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

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***Abstract*— Falls significantly contribute to frailty and functional decline in elderly individuals. The Risk Of Falling (ROF) is linked to three dimensions: physical/organic, socio-environmental, and thymic/cognitive. Therefore, fall prevention protects older individuals from multiple comorbidities. The reliability of predictive studies depends on the quality and consistency of data collection. In most studies, data for model construction were collected from hospitals, research laboratories, or participants' homes. Recent fall prediction models increasingly rely on machine learning, deep learning, and computer vision. Predictive models assist specialists in decision-making. Using home-collected data, our objective is to develop an optimized predictive model with minimal features. In this paper, we aim to identify the optimal model for predicting falls using this strategy with the objective of building a robust dataset as the entry of an Artificial Intelligence (AI) process.**

Keywords - fall; older population; data; prevention; AI.

I. INTRODUCTION

According to the World Health Organization (WHO), older individuals are those aged ≥ 60 years. The proportion of older individuals worldwide is expected to nearly double between 2015 and 2050, increasing from 12% to 22% [1]. The National Institute of Statistics and Economic Studies (INSEE) estimates that one in three individuals in France will be aged ≥ 60 years by 2060, compared to one in four individuals in 2021 [2]. Aging leads to a gradual decline in functional capacity, increasing the ROF [3]. Early identification of ROF facilitates the administration of personalized interventions for individuals [4].

Most recent studies predict falls using sensors or Electronic Health Records (EHRs). With data collected directly from elderly individuals' homes, our objective is to develop an effective predictive model using the fewest possible features. Our initial models, built with a comprehensive approach, have demonstrated satisfactory performance. In this work, we briefly discuss fall prediction strategies, the dimensions of ROF, and relevant studies in the field. In Section II, we define falls using a holistic approach. In Section III, we discuss the findings from previous studies as well as the best predictive model we developed. Finally, in Section IV, we present a concise and synthetic conclusion.

II. RISK OF FALLING

Falls can be caused by various factors. A fall occurs when a person involuntarily lands on the ground or at a lower level than their starting position [5]. It can occur multiple times a year. Geriatrics who experience at least two falls within 12 months are classified as "fallers" [6].

A holistic fall prediction approach considers three key dimensions:

- The physical/organic dimension gathers data related to an individual's medical history and current symptoms, diagnosis of underlying health issues, and treatment effectiveness.
- The thymic/cognitive dimension refers to an individual's mental, emotional, and cognitive states.
- The socio-environmental dimension refers to age, gender, family and social support, housing conditions, home configuration, the presence of slippery rugs, stairs without railings, uneven surfaces, and inadequate lighting.

Evaluating the ROF involves at least a gait and balance assessment of the physical/organic dimension and the age and gender of the socio-environmental dimension. Data involving the thymic/cognitive dimension allows for a

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comprehensive review of the potential causes of a fall. The term "dimension" refers to the types of factors that contribute to the ROF and their evaluation.

Hospitalized patients often receive incomplete health assessments across all dimensions. Our home-collected data encompasses features from all three dimensions.

III. Predictive factors for falls in the older population

Not every feature within the three ROF dimensions is a predictive factor for falls. The effectiveness of a predictive factor depends on its statistical significance, correlation with fall occurrences, and its interaction with other variables across the physical/organic, socio-environmental, and cognitive dimensions. In some studies, the identified predictive variables did not encompass all three dimensions of ROF. Kawazoe et al. [7], Ikeda et al. [8], and Cella et al. [9] demonstrated that age category related to socio-environmental was a predictor of falls, suggesting a strong association between age and falls. Bath et al. found that the predictive variables related to the socio-environmental dimension are diverse and varied, contributing to effective prevention [10]. In fact, a higher number of variables related to gait and balance is associated with a more robust predictive model for falls.

