Experimental Gerontology 81 (2016) 51–55

Contents lists available at ScienceDirect

Experimental Gerontology

journal homepage: www.elsevier.com/locate/expgero

A decision model to predict the risk of the first fall onset

Thibault Deschamps [a,⁎,1], Camille G. Le Goff [b,1], Gilles Berrut [a,c], Christophe Cornu [a], Jean-Baptiste Mignardot [a,b,⁎,2]

[a] Laboratory MIP (UPRES-EA4334), University of Nantes, France
[b] Laboratory Courtine, Swiss Federal Institute of Technology (EPFL), Lausanne, Switzerland
[c] Centre Hospitalier Universitaire de Nantes, Pole de Gérontologie Clinique, Hôpital Bellier, Nantes, France

ARTICLE INFO

Article history:
Received 15 December 2015
Received in revised form 18 March 2016
Accepted 21 April 2016
Available online 23 April 2016

Section Editor: Diana Van Heemst

Keywords:
Risk of fall
Machine learning
Prediction model
Prospective follow-up
Posture

ABSTRACT

Background: Miscellaneous features from various domains are accepted to be associated with the risk of falling in the elderly. However, only few studies have focused on establishing clinical tools to predict the risk of the first fall onset. A model that would objectively and easily evaluate the risk of a first fall occurrence in the coming year still needs to be built.
Objectives: We developed a model based on machine learning, which might help the medical staff predict the risk of the first fall onset in a one-year time window.
Participants/measurements: Overall, 426 older adults who had never fallen were assessed on 73 variables, comprising medical, social and physical outcomes, at *t0*. Each fall was recorded at a prospective 1-year follow-up. A decision tree was built on a randomly selected training subset of the cohort (80% of the full-set) and validated on an independent test set.
Results: 82 participants experienced a first fall during the follow-up. The machine learning process independently extracted 13 powerful parameters and built a model showing 89% of accuracy for the overall classification with 83%–82% of true positive fallers and 96%–61% of true negative non-fallers (training set vs. independent test set).
Conclusion: This study provides a pilot tool that could easily help the gerontologists refine the evaluation of the risk of the first fall onset and prioritize the effective prevention strategies. The study also offers a transparent framework for future, related investigation that would validate the clinical relevance of the established model by independently testing its accuracy on larger cohort.

1. Introduction

Approximately 30% of seniors aged 65 and older experience one or more falls annually (Tinetti et al., 1988). Hence, in view of the dramatic consequences of falls in older adults in various domains, including impaired mobility (Dai et al., 2012), quality of life (Davis et al., 2015), or the overall economic cost (Davis et al., 2010), the capacity to predict a future fall constitutes a clinical target, which continually needs to be refined. Even if numerous parameters associated with the risk of falling have already been identified (e.g., (Bloch et al., 2013; Gillespie et al., 2012)), the medical community still lacks an easy-to-use tool that could accurately predict the risk of the first fall onset. Indeed, falls in the elderly result from intricate interactions between extrinsic and intrinsic risk factors related to iatrogenic component, medical histories, or physical characteristics (for a detailed review (Bloch et al., 2013)). Many studies reported models that can predict the risk of falling in the elderly (Ivziku et al., 2011; Kojima et al., 2015; Schoene et al., 2013; Verghese et al., 2009). However, most of them were based on large cohorts of heterogeneous elderly population without specifying whether participants had ever fallen before their enrolment in the study (for notable exceptions see Beauchet et al. (2008), Mignardot et al. (2014)).

Up to now, no studies have identified a subset of relevant parameters and the way in which they should interact (hierarchical sorting) to develop a powerful model. Yet, many studies have proposed fall prediction models using risk-scoring system (Stalenhoef et al., 2002; Whitney et al., 2012; Yoo et al., 2015). However, the statistical properties of a prediction model of falls, such as the trade-off between sensitivity and specificity, determine how the prediction model can be effectively used. Hence, the false positive and false negative rates in many models question their clinical application. Finally, as another pitfall, the lack of control associated with independent testing sets is of overriding importance in health care practice.

