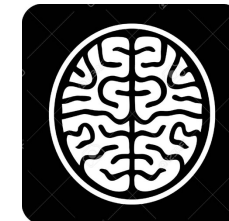


Integrating gait sensor data with other multimodal datasets to predict PD outcomes

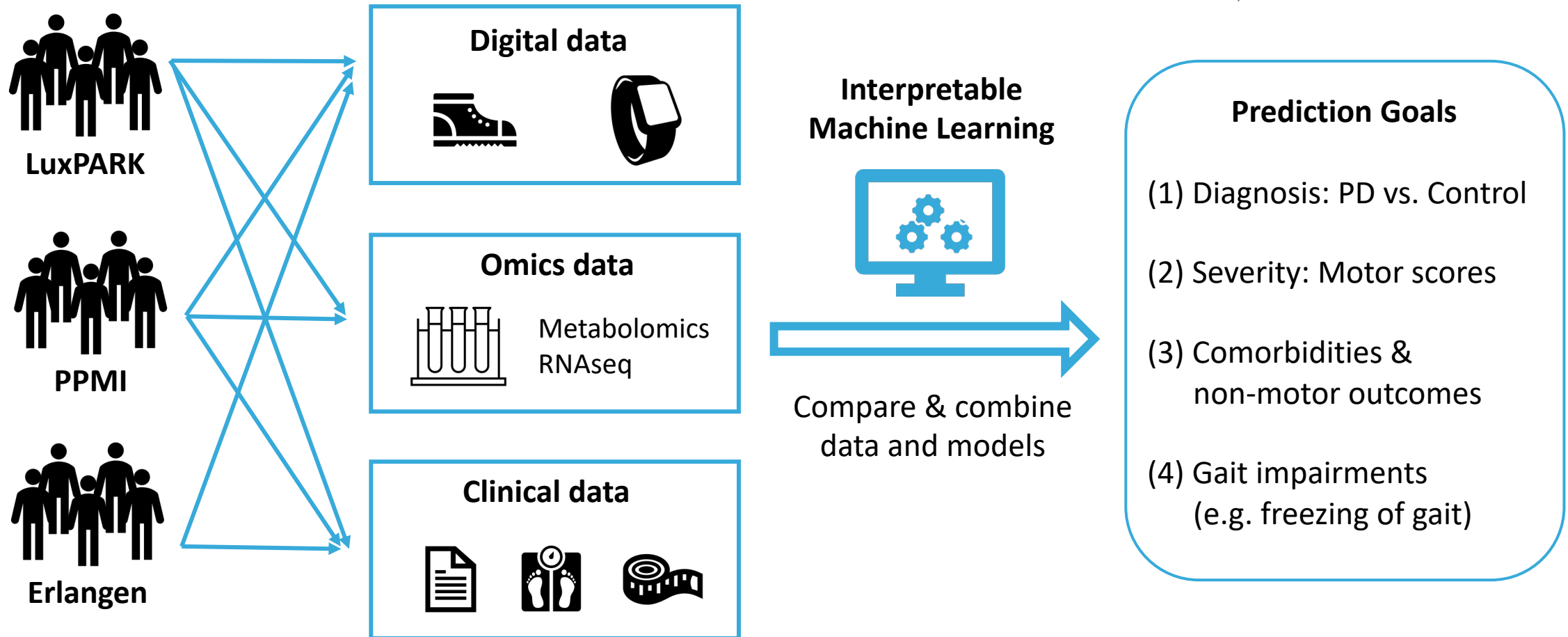
Speaker: Enrico Glaab, University of Luxembourg



Project overview & goals



Validating DIGItal biomarkers for better personalized treatment of Parkinson's Disease



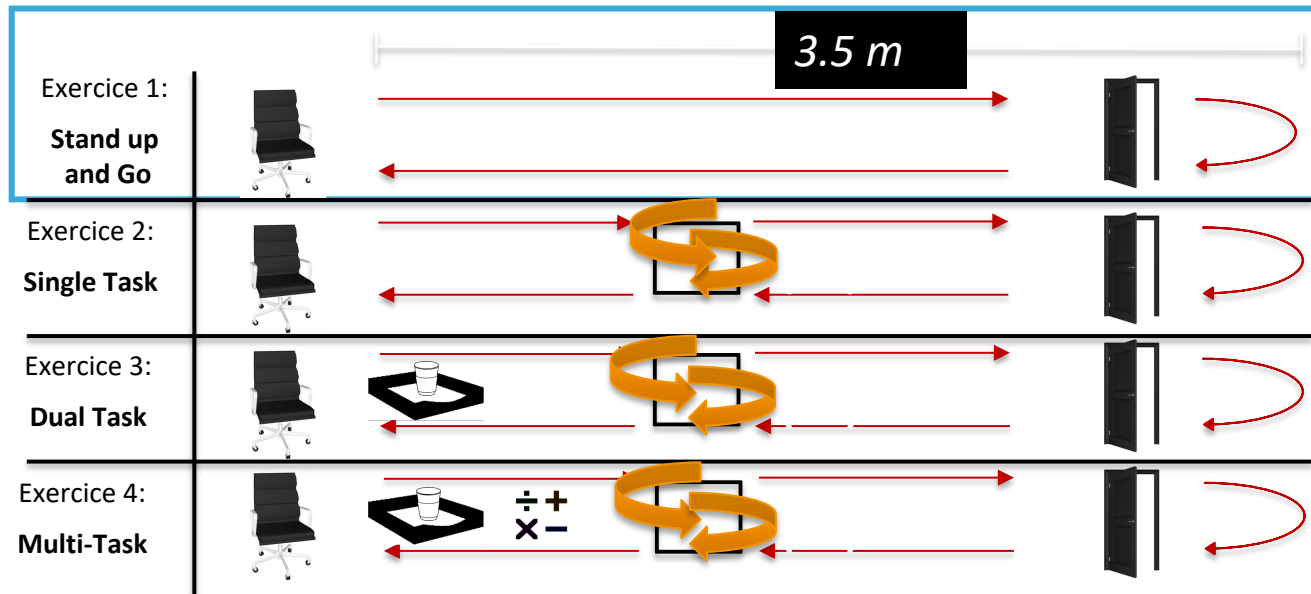
Main dataset

- **Type of data:** eGaIT (embedded Gait analysis using Intelligent Technologies)
- **Sample sizes:** 301 subjects (205 PD patients + 96 controls)

