



# Explainable ML for Fall Risk & Post-Fall Mortality Prediction in Nursing Home Residents

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PREDICTIVE ANALYTICS

Building models to predict outcomes and support decisions.




KNOWLEDGE GRAPHS

Structuring and linking biomedical knowledge.




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Developing intelligent tools to support healthcare professionals.



OUR MISSION

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# About us: ALBA members



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# Introduction

Falls are a major cause of **morbidity, mortality, and functional decline** in older adults – with a particularly high burden in nursing home residents, who frequently present frailty, mobility limitations, and multiple chronic conditions.

## Clinical Impact

Falls lead to injuries, hospital admissions, loss of autonomy, and increased care needs.

## Limitations of Current Tools

Conventional scales and clinical judgement may be limited when used in isolation, especially for complex or severe outcomes.

## The Gap

Most published models focus on fall occurrence; far less attention has been paid to post-fall mortality or fall burden.

# State of the art

How can AI improve fall risk assessment and outcome prediction in institutionalized older adults?



**Traditional approaches** relied on **wearable sensors** and **motion-capture systems** to detect gait instability and abnormal movement patterns.



**Recent research** increasingly uses **structured clinical data** from EHRs and institutional records, enabling **scalable** and **low-cost** fall risk prediction.



**Explainable AI (XAI)** techniques such as **SHAP** have become widely adopted, providing transparency and supporting clinical decision-making.



**Class imbalance** remains a major challenge. **Synthetic data generation** (e.g., VAEs and generative models) has been proposed to improve model robustness.



Most studies focus on **fall occurrence prediction**, while clinically relevant outcomes such as **recurrent falls**, **post-fall mortality**, and **injury severity** remain underexplored.



**Research gap:** Few works simultaneously address **multiple fall-related outcomes** while combining **imbalance-aware learning** and **explainable machine learning**.

# Datasets & Main Goal of the Project

## Three Task-Specific Datasets

### Resident-Year Dataset

N = 1,445 — fall occurrence;  
~42% fall events

### Falls-Only Cohort

N = 1,368 — post-fall  
mortality; only ~6% positive  
cases

### Functional Subset

N = 200 — includes Tinetti & Berg scores

## Predictor Variables

All predictors are **routinely collected structured variables**:

- Age & sex
- Institutionalisation time
- Mobility aid usage
- Fall history indicators
- Tinetti & Berg Balance Scale scores (subset only)

## Main Goal: Three Prediction Tasks

- **Fall occurrence** — binary classification
- **Post-fall mortality** — binary, falls-only cohort
- **Fall-count severity** — multiclass (0, 1, 2-3, ≥4 falls)



# Models & Dataset split

## 10 Algorithms Evaluated

Logistic Regression, Decision Trees, Random Forest,  
Gradient Boosting, AdaBoost, KNN, SVM, Gaussian  
Naive Bayes, LDA, XGBoost

## Grid-Search Optimization

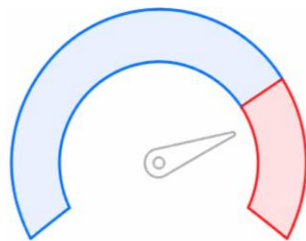
Hyperparameters tuned on training data only. Model  
selection guided by **Macro-F1**, which gives equal weight  
to all classes — critical in imbalanced settings.

## Tinetti and Berg tests

Tinetti and Berg scores provide objective measures of  
**mobility** and **balance**.