⁎ Corresponding authors at: Laboratory MIP (UPRES-EA4334), University of Nantes, France.
E-mail addresses: thibault.deschamps@univ-nantes.fr (T. Deschamps), mignardot.jb@gmail.com (J.-B. Mignardot).
[1] Equal contribution.
[2] Ecole Polytechnique Fédérale de Lausanne, Laboratoire UP-COURTINE - station 19, CH-1015 Lausanne, Switzerland.

http://dx.doi.org/10.1016/j.exger.2016.04.016
0531-5565/

We seek to alleviate these issues by performing data mining on a database that contains most of relevant parameters associated with the risk of fall (neurologic, cardiovascular, cognitive, anthropometric, motor function, and socio-educational assessments). We built a predictive model for the occurrence of a first fall from a cohort comprising 426 older adults who were followed prospectively over one year. The machine learning technique we used has generated a decision tree with a set of simple classification rules. We were also concerned about the validity of these extracted rules; thus, we performed a blind control on an independent set to evidence its clinical relevance.

2. Methods

2.1. Participants

A cohort of 426 older adults (mean age 69.5 ± 2.6 years; 61.5% women) who never experienced a fall experience were recruited for a prospective observational multicenter study designed to identify the risk factors for the first fall in elderly community-dwellers. The Local Ethical Committee of the Region of Pays de la Loire (France) approved this study (ref: no. 2004/05). The data collection procedure has been described elsewhere in detail (Mignardot et al., 2014). In summary, eligibility criteria were age between 66 and 75 years, living at home, never fallen, and an ability to walk without assistance for at least 30 s. For the present analysis, exclusion criteria were refusal to give consent or lack capacity to give consent or if the participant was hospitalized at the time of screening. Participants were included after having given their written informed consent for research.

2.2. Screening of falls and prospective follow-up

Before the enrolment in the study, the faller status in older participants was evaluated during the first information meeting, where they were questioned about their past. A geriatric doctor explained the WHO definition of a fall (WHO, 2007) to the participants using case examples. Subjects were excluded if they already experienced a fall. Of note, the non-faller status of healthy adults was double-checked at the inclusion visit. During this same visit, all baseline characteristics described in the following "data collection" section were collected. The research medical staff designed a standard phone call that aimed to prospectively monitor any fall onset (date, circumstances, causes and consequences) and/or major events each month for one year. Trained interviewers performed the phone calls, similar to the procedure used in the literature (Stalenhoef et al., 2002). At the end of the follow-up period, a committee of geriatric doctors analyzed the circumstances of each fall recorded during the prospective follow-up in order to verify and, if appropriate, validate that the fall occurred during usual living conditions and in line with the WHO definition-related criteria of a fall (WHO, 2007). The expert committee rejected 5% of collected falls. During the 12-month follow-up period, 82 subjects (19.2%) reported falling at least once. Note also that the committee kept blind for the results as the geriatric M.D. met, and none of them has been involved in the construction of the decision tree.

2.3. Data collection

Medical staff screened each participant at t_0 for various baseline characteristics that have been found to be predictors of falls: gender, taking medications, impaired cognition (e.g., Frontal Assessment Battery "FAB"), postural sway during upright quiet standing with eyes open and eyes closed (51.2 s.), the body composition associated with anthropometrical measures, the functional autonomy and physical lifestyle, and various systemic domains, such as vision, hearing, cardiovascular, sensory features and executive functions (see Table 1).

2.4. Decision tree learning procedure

The final database comprised 426 subjects providing 31,098 values and 73 variables divided into 50 unordered categorical and 23 continuous variables describing the status of each older adult (see Table 1). Based on those input variables, the outcome variable was the occurrence of the first fall in the next 12 months. Considering the status of each subject and categorical nature of the data, a decision tree revealed to be the most adequate supervised machine learning algorithm to develop a direct and easy-to-use tool (for details about decision trees definition and implementation see Kotsiantis (2007)). A classification tree is created by splitting the initial training set (called the root node) into two subsets based on the most discriminative variable. This process is then recursively repeated on the new subsets until the splitting no longer brings value to the prediction. The final subsets are called leaves while the intermediate ones are named internal nodes.

