Enhancing Fall Prediction in Older Adults: A Data-Driven Approach to Key Parameter Selection

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PhD Research: AI for Fall Prevention in Older Adults

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I am a PhD candidate specializing in artificial intelligence applied to geriatric health.

My research focuses on the development and validation of an AI algorithm to prevent falls in older adults, based on real-life data collected in home settings.

The model integrates three key dimensions of fall risk:

- physical/organic,
- thymic/cognitive,
- socio-environmental.

By cleaning and preparing complex datasets, I aim to create a practical tool that healthcare professionals—particularly physicians and nurses—can use to support fall prevention in clinical practice.

Older Adults and Falls

- An older person according to WHO (60 years and older)
- Fall as a medical concept
    - Walking
    - Balance
- Fall as a mathematical concept
    - What types of data inform the occurrence of a fall?
    - Is the fall variable categorical or numerical?
    - Which variables are correlated with the fall variable?

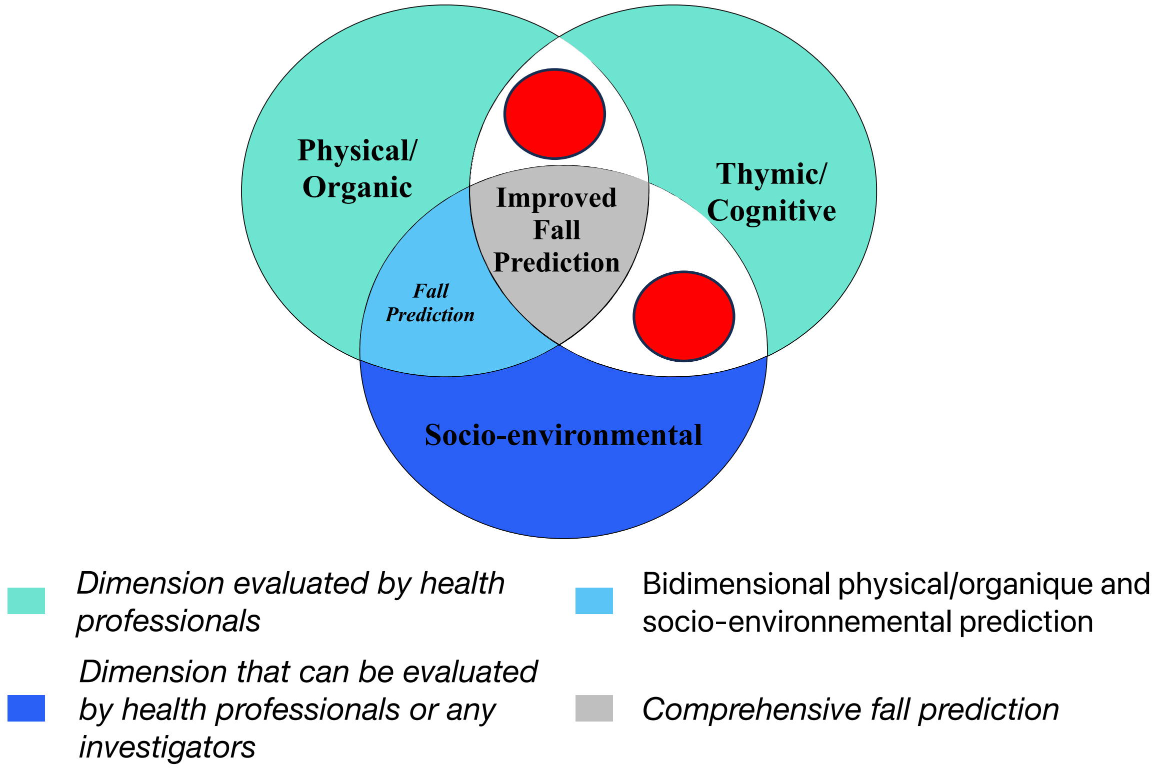
Which variables have the strongest influence on fall occurrence?