## Dataset distribution

**Stratified split** to maintain the proportion of  
samples from each class among the process.



**80% / 20%**

● Training ● Test

## Data imbalance

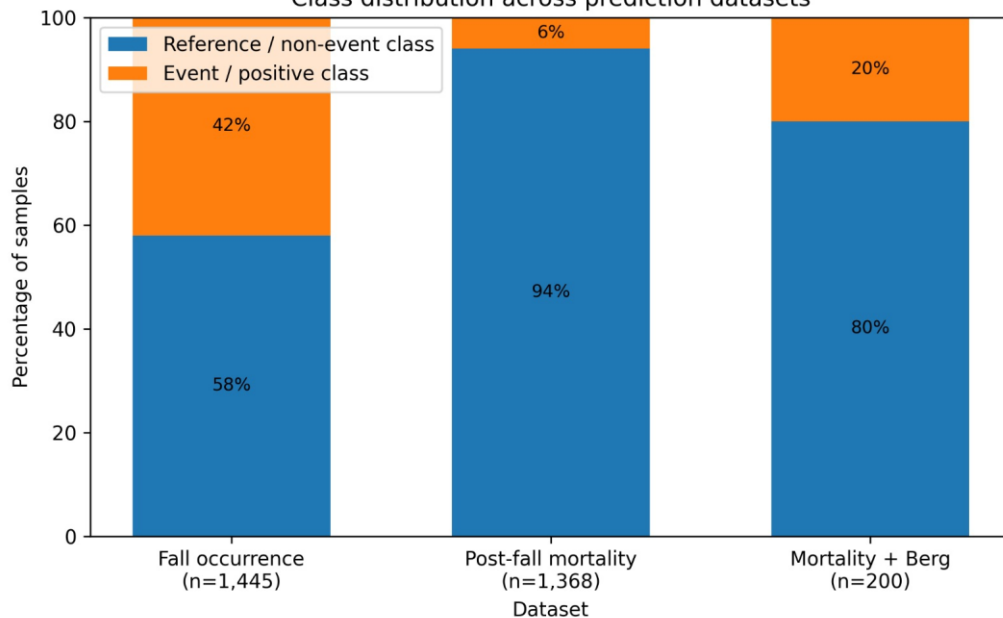
Task	Positive Class	Positive (%)	Negative (%)	Samples
 Fall Occurrence	Fall	<b>42%</b>	58%	1,445
 Post-Fall Mortality	Mortality	<b>6%</b>	94%	1,368
 Mortality + Berg	Mortality	<b>20%</b>	80%	200



Severe class imbalance in mortality prediction tasks,  
motivating the use of synthetic data augmentation techniques.

# Data Imbalance: Autoencoder Augmentation

Class distribution across prediction datasets



## The Problem

Post-fall mortality has only ~6% positive cases. Standard models fail to learn stable decision boundaries for rare events.

## The Solution

An **autoencoder-based synthetic data augmentation** strategy generates minority-class samples in latent space. Applied **only to the training partition** – the test set remains untouched to ensure fair evaluation. This improves model exposure to rare-event patterns without contaminating evaluation.

# Predictive Performance Results

## 0.89: Fall Occurrence

Gradient Boosting — strongest result; routine variables carry substantial predictive signal

## 0.60: Mortality + Berg

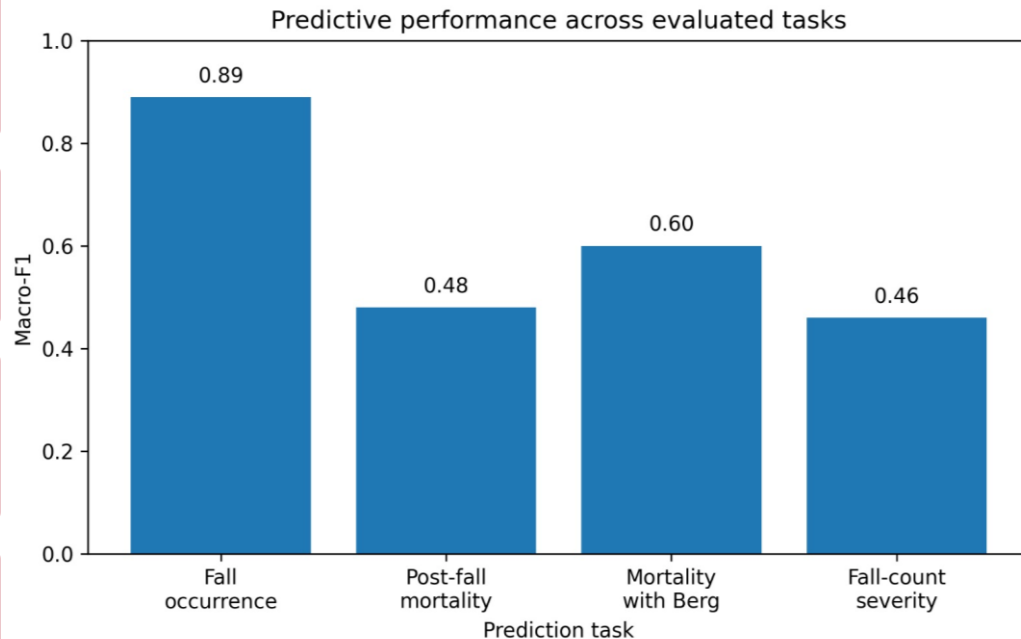
KNN — Berg Balance Scale improves performance, reflecting frailty signal