2.4.1. Random attribution of the data for the training or testing sets

Among the 426 subjects, 82 experienced the first fall onset within 12 months and formed the faller group (F group). Overall, 344 subjects have not shown any sign of fall onset, and they were considered as control non-faller subjects (NF group). To respect the assumption of samples equality in both groups (Breiman et al., 1984), we have randomly and blindly selected 25% of the subjects from the NF group (86 subjects) to balance the number of subjects in both groups (F and NF groups). Then, the reduced database was split into training and test sets. Overall, 80% of the subjects from F group were blindly assigned to the training set (65 subjects); the remaining subjects were assigned to the test set (17 subjects). Identically, 80% of the subjects from the NF group were assigned to the training set (68 subjects) while the others were assigned to the test set (18 subjects).

2.4.2. Model accuracy assessment

The decision tree was implemented in Matlab® using the Statistics toolbox with the *classregtree* function to perform classification (Breiman et al., 1984). The parameters of this function have been adjusted to obtain the highest accuracy (subsets must have at least 10 training samples to be split, the Gini's diversity index (Raileanu and Stoffel, 2004) was used as the split criterion, all variables were assigned the same weight, and prior probabilities belonging to one class were equal). Subjects with missing values were retained, as long as the algorithm was able to handle them. The optimal tree, as determined by the algorithm on the training set, was then tested on the test set. Confusion matrices and the area under the receiver operating characteristics curves (AUC) on both sets were used to determine the accuracy of the model.

3. Results

All statistical results are summarized in Table 1, with mean ± standard deviations representing baseline continuous variables and number of subjects in percentages representing categorical variables. No significant differences in baseline characteristics were found between F and NF groups, except for gender. Overall, no significant differences emerged between groups, regardless of the baseline characteristics (postural balance, body composition and anthropometry, physical lifestyle and autonomy, hearing, vision, cardiovascular, orthopedy, neurology, executive functions).

The decision tree was built on the training set (comprising 9709 values), and 2555 values have been used for the independent evaluation of model accuracy. Fig. 1A displays the final decision tree with its 15 internal nodes and 17 leaves. For each internal node, the split criterion is indicated. The tree demonstrates that the two first levels of splitting are related to nutrition and anthropometry. The root of the tree starts by the mini nutritional assessment, followed by the body mass index (BMI) and the lean body mass at the second level. The field of sensory disabilities, including the ankle hypoesthesia, the visual acuity, and the

Table 1
Baseline characteristics of the studied sample (n = 426) according to their faller status (faller vs. non-faller). $p < 0.05$: *.