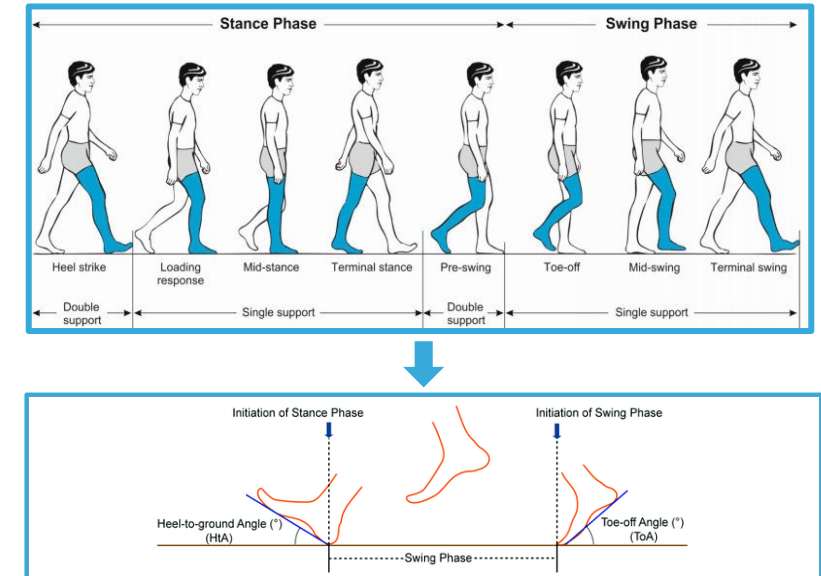


Raw sensor data + standard feature extraction

Tasks:



Extracted features:

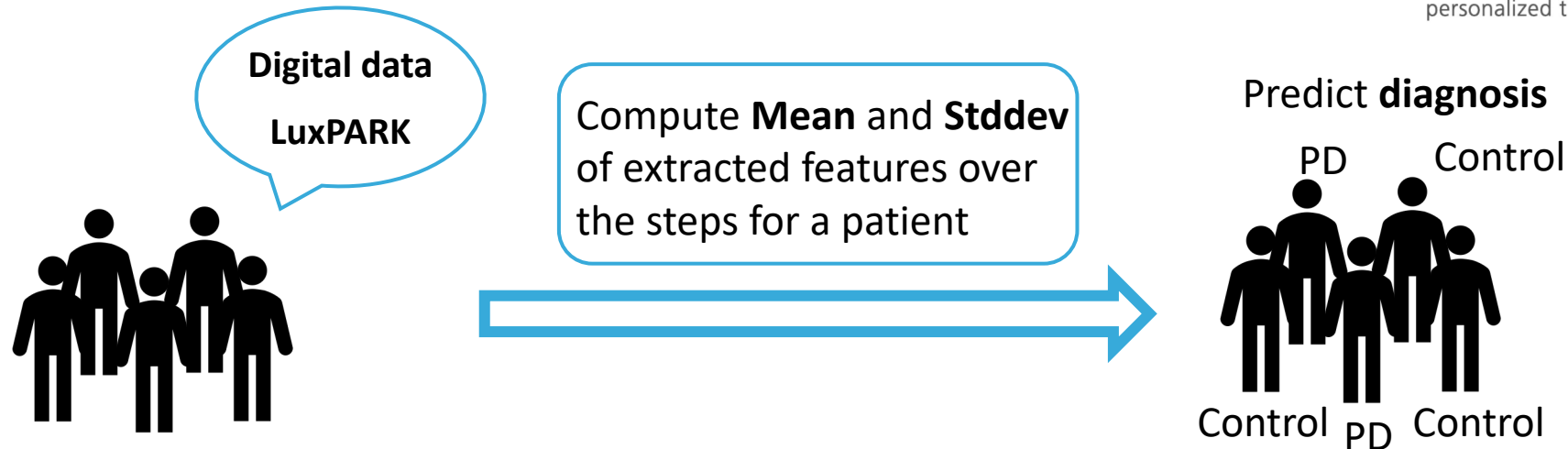


DIGIPD

Validating DIGital biomarkers for better personalized treatment of Parkinson's Disease



PD vs. Control classification (gait features)



Cross-validated predictive performance:

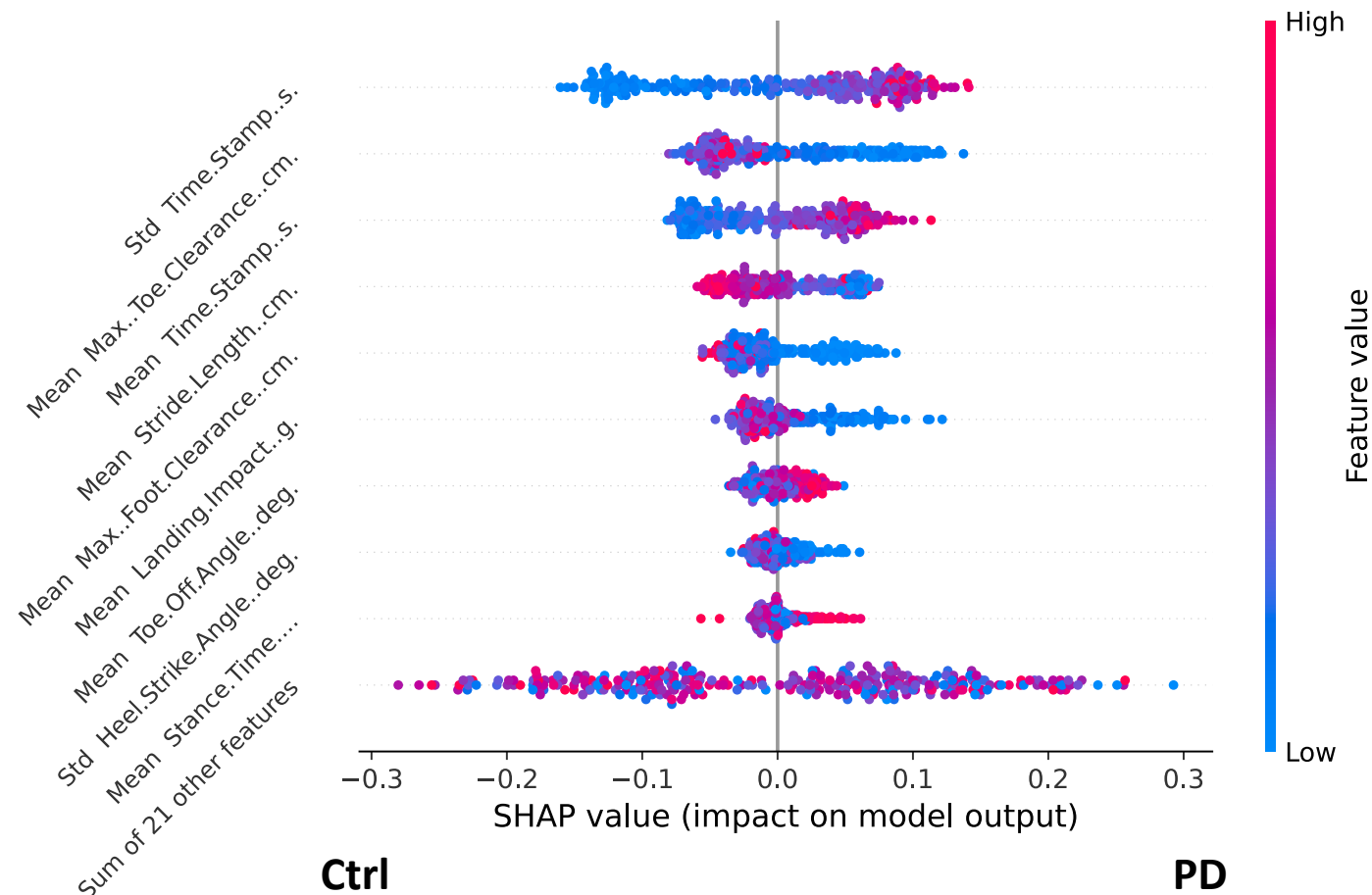
Models	Linear SVM	RBF SVM	Random Forest	Gradient Boosting	Adaboost	Clinical covariates (mean)
10-fold CV AUC mean(std)	0.701 (0.15)	0.784 (0.06)	0.794 (0.04)	0.798 (0.06)	0.783 (0.05)	0.63 (0.11)

UK Parkinson's Disease Society Brain Bank diagnostic criteria: 76% specificity (Berg et al., 2013)

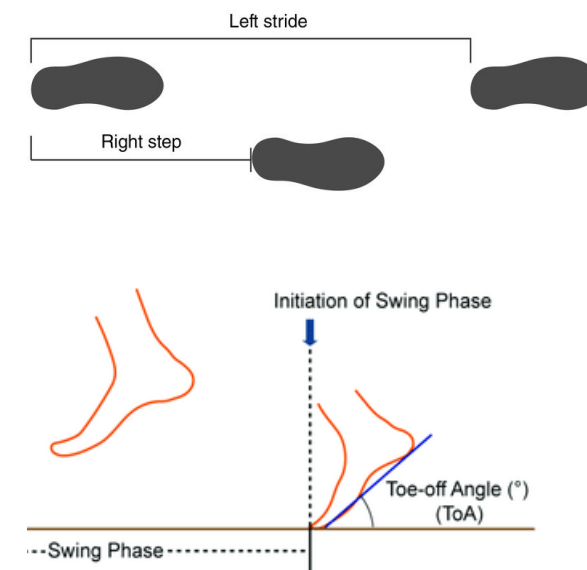
PD vs. Control classification – Most predictive features



Validating DIGital biomarkers for better personalized treatment of Parkinson's Disease



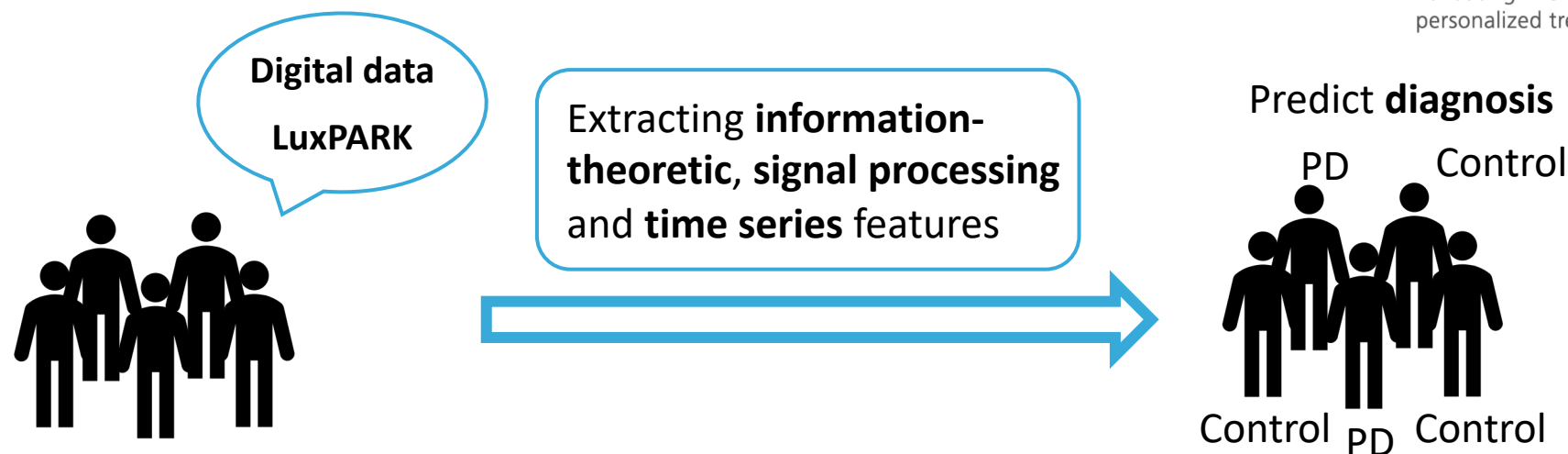
Timestamp, foot and toe-clearance, and stride length related features most predictive