In the literature review conducted by Rubenstein, only cognitive impairment was identified as a predictive variable related to the thymic/cognitive [11]. Conversely, Ikeda et al. [8], Kawazoe et al. [7], and Bath et al. [10] identified at least two predictive variables involving the thymic/cognitive dimension, providing a better understanding of the ROF associated with the thymic/cognitive dimension and facilitating preventive measures. In those features, we can find fear of falling, depressive symptoms, self-rated health, impaired consciousness, and dementia at admission. Recent studies by Ikeda et al. [8] and Kawazoe et al. [7] achieved Area Under the receiver operating characteristic Curve (AUC) scores of 88% and 85%, respectively, using comprehensive approaches. Ikeda et al. employed a Random Forest-based Boruta algorithm for feature selection, while Kawazoe et al. used a combination of Bidirectional Encoders and Bidirectional Long Short-Term Memory (BiLSTM) networks to process sequential data. These AUC scores indicate strong model performance, reflecting high discriminative ability in classification tasks [12].

The reliability of predictive studies depends on the quality and consistency of data collection. Unlike hospitals, where data is gathered only when patients seek care, home-based data collection requires practitioners to schedule visits at fixed intervals. Our study followed 1,648 community-dwelling older adults (⩾60 years) between September 2011 and September 2023. Participants were assessed at home by the Unit for Prevention, Monitoring and Analysis of Ageing (UPSAV – *Unité de Prévention, de Suivi et d'Analyse du Vieillissement*) at Limoges University Hospital, Limoges, France. Each patient underwent an initial visit followed by a second visit six months later. After the second visit, annual follow-ups were conducted for up to six years, as long as the patient remained in their home. Data collection included cardiovascular risk factors, fall occurrences, socio-environmental characteristics, and a comprehensive geriatric assessment summary score. To ensure coherence, our predictive model accounts for temporality by predicting falls every six months. Out of thirty input features, eleven were identified as the most relevant fall predictors using multinomial logistic regression: Gender, Hypertension, Obesity, 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), Leisure activity, Pathological Single-Leg Balance (SLB), and history of falling in the past year.

Of the 1,648 patients assessed at the first visit, 954 remained for the second visit. The AI model was subsequently built using data from these 954 patients. The most relevant fall predictors were used to develop several predictive models, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and eXtreme Gradient Boosting (XGBoost). The area under the receiver operating characteristic curve (AUC) was used to evaluate the predictive performance of these models. Among them, Random Forest and XGBoost achieved the highest performance, with AUCs of 77 and 76, on the test set. XGBoost achieved a Brier score of 0.19, while that of Random Forest was 0.2.

The Brier score measures the accuracy of probabilistic predictions; it is calculated as the mean squared difference between predicted probabilities and actual outcomes. Lower values indicate better calibration [13].

Due to its low Brier score and suitability for interpretation, the XGBoost model was selected for SHapley Additive exPlanations (SHAP) analysis to interpret its predictions at the individual level. SHAP analysis revealed that fall history, balance performance, cognitive status, and functional ability were the most influential predictors.

SHAP is an explainable AI method that provides insights into the contribution of each feature both globally (across the entire dataset) and locally (for individual predictions) [14].

As with most AI models, ours can be continuously refined with additional data over time. In our case, improving the model also provides an opportunity to collect data from patients' homes while offering them personalized fall prevention advice. During the intervals between practitioner visits, necessary adjustments to home configurations can also be made if needed.

The limitations of this study include the use of data that did not account for medications taken by participants or treatments for specific comorbidities, which may influence fall risk. Additionally, the study population was limited to older adults residing in France, potentially affecting the generalizability of the findings to other geographic or cultural contexts. Future research should aim to include more diverse populations to enhance the external validity and applicability of the results.

IV. CONCLUSION

This study contributes to advancing fall prevention by leveraging a 12-year dataset collected in home settings to develop an AI-based predictive model. Our approach integrates the three dimensions of ROF, optimizing model performance while reducing the number of required input features.

By applying explainable AI techniques, we identified the contribution of each feature to fall risk, thereby supporting the development of more targeted and effective intervention strategies. These findings may help enhance the quality of elderly care by informing personalized prevention efforts and guiding future research in geriatric risk assessment.

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