	Fallers ($n = 82$)	Non-fallers ($n = 344$)	Total ($n = 426$)
Baseline characteristics			
Female gender, n (%)*	**41 (50.0)**	**224 (65.1)**	**265 (62.2)**
Age (years), mean ± SD [a (1, 2, 3)]	69.5 ± 2.8	69.5 ± 2.6	69.5 ± 2.6
Taking medications (yes), n (%)	72 (87.8)	267 (77.6)	339 (79.6)
Family status (in couple vs. single), n (%)	65 (79.3)	283 (82.3)	348 (81.7)
Postural balance			
Eyes open			
Area (95% confidence ellipse) (mm^2)	167 ± 135.6	152 ± 106	154.8 ± 112.3
COP mediolateral length (mm)	240.6 ± 85.2	241 ± 92.3	240.9 ± 90.9
COP antero-posterior length (mm)	270.3 ± 93.3	274.2 ± 103	273.4 ± 101.1
Eyes closed			
Area (95% confidence ellipse) (mm^2)	285.3 ± 296.1	247.4 ± 176.2	254.7 ± 204.9
COP mediolateral length (mm)	344.5 ± 160.5	347.3 ± 158.3	346.8 ± 158.6
COP antero-posterior length (mm)	448.7 ± 210.3	454.3 ± 218	453.2 ± 216.3
Body composition and anthropometry			
Body mass index (kg/m^2), mean ± SD	26.4 ± 4	26 ± 3.7	26.1 ± 3.7
Weight (kg), mean ± SD	70.2 ± 12	70.9 ± 12.4	70.7 ± 12.3
Height (cm), mean ± SD	162.9 ± 9.5	164.6 ± 8.6	164.3 ± 8.8
Right brachial circumference, mean ± SD	28.9 ± 3.3	29 ± 3.3	29 ± 3.3
Calf brachial circumference, mean ± SD	36.1 ± 3.3	35.9 ± 3.1	36 ± 3.1
Mini-nutritional assessment score (/30 points), mean ± SD	27.5 ± 1.7	28 ± 4.2	27.9 ± 3.9
Fat mass (kg), mean ± SD	21.4 ± 7	20.3 ± 6.6	20.5 ± 6.7
Lean mass (kg), mean ± SD	48.4 ± 9.7	50.4 ± 9.7	50 ± 9.7
Total body water (kg), mean ± SD	35.7 ± 6.9	37.2 ± 7.1	36.9 ± 7.1
Physical lifestyle and autonomy			
Index of independence in activities of daily living (Katz index/6), mean ± SD	5.8 ± 0.4	5.9 ± 0.3	5.9 ± 0.3
Daily life activities (/27 = without aid), mean ± SD	26.6 ± 1	26.7 ± 1.1	26.7 ± 1.1
Physical activity (walk) > = 30 min/day, n (%)	64 (78.0)	280 (81.4)	344 (80.8)
One leg standing >5 s (yes), n (%)	75 (91.5)	323 (93.9)	398 (93.4)
Vision			
Visual Object and Space Perception Battery, (/10 points), mean ± SD	8.8 ± 1.5	8.6 ± 1.8	8.7 ± 1.7
Distance visual acuity (right eye) (/10), mean ± SD	8.2 ± 3.2	8.3 ± 2.5	8.3 ± 2.6
Distance visual acuity (left eye) (/10), mean ± SD	8.1 ± 3	8.2 ± 2.5	8.2 ± 2.6
Near visual acuity (right eye) (/10), mean ± SD	23.6 ± 36.6	20.1 ± 17.8	20.8 ± 22.6
Near visual acuity (left eye) (/10), mean ± SD	17.5 ± 7.3	18.4 ± 9	18.2 ± 8.7
Vision with glasses (yes), n (%)	81 (98.8)	343 (99.7)	424 (99.5)
Glasses (bifocal/progressive lenses), n (%)	70 (85.4)	303 (88.1)	373 (87.6)
Cataract (yes), n (%)	18 (22.0)	86 (25.0)	104 (24.4)
Hearing			
Hearing surgery (yes), n (%)	2 (2.4)	16 (4.7)	18 (4.2)
Hearing aid (right ear), n (%)	3 (3.7)	10 (2.9)	13 (3.1)
Hearing aid (left ear), n (%)	4 (4.9)	12 (3.5)	16 (3.8)
Hearing deficiency (>30 dB) (yes), n (%)	69 (84.1)	275 (79.9)	344 (80.8)
Presbycusis (yes), n (%)	68 (82.9)	274 (79.7)	342 (80.3)
Cardiovascular			
Normal electrocardiogram (yes), n (%)	69 (84.1)	289 (84.0)	358 (84.0)
Systolic blood pressures (supine/standing ratio), mean ± SD	0.99 ± 0.09	0.9 ± 0.08	0.9 ± 0.08
Orthopedy			
Orthopedic surgery of lower limbs, n (%)	15 (18.3)	55 (16.0)	70 (16.4)
Spinal surgery, n (%)	8 (9.8)	14 (4.1)	22 (5.2)
Paralyzing sciatica, n (%)	5 (6.1)	15 (4.4)	20 (4.7)
Herniated disc, n (%)	10 (12.2)	35 (10.2)	45 (10.6)
Coxarthrosis, n (%)	6 (7.3)	35 (10.2)	41 (9.6)
Knee osteoarthritis, n (%)	10 (12.2)	38 (11.0)	48 (11.3)
Limited hip range of motion, n (%)	8 (9.8)	21 (6.1)	29 (6.8)
Limited knee range of motion, n (%)	1 (1.2)	19 (5.5)	20 (4.7)
Frozen ankles, n (%)	3 (3.7)	2 (0.6)	5 (1.2)
Orthopedic shoes, n (%)	3 (3.7)	5 (1.5)	8 (1.9)
Feet pathology, n (%)	30 (36.6)	108 (31.4)	138 (32.4)
Neurology			
Sensory features			
Stroke, n (%)	3 (3.7)	8 (2.3)	11 (2.6)
Diziness, n (%)	9 (11.0)	32 (9.3)	41 (9.6)
Romberg's test (positive result), n (%)	27 (32.9)	100 (29.1)	127 (29.8)
Left distal hypopallesthesia of medial malleolus, n (%)	4 (8.5)	42 (12.2)	46 (11.5)
Left distal hypopallesthesia of lateral malleolus, n (%)	12 (14.6)	42 (12.2)	54 (12.7)
Left distal hypopallesthesia of heel, n (%)	18 (22.0)	55 (16.0)	73 (17.1)
Left distal hypopallesthesia of foot arch, n (%)	10 (12.2)	40 (11.6)	50 (11.7)
Right distal hypopallesthesia of medial malleolus, n (%)	9 (11.0)	57 (16.6)	66 (15.5)
Right distal hypopallesthesia of lateral malleolus, n (%)	5 (6.1)	51 (14.8)	56 (13.1)
Right distal hypopallesthesia of heel, n (%)	17 (20.7)	61 (17.7)	78 (18.3)
Right distal hypopallesthesia of foot arch, n (%)	10 (12.2)	51 (14.8)	61 (14.3)
Left distal hypoesthesia of medial malleolus, n (%)	3 (3.7)	10 (2.9)	13 (3.1)
Left distal hypoesthesia of lateral malleolus, n (%)	3 (3.7)	8 (2.3)	11 (2.6)