PD vs. Control classification (raw signal data)



Validating DIGItal biomarkers for better personalized treatment of Parkinson's Disease



Cross-validated predictive performance:

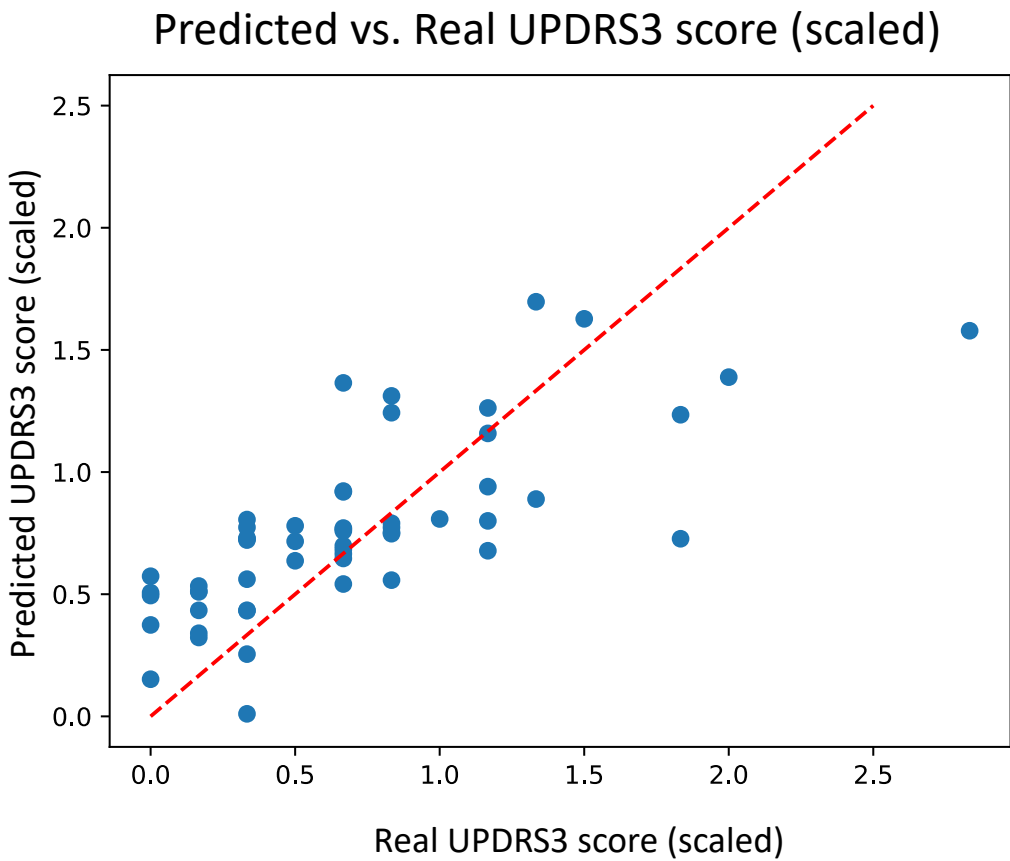
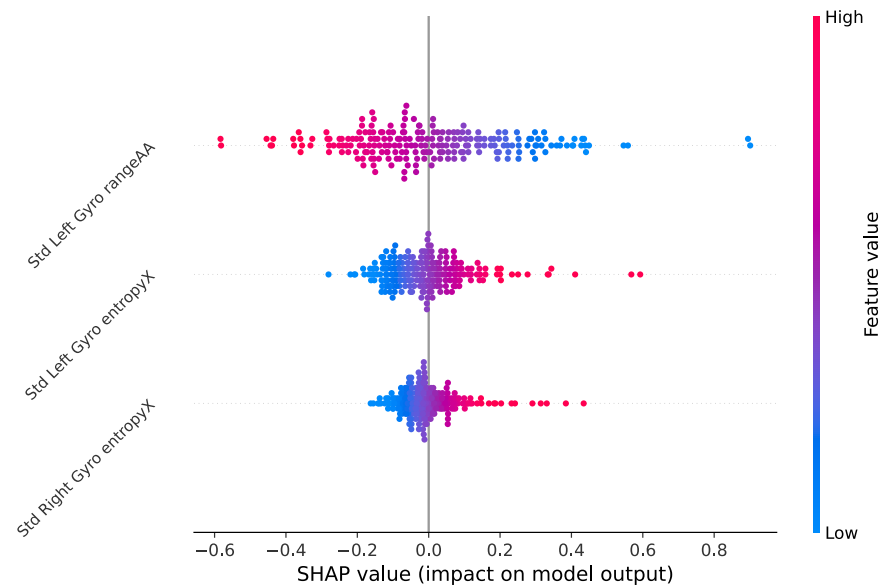
Models	Linear SVM	RBF SVM	Random Forest	Gradient Boosting	Adaboost	Logistic	Clinical covariates (mean)
10-fold CV AUC mean(std)	0.881 (0.04)	0.870 (0.03)	0.878 (0.05)	0.852 (0.06)	0.859 (0.05)	0.882 (0.04)	0.63 (0.11)

Prediction of UPDRS 3 score (digital surrogate biomarker)



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Most predictive features:



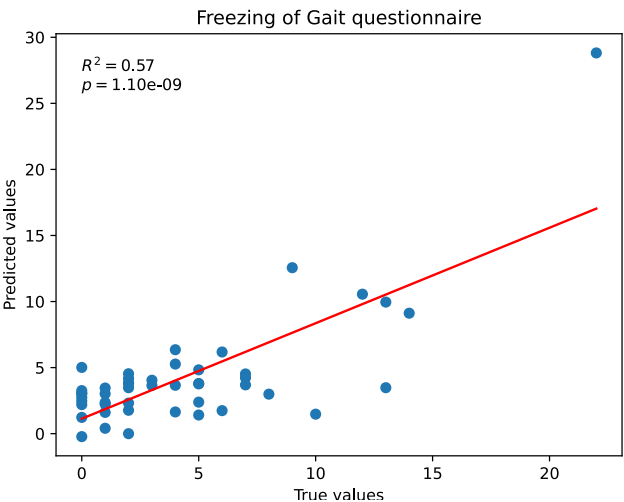
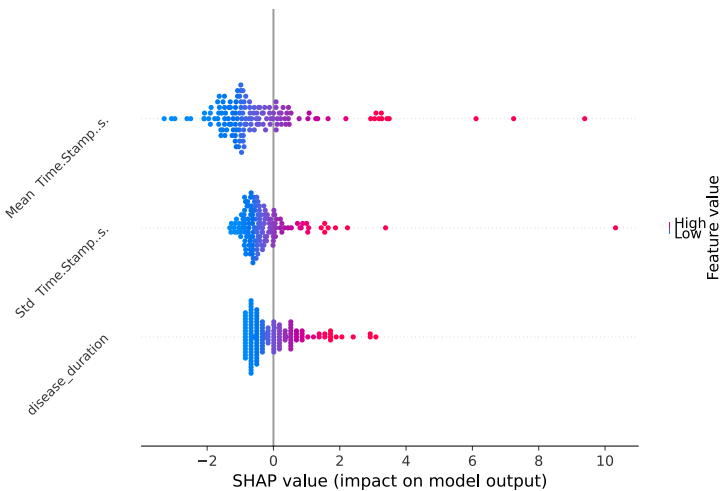
Cross-validation results (raw data):

Models	Linear SVR	RBF SVR	Random Forest	GBoost	Neural Network	Ada-boost	Ridge	OLS
CV-10: R ² mean(std)	0.381 (0.16)	0.307 (0.20)	0.37 (0.10)	0.349 (0.14)	0.421 (0.16)	0.364 (0.12)	0.442 (0.15)	0.433 (0.15)

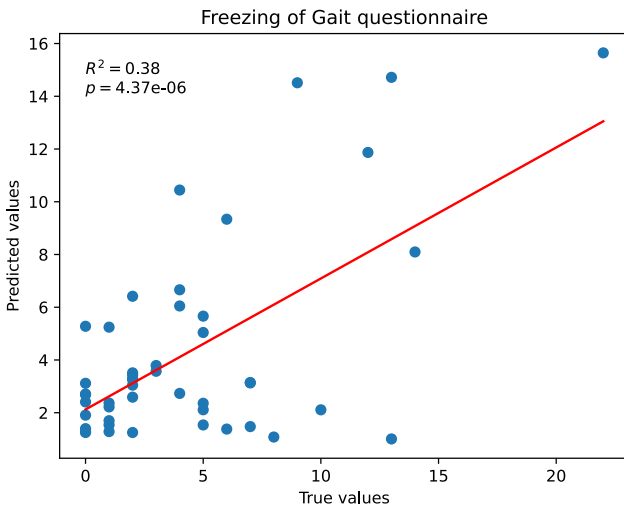
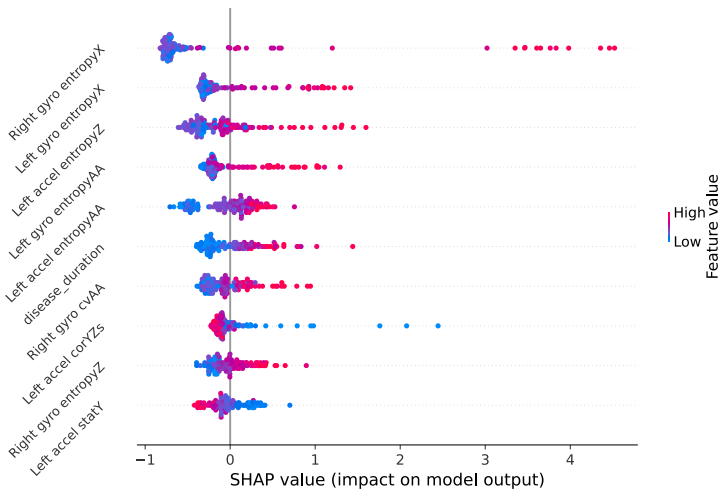
Freezing of gait prediction



Validating DIGItal biomarkers for better personalized treatment of Parkinson's Disease



← Prediction using gait-specific features (more interpretable & predictive)

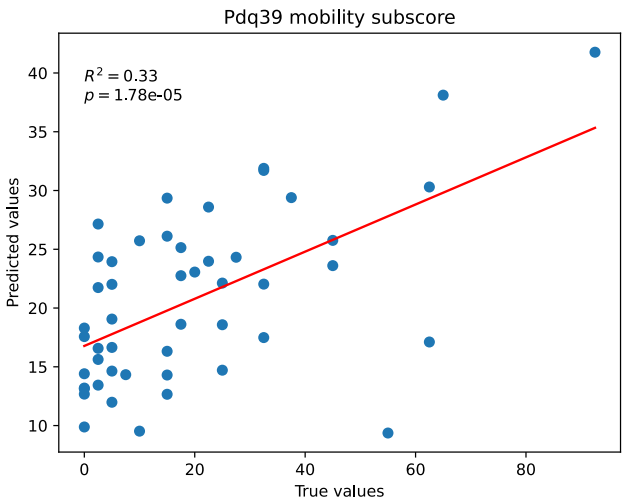
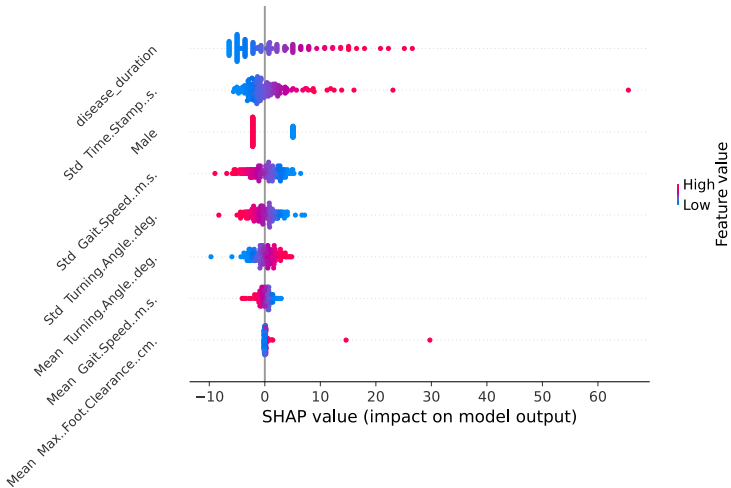


← Prediction using raw / time series features

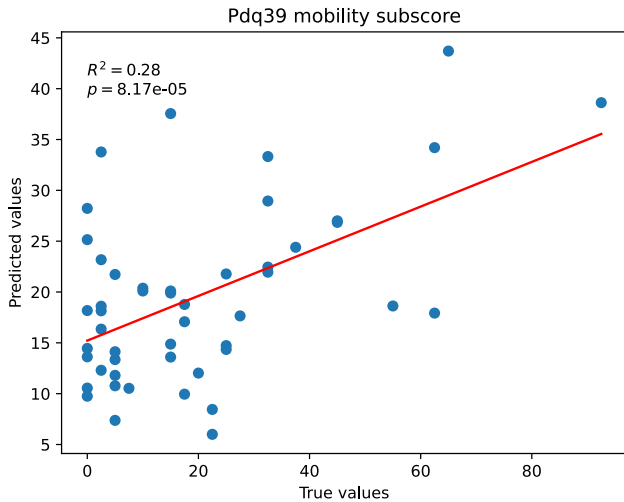
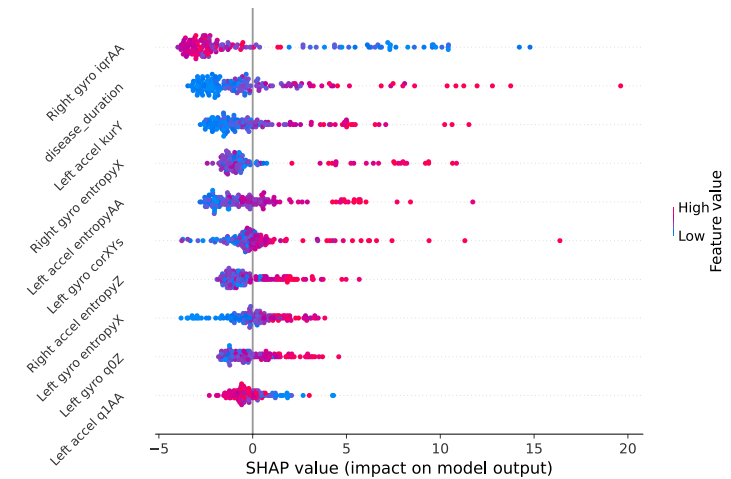
Quality of life (PDQ39) – Mobility sub-score prediction



Validating DIGItal biomarkers for better personalized treatment of Parkinson's Disease



← Prediction using gait-specific features (more interpretable and similar predictivity)



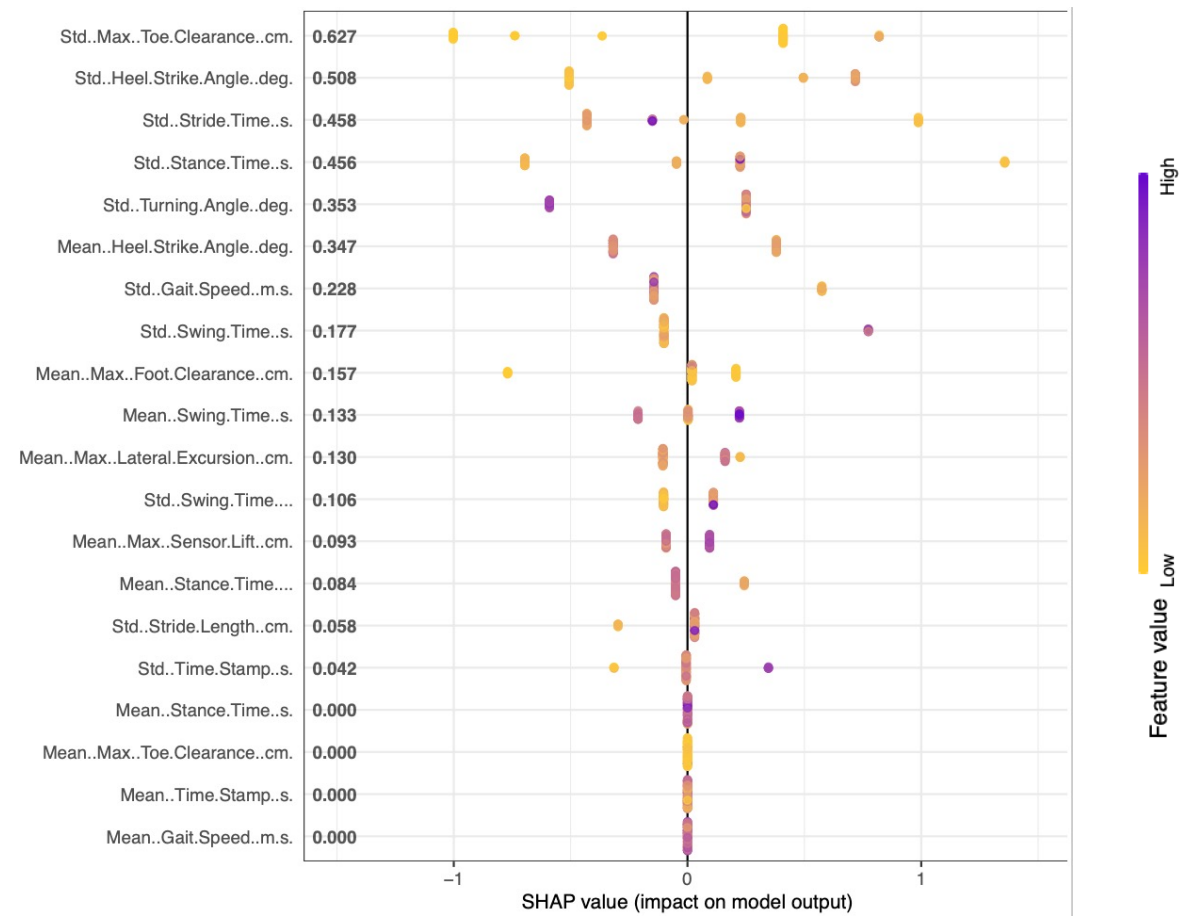
← Prediction using time series features

Prediction of akinetic-rigid vs. other phenotypes



Validating DIGital biomarkers for better personalized treatment of Parkinson's Disease

Most predictive features (gait-specific):



Cross-validation results (gait-specific features):

Models	GBM	SVM	ROTF	XGB	DEEP	RF	GAUSS
10-folds AUC mean(std)	0.562 (0.24)	0.505 (0.18)	0.565 (0.1)	0.63 (0.14)	0.641 (0.21)	0.583 (0.2)	0.491 (0.16)

Cross-validation results (time series features):

Models	GBM	SVM	ROTF	XGB	DEEP	RF	GAUSS
10-folds AUC mean(std)	0.48 (0.17)	0.491 (0.21)	0.498 (0.2)	0.538 (0.22)	0.671 (0.22)	0.518 (0.2)	0.441 (0.19)

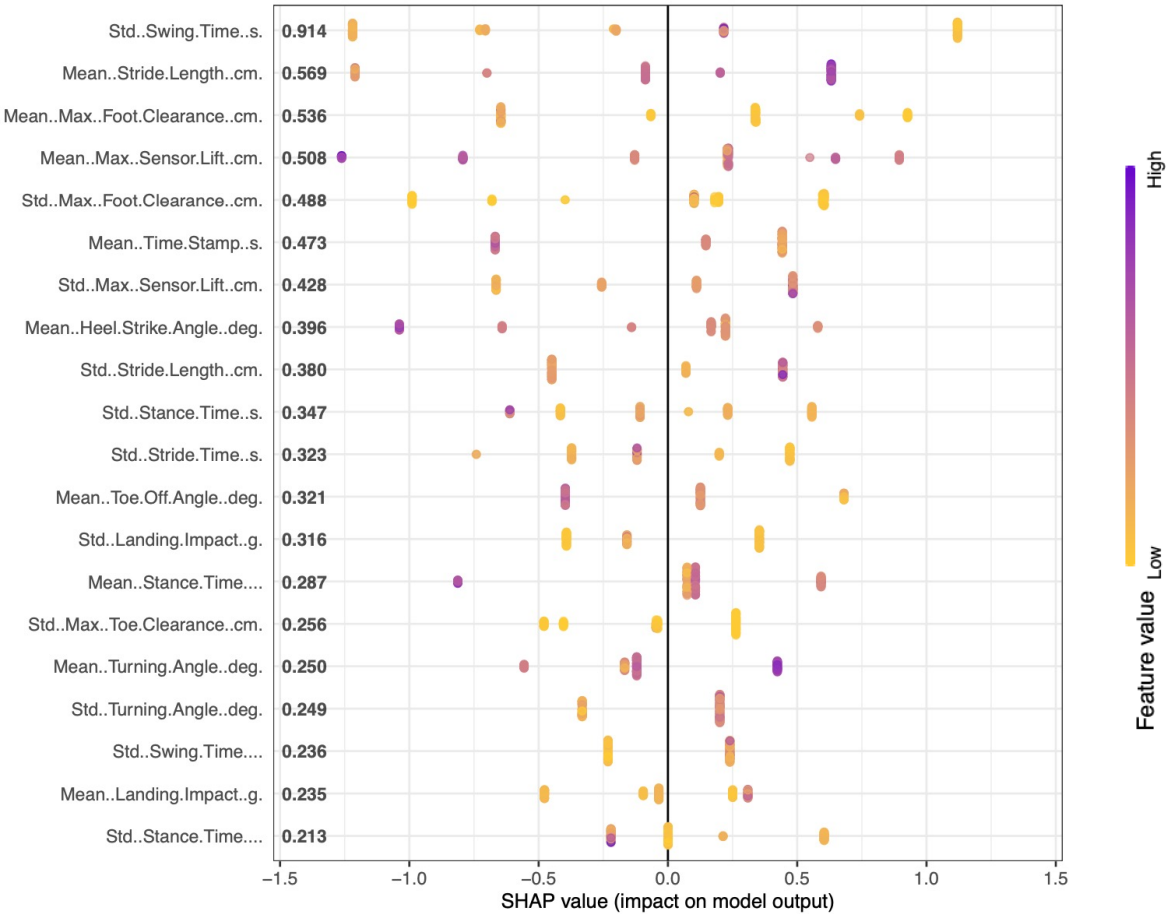
→ gait-specific attributes in most cases superior

Prediction of gait disorder occurrence in PD



Validating DIGital biomarkers for better personalized treatment of Parkinson's Disease

Most predictive features (gait-specific):



Cross-validation results (gait-specific features):

Models	GBM	SVM	ROTF	XGB	DEEP	RF	GAUSS
10-folds AUC mean(std)	0.67 (0.1)	0.67 (0.19)	0.688 (0.16)	0.727 (0.1)	0.712 (0.12)	0.673 (0.11)	0.67 (0.15)

Cross-validation results (time series features):

Models	GBM	SVM	ROTF	XGB	DEEP	RF	GAUSS
10-folds AUC mean(std)	0.685 (0.09)	0.66 (0.17)	0.666 (0.19)	0.751 (0.17)	0.646 (0.22)	0.626 (0.17)	0.668 (0.19)

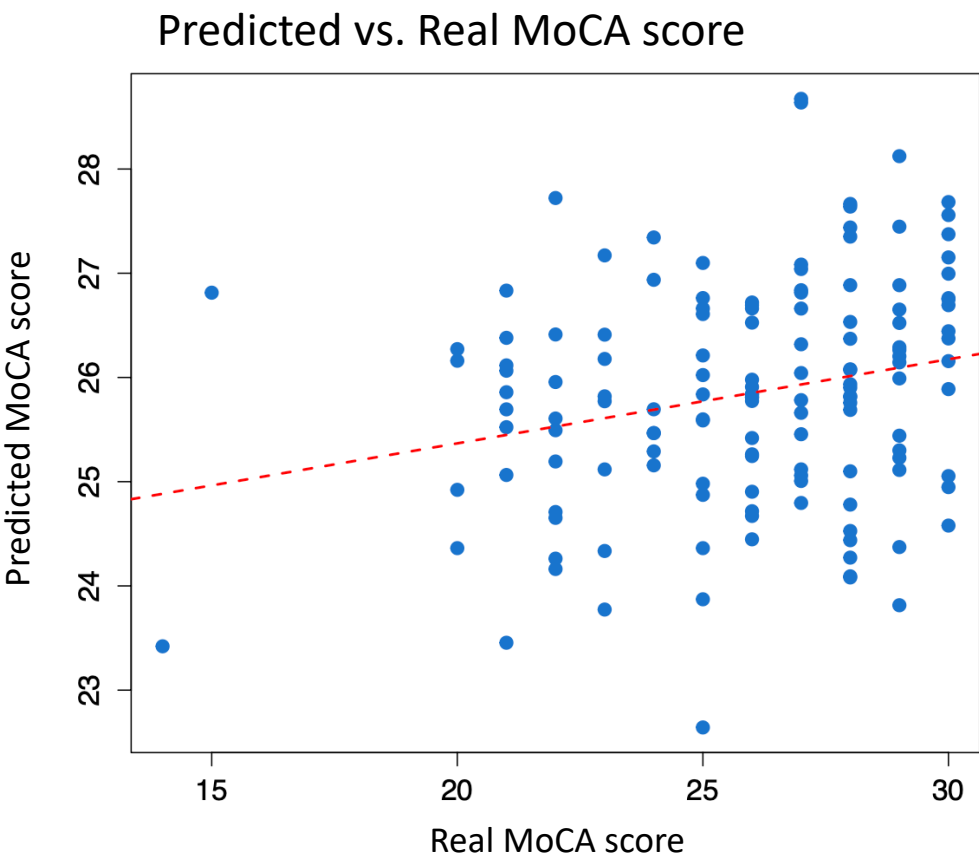
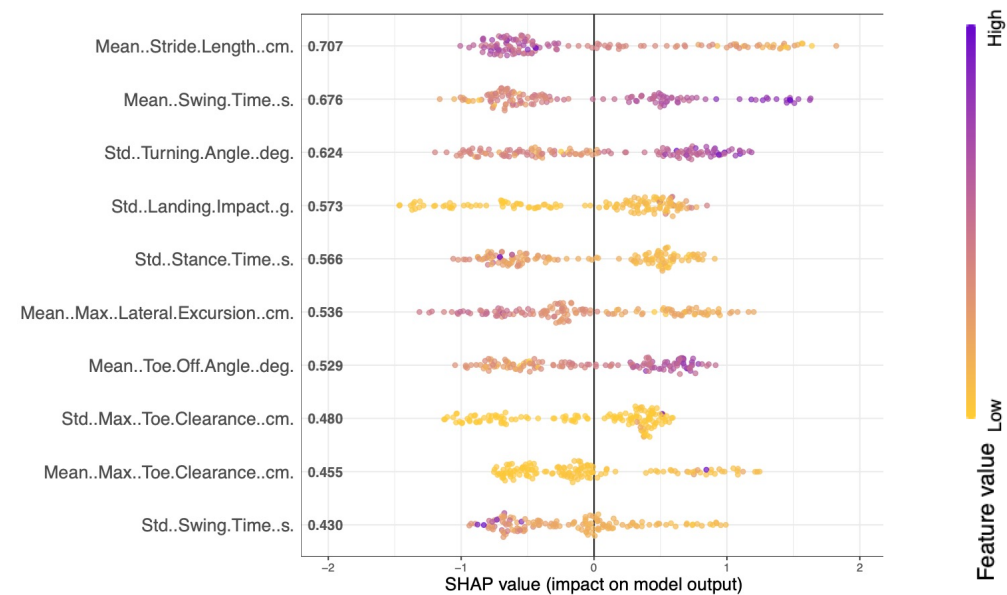
→ Similar performance for gait-specific attributes and time series attributes

Prediction of cognitive decline (MoCA, follow-up visit)



Validating DIGItal biomarkers for better personalized treatment of Parkinson's Disease

Most predictive features:



Cross-validation results (raw data):

Models	GBM	SVM	ROTF	XGB	DEEP	RF	GAUSS	Clinical covariates (mean)
10-folds AUC mean(std)	0.614 (0.15)	0.595 (0.14)	0.643 (0.13)	0.629 (0.17)	0.631 (0.15)	0.642 (0.08)	0.617 (0.19)	0.608 (0.14)

Prediction of comorbidities using eGaIT data (follow-up visit)

Analysis: Prediction of further disease-associated outcomes in PD
(Algorithm: XGBoost, 10-fold CV)

AUC statistics:

Outcome	Min.	1st Qu.	Mean	3rd Qu.	Max.	Clinical	Metabolomics
Cognitive decline (MoCA)	0.400	0.491	0.629	0.759	0.867	0.608	0.648
Impulse control disorders (QUIP)	0.192	0.519	0.642	0.817	1.000	0.604	0.563
Depression (BDI)	0.357	0.500	0.575	0.651	0.750	0.596	0.526
Hallucinations	0.333	0.444	0.536	0.573	0.833	0.536	0.578
Dyskinesias	0.282	0.427	0.557	0.646	0.962	0.573	0.669
Apathy (Starkstein scale)	0.375	0.481	0.574	0.634	0.850	0.546	0.593
Quality of life (PDQ-39)	0.375	0.542	0.593	0.673	0.729	0.559	0.574

Median AUCs
between 53% to
64%, depending
on the outcome

Summary & Outlook



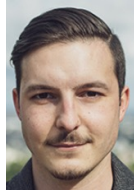
■ Summary:

- Significant performances for PD vs. Control and motor severity prediction
- Promising initial results for predicting gait impairments and some comorbidities

■ Outlook / Future Follow-Up:

- Test alternative feature definitions for improved interpretability / predictivity
- Collect comparable data across distinct cohorts / populations for cross-study validation
- Expand to other digital data types (Smartwatch sensors, Fitbit, etc.)

Thank you!



Cyril Brzenczek

(Machine learning analysis)



Sophie Lebars

(Omics analysis)



Quentin Klopfenstein

(Machine learning analysis)



Rebecca Ting Jiin Loo

(Machine learning analysis)

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- **Télécom SudParis:** Dijana Petrovska, Mounim A. El Yacoubi, Anas Filali Razzouki
- **University Hospital Erlangen:** Jürgen Winkler
- **University of Namur:** Jean-Marc Van Gyseghem, Noémi Bontridder



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