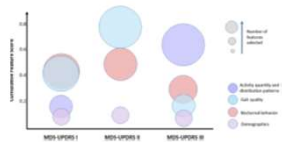


Recall in this context is also referred to as the true positive rate or *sensitivity*.

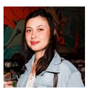
Recall level now acceptable across all levels of chorea.

D Schwartz et al. in prep

Digital Mobility Measures: A Window into Real-World Severity and Progression of Parkinson's Disease



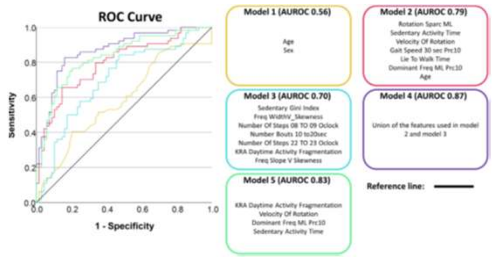
The size of the bubble represents the number of features

Nocturnal behavior:	24 features
Physical Activity quantity and distribution patterns:	106 features
Gait quality:	301 features

A Mirelman, J Volkov, A Salomon et al., *Movement Disorders*, 2023

Physical activity, Nocturnal Movement, and Gait Quality All Help to Discriminate between Controls and Early PD

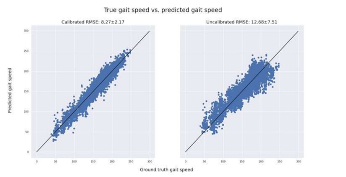


A Mirelman, J Volkov, A Salomon et al., *Movement Disorders*, 2023

https://ismpb.org/2024-rennes/ Abstract submissions close Monday, March 18th

Machine Learning in IMUs for Studying Daily Living Gait

- ML can help better estimate certain features (e.g., gait speed)
- ML can leverage physiologic measures (e.g., heart rate) to better classify groups and improve clinical utility



Mobilise-D

This project has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No 820820. This Joint Undertaking receives support from the European Union's Horizon 2020 research and innovation programme and EFPIA.
www.imi.europa.eu

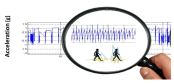
www.mobilise-d.eu

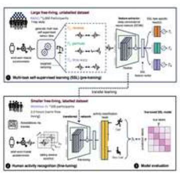
This presentation reflects the author's view and neither IMI nor the European Union, EFPIA, or any Associated Partners are responsible for any use that may be made of the information contained herein.

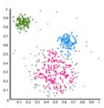
innovative medicines initiative efpia

Machine Learning to Study Daily Living Gait

1 + 1 > 2 !







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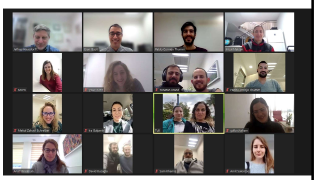


Or Perlman


Ran Gilad-Bachrach


Aron Buchman


Shahram Oveisgharan

NIH National Institute of Health · BSF United States - Israel Binational Science Foundation · PARKINSON'S FOUNDATION · Sixth Framework Programme · European Commission · The Michael J. Fox Foundation for Parkinson's Research · MS National Multiple Sclerosis Society · Seventh Framework Programme