(continued on next page)

Table 1 (*continued*)

	Fallers ($n = 82$)	Non-fallers ($n = 344$)	Total ($n = 426$)
Neurology			
Sensory features			
Left distal hypoesthesia of heel, n (%)	3 (3.7)	34 (9.9)	37 (8.7)
Left distal hypoesthesia of foot arch, n (%)	4 (4.9)	17 (4.9)	21 (4.9)
Right distal hypoesthesia of medial malleolus, n (%)	1 (1.2)	8 (2.3)	9 (2.1)
Right distal hypoesthesia of lateral malleolus, n (%)	1 (1.2)	9 (2.6)	10 (2.3)
Right distal hypoesthesia of heel, n (%)	3 (3.7)	33 (9.6)	36 (8.5)
Right distal hypoesthesia of foot arch, n (%)	3 (3.7)	20 (5.8)	23 (5.4)
Executive functions			
Frontal assessment battery (Score/18 ± *SD*)	14.8 ± 2.3	14.6 ± 2.4	14.7 ± 2.4
Gear wheel test, (yes), n (%)	0 (0.0)	2 (0.6)	2 (0.5)
Repeat three words (“lemon, key, balloon”), (yes), n (%)	82 (100.0)	343 (99.7)	425 (99.8)
Spell the word “world” backwards, (yes), n (%)	76 (92.7)	328 (95.3)	404 (94.8)
Recall the three words (“lemon, key, balloon”) without aid			
0 word, n (%)	1 (1.2)	3 (0.9)	4 (0.9)
1 word, n (%)	10 (12.2)	39 (11.3)	49 (11.5)
2 words, n (%)	25 (30.5)	87 (25.3)	112 (26.3)
3 words, n (%)	46 (56.1)	215 (62.5)	261 (61.3)

presbycusis, and the variables related to quiet standing postural control, both during eyes opened and eyes closed conditions, contributes strongly to the decision tree (Fig. 1A–B). Finally, the disabilities at the distal part of the lower limbs also represent an important part of the tree. Indeed, in addition to the hypoesthesia at the ankle level, an overall pathology at the foot level and/or a limited range of motion at the knee level need to be diagnosed to complete the model.