Geriatrics, the Fall Prevention Plan and "Aging Well"

- Geriatrics and Aging Well
- France’s Fall Prevention Plan for the Elderly
  - Annual Report
    - 10,000 fatal falls
    - 136,000 disabling falls (among people aged over 60)
  - Five Key Areas
    - Axis 1: Knowing how to identify fall risks and raise the alarm
    - Axis 2: Adapting the home and going out safely
    - Axis 3: Mobility aids accessible to everyone
    - Axis 4: Physical activity, the best weapon against falls
    - Axis 5: Teleassistance for all

Source: *Health.gouv*. (n.d.). Retrieved March 29, 2023, from https://sante.gouv.fr/IMG/pdf/dp_plan-antichute-accessible28-02-2022.pdf

Fall Prediction Through Fall Risk Dimensions



Venn diagram describing the multifactorial dimensions related to fall risk prediction

- Fall Prediction
  - Supervised Learning
  - Unsupervised Learning
  - Deep Learning
- Detection then Prediction of Falls
  - Reinforcement Learning (with an autonomous agent
  - For example: robot, conversational agent, character in a video game, etc.)

Source: Pynoos, J., Steinman, B. A., & Nguyen, A. Q. D. (2010). Environmental Assessment and Modification as Fall-Prevention Strategies for Older Adults. *Clinics in Geriatric Medicine*, *26*(4), 633–644. https://doi.org/10.1016/j.cger.2010.07.001,
Wason, R. (2018). Deep learning: Evolution and expansion. *Cognitive Systems Research*, *52*, 701–708. https://doi.org/10.1016/j.cogsys.2018.08.023

Data Types and the Specificity of Sensor-Derived Data

- Electronic Health Data
  - Textual Data
  - Tabular Data
- Questionnaires
  - Interviews
  - Focus Groups
- Sensors
  - *Falls*
  - Near-Fall
  - Activities of Daily Living

Source: Alam, E., Sufian, A., Dutta, P., & Leo, M. (2022). Vision-based human fall detection systems using deep learning: A review. *Computers in Biology and Medicine*, *146*, 105626. https://doi.org/10.1016/j.compbiomed.2022.105626,
Aziz, O., Klenk, J., Schwickert, L., Chiari, L., Becker, C., Park, E. J., Mori, G., & Robinovitch, S. N. (2017). Validation of accuracy of SVM-based fall detection system using real-world fall and non-fall datasets. *PLOS ONE*, *12*(7), e0180318. https://doi.org/10.1371/journal.pone.0180318,
Bath, P. A., Pendleton, N., Morgan, K., Clague, J. E., Horan, M. A., & Lucas, S. B. (2000). New approach to risk determination: Development of risk profile fornew falls among community-dwelling older people by use of a GeneticAlgorithm Neural Network (GANN). *The Journals of Gerontology: Series A*, *55*(1), M17–M21. https://doi.org/10.1093/gerona/55.1.M17

Our Study

1,648 community-dwelling older adults (⩾ 60 years)
Between September 2011 and September 2023

Through multiple home visits by UPSAV

- Initial visit at home
- Second visit at 6 months
- Annual follow-ups thereafter
- Follow-ups conducted only if the patient remained at home

A letter of consent was sent to each patient beforehand for the use of their data in our AI model.