## 0.48: Post-Fall Mortality

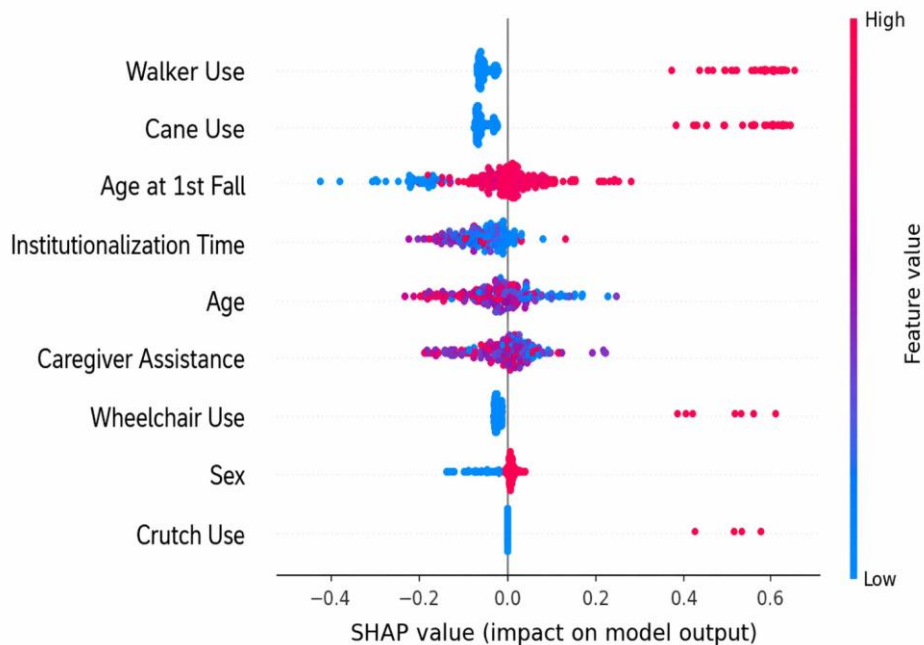
KNN — limited by severe class imbalance and scarce positive training cases

## 0.46: Fall-Count Severity

Random Forest — above chance in a 4-class task; structured data captures partial gradient



# SHAP-Based Explainability



## Top Predictors — Fall Occurrence

- Age at first fall
- Institutionalization time
- Chronological age
- Mobility aid usage (walker, cane, wheelchair)

## Top Predictors — Mortality (with Berg)

The Berg Balance Scale was the strongest contributor to mortality risk prediction, followed by age and accumulated fall history. SHAP analysis confirms models rely on clinically coherent predictors rather than spurious patterns — supporting trust in decision-support settings.

# Discussion: A Gradient of Predictive Difficulty

1

**Fall-Count Severity — Macro-F1: 0.46**

Most complex; requires medication, environmental, and comorbidity data not available in routine records

2

**Post-Fall Mortality — Macro-F1: 0.48 / 0.60**

Rare event; augmentation helps but cannot replace real minority-class observations

3

**Fall Occurrence — Macro-F1: 0.89**

Strongest signal; routine demographic, mobility, and fall-history variables are highly informative

Performance decreases as the prediction target becomes more specific and clinically severe — a pattern consistent with the increasing rarity and complexity of the modelled outcomes.

# Conclusions & Future Work

## Key Findings



Strong predictive performance  
**Macro-F1 = 0.89**



Relies on routinely available structured variables  
**No sensors required**



Explainable predictions  
**SHAP improves transparency and clinical interpretability**



Multiple clinically relevant endpoints in a unified framework

## Limitations



Severe class imbalance  
**Especially for post-fall mortality (6%)**



Single institutional source  
**Generalizability uncertain**



Synthetic augmentation  
**Cannot replace real minority-class data**



No unstructured clinical notes or medication details included

## Future Work



Validate in larger, multi-institutional datasets



Explore temporal modelling for dynamic risk prediction



Incorporate richer clinical variables



Conduct prospective evaluation of real-world impact on fall prevention

## Practical Impact

The framework can serve as an **initial screening layer** within routine nursing home workflows — not replacing clinical judgement, but **supporting early identification** of residents who may benefit from closer monitoring or functional evaluation.



Routinely Collected Structured Data



ML Framework (Explainable)



Risk Prediction (Falls, Mortality, Severity)



Early Intervention & Clinical Assessment



**Better outcomes** for nursing home residents



Fall occurrence can be predicted accurately using routinely collected structured data (**Macro-F1 = 0.89**), enabling explainable and scalable risk screening in nursing homes.



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