The detailed prediction results of the training and test datasets are presented in the form of confusion matrixes and ROC curves (Fig. 1C–D). In the training set, the overall classification accuracy was 89% (AUC = 0.89), with accuracy rate of 83% for fallers and 96% for non-fallers. Further, for older adults classified by the decision tree as fallers, 54 cases (95%) were actually fallers. For the 18 non-fallers in the test dataset, the decision tree correctly classified 11 older adults (61%). The prediction model accurately identified older adults at high risk for first fall with an accuracy rate of 82% for the 17 fallers (AUC = 0.72 for both curves).

4. Discussion

Considering the WHO recommendations (WHO, 2007), the development of long term targeted fall-prevention programs to prevent falls in older adults as soon as possible is a health priority. Thus, the early identification of people at high risk of falls should be based on an “easy to use”

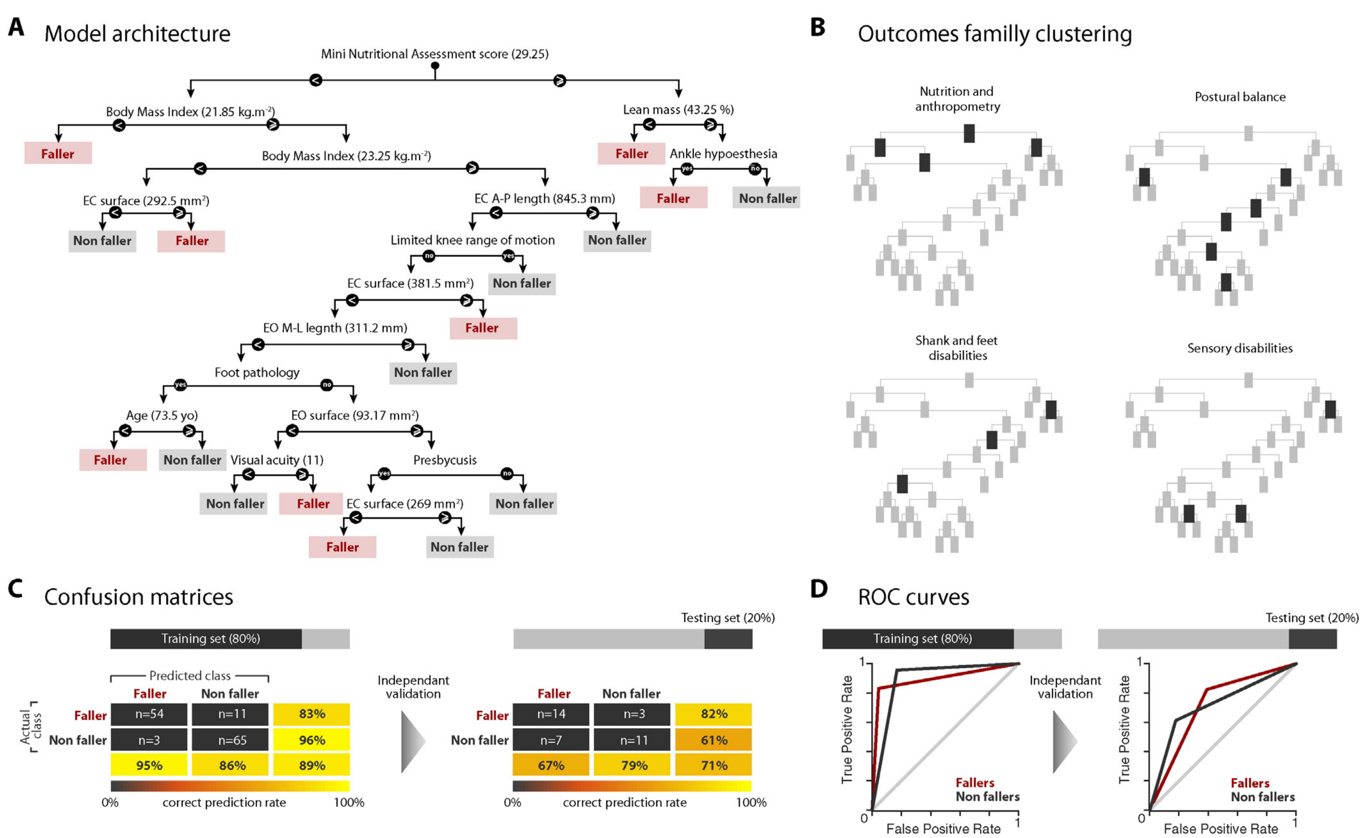

Fig. 1. Decision tree architecture, which objectively shows the ‘*If*’-‘*Then*’ *rules* (A), the clustering of the selected parameters to enhance understanding (B) and the accuracy of the model both for the training set and the independent testing set through confusion matrices (C) and receiver operating characteristics (ROC) curves (D). *Note*. EC: eyes closed; EO: eyes open; A-P: antero-posterior axis; M-L: mediolateral axis.

predictive models built on a randomly selected training subset of the cohort and validated on an independent test set. These objectives guided this pilot study conducted with a very original cohort (namely home-dwelling older adults who had never fallen). We developed the first algorithm using machine-learning technique leading to a set of simple rules to estimate the probability of the risk of the first fall onset in the coming year. As a striking result, we found a high classification accuracy of true fallers in the training dataset (83%), which was consistently confirmed by the decision tree analysis in the independent test set (82%).