Overview of Baseline Characteristics According to falls of the study

Features of the study	Total sample (N = 1,648) n (%)	Falls of the study: No falls (n = 794, 48.2%)	Falls of the study: Falls (n = 854, 51.8%)	p-value[1]
Woman	**1,113 (68%)**	**500 (63%)**	**613 (72%)**	**<0.001**
Age, mean ± SD, years	**83 ± 6**	**82 ± 6**	**83 ± 6**	**0.001**
Diabetes	**339 (21%)**	**146 (18%)**	**193 (23%)**	**0.035**
Leisure	**1,377 (84%)**	**689 (87%)**	**688 (81%)**	**<0.001**
Social activity	**288 (17%)**	**162 (20%)**	**126 (15%)**	**0.003**
Human assistance	**1,402 (85%)**	**644 (81%)**	**758 (89%)**	**<0.001**
ADL, mean ± SD	**5 ± 1**	**5 ± 1**	**5 ± 1**	**<0.001**
IADL, mean ± SD	**6 ± 2**	**6 ± 2**	**5 ± 2**	**<0.001**
MMSE, mean ± SD	**23 ± 7**	**24 ± 7**	**23 ± 7**	**0.006**
Pathological CDT	**585 (35%)**	**244 (31%)**	**341 (40%)**	**<0.001**
Pathological verbal fluency	**672 (41%)**	**269 (34%)**	**403 (47%)**	**<0.001**
MNA, mean ± SD	**24 ± 4**	**24 ± 4**	**23 ± 4**	**<0.001**
SPPB, mean ± SD	**7 ± 4**	**7 ± 4**	**6 ± 4**	**<0.001**
Pathological GDS	**449 (27%)**	**176 (22%)**	**273 (32%)**	**<0.001**
Pathological SLB	**708 (43%)**	**261 (33%)**	**447 (52%)**	**<0.001**

[1]Pearson's Chi-squared test; Wilcoxon rank sum test. Statistically significance (p-value < .05).

SD, Standard deviation; SLB, Single leg balance; CDT, Clock-drawing test; ADL, Activities of Daily Living; IADL, Instrumental Activities of Daily Living; MMSE, Mini-Mental State Examination; MNA, Mini Nutritional Assessment; SPPB, Short Physical Performance Battery; GDS, Geriatric Depression Scale.

Predicting Falls Within Six Months

Model used:

Support Vector Machine,
Random Forest,
Logistic Regression, and
Extreme Gradient Boosting

We conducted our analysis on patients with at least six years of follow-up.

Out of **30** input features, **11** were identified as the most relevant fall predictors using multinomial logistic regression:

- Gender,
- Hypertension,
- Obesity,
- Leisure activity,
- Activities of Daily Living (ADL),
- Mini-Mental State Examination (MMSE),
- Short Physical Performance Battery (SPPB),
- Pathological Geriatric Depression Scale (GDS),
- Instrumental Activities of Daily Living (IADL),
- Pathological Single-Leg Balance (SLB),
- History of falling in the past year.