The model extracted a restricted amount of relevant parameters, which includes anthropometric, sensory-motor, and postural balance parameters, from an initial set of 73 variables. These variables constituted a subset of the determinants already known to be associated with the risk of falls in significant meta-analyses (Bloch et al., 2013; Gillespie et al., 2012). Abnormal balance test [OddsRatio = 2.26 (1.79–2.85)], low body mass index [*OR* = 2.05 (1.70–2.48)], fracture history [*OR* = 1.89 (1.53–2.34)], hearing impairment [*OR* = 1.37 (1.27–1.48)], vision impairment [*OR* = 1.49 (1.39–1.59)], sensory disorders [*OR* = 2.2 (1.56–3.11)] or lower extremity disability [*OR* = 1.89 (1.65–2.17)] are important intrinsic predictors of falls. They are consistent with the parameters used by our algorithm, which include the mini nutritional assessment score (/30 points) (Rubenstein et al., 2001), body mass index, lean body mass, clinical balance measures (the surface and the path length of the COP during quiet stance trials with eyes open or eyes closed), presbycusis or visual acuity impairment, and shank/ft disabilities (ankle hypoesthesia, limited knee range of motion or foot pathology such as hallux valgus). Overall to be an older adult, with nutritional disturbances, limited knee range of motion or ankle hypoesthesia, and hearing and visual deficits tend to impair the postural, indicative of an increased risk of the first fall. Other things being equal, this might be the first insights in pathophysiological mechanisms underlying the phenotype of fallers.

The clustering of these parameters in four families (Fig. 1B) illustrates the importance of considering simultaneously the fields of nutrition/body composition, the sensory-motor features at the lower limb level, and the control of postural balance for an optimized integrative prevention strategy. Indeed, both the morphological states (i.e., overweight and restricted joint range of motion), the muscle strength at the ankle joint, and the feet sensitivity strongly influence the postural control skills and *in fine* the risk of fall. (Cattagni et al., 2014; Mignardot et al., 2013; Perry, 2006)

One of key aspects of this pilot regression tree analysis is the simple conversion of main findings into a collection of '*If*'-'*Then*' rules easily useable in clinical