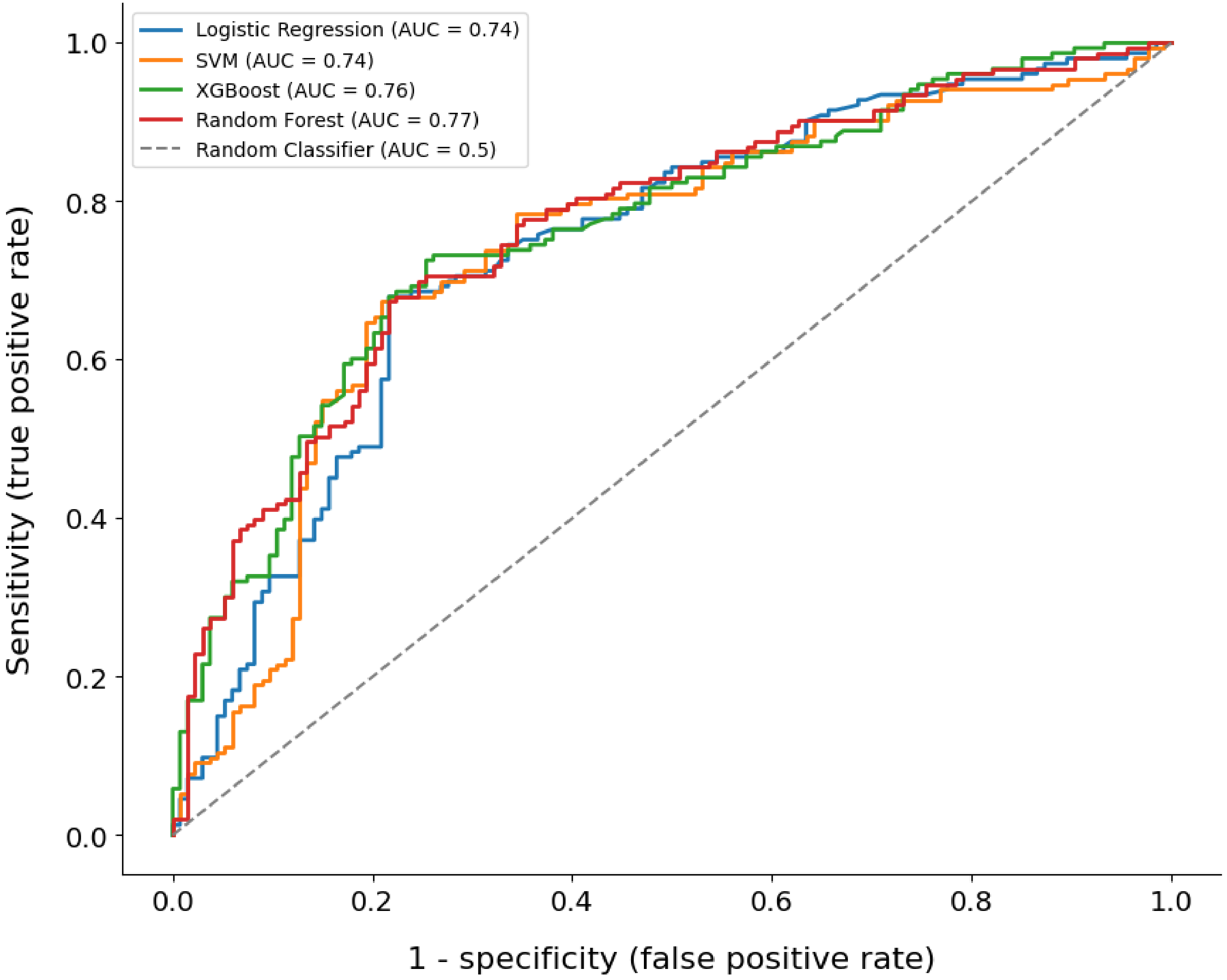
Source: Böhning, D. (1992). Multinomial logistic regression algorithm. Annals of the Institute of Statistical Mathematics, 44(1), 197–200. https://doi.org/10.1007/BF00048682

Predicting Falls Within Six Months

First visit: 1,648 patients
Second visit: 954 patients
Patients included in the AI model: 954

Selected Baseline Characteristics at the Second Visit.

Features of the study	Total sample (N = 954) n(%)
Woman	664 (70)
Age, mean ± SD, years	83 ± 6
Fell in past six months	502 (53)
Hypertension	485 (51)
Social activity	172 (18)

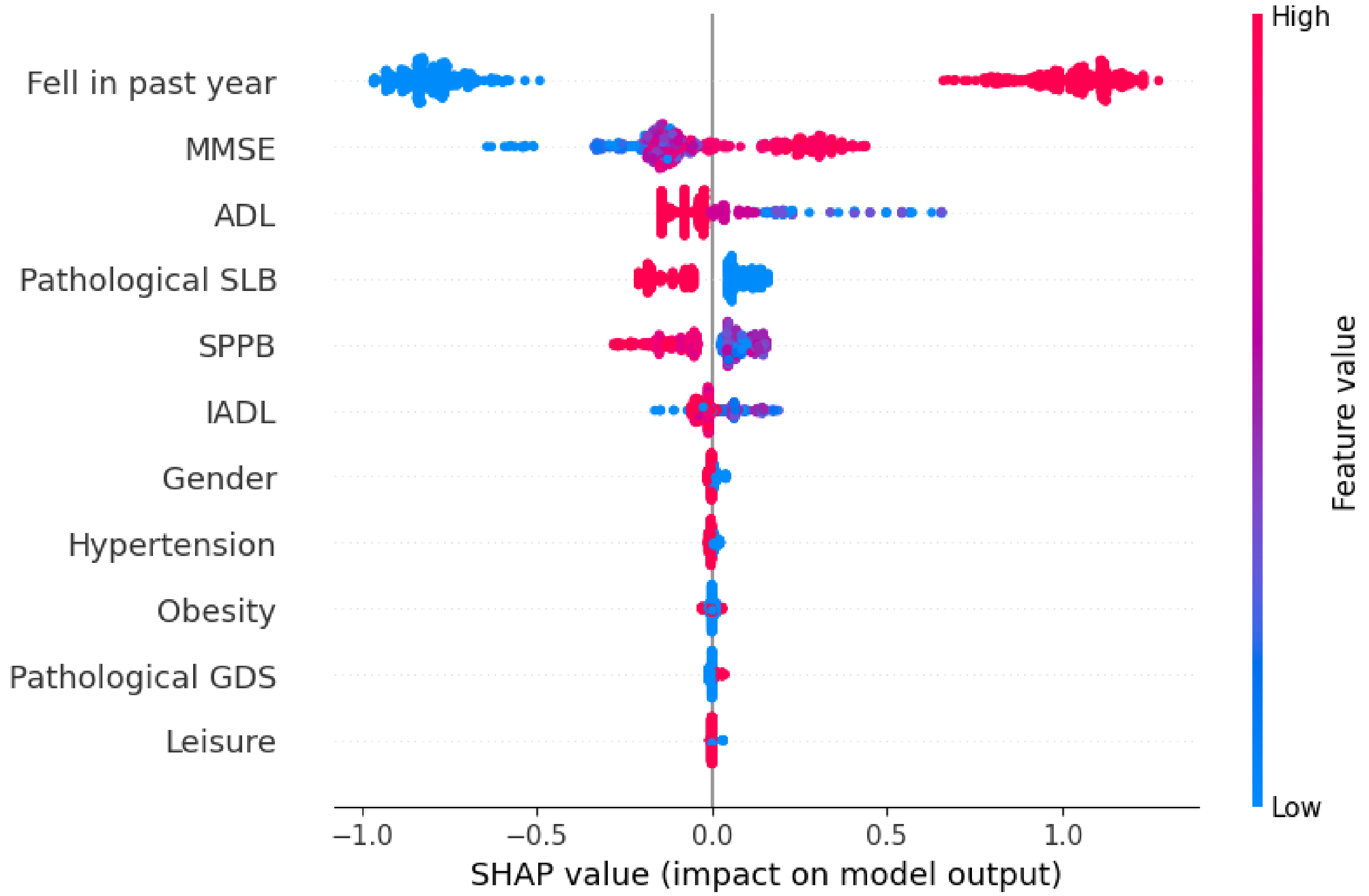


Comparative Modeling of Predictive Factors from Gait Trajectories and Fall History

Metric (Meaning)	Logistic Regression	SVM	XGBoost	Random Forest
AUC (Ability to distinguish between classes)	0.74	0.74	**0.76**	**0.77**
Accuracy (Overall correctness of predictions)	0.73	0.73	0.72	0.72
Balanced Accuracy (Average of sensitivity and specificity)	0.73	0.73	0.73	0.72
Precision (PPV) (Correct positive predictions out of all predicted positives)	0.78	0.78	**0.78**	0.77
Recall (Sensitivity) (Correct positive predictions out of actual positives)	0.68	0.68	0.67	0.68
Specificity (TNR) (Correct negative predictions out of actual negatives)	0.78	0.78	0.78	0.77
NPV (Correct negative predictions out of predicted negatives)	0.68	0.68	0.68	0.68
F1 Score (Harmonic mean of precision and recall)	0.73	0.73	0.72	0.72
Brier Score (Mean squared error of predicted probabilities)	0.2	0.2	**0.19**	0.2

Source : Bradley, A. P. (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. Pattern Recognition, 30(7), 1145–1159. https://doi.org/10.1016/S0031-3203(96)00142-2
Hoessly, L. (2025). *On misconceptions about the Brier score in binary prediction models* (arXiv:2504.04906). arXiv. https://doi.org/10.48550/arXiv.2504.04906

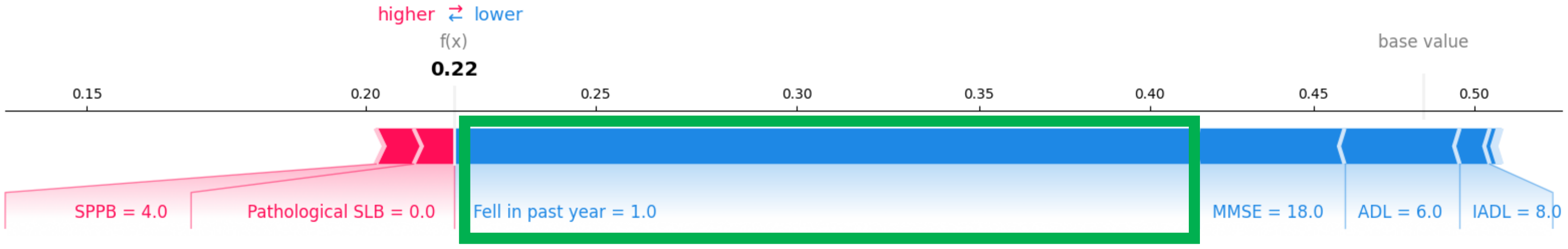
XGBoost Model – SHAP Beeswarm Plot of Feature Contributions



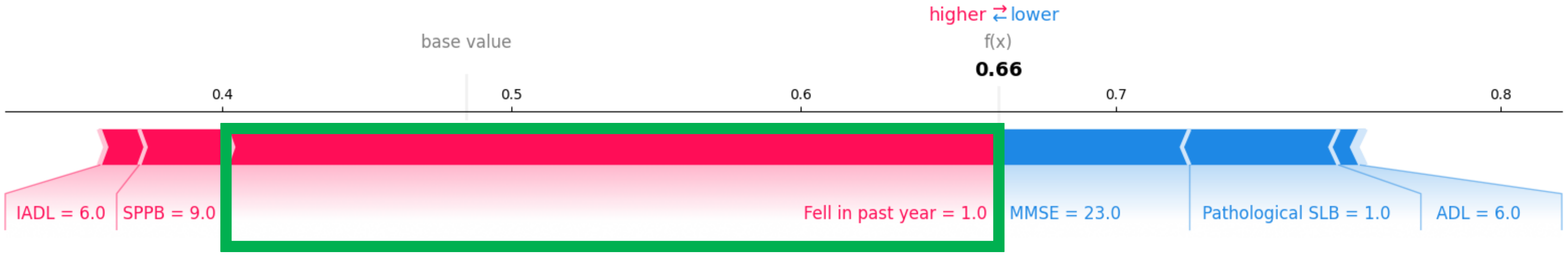
Source: *Beeswarm plot—SHAP latest documentation*. (n.d.). Retrieved May 11, 2025, from https://shap.readthedocs.io/en/latest/example_notebooks/api_examples/plots/beeswarm.html

How the Model Thinks: SHAP Force Plot for Good and Bad XGBoost Predictions

- Example of a Correct Prediction



- Example of a Bad Prediction



Source: *Decision plot—SHAP latest documentation*. (n.d.). Retrieved May 11, 2025, from https://shap.readthedocs.io/en/latest/example_notebooks/api_examples/plots/decision_plot.html#

Take-Home Message

- XGBoost was the best-performing model for predicting falls within six months, showing strong discrimination and calibration (Brier score = 0.19).
- SHAP analyses revealed that fall history, balance performance, cognitive status, and functional ability were the most influential predictors.
- Collecting data through a Comprehensive Geriatric Assessment (CGA) at home enables a more holistic and context-aware approach to fall risk prediction.
- These results support the integration of clinical, cognitive, and functional data for early identification of individuals at high risk of falling, enabling timely preventive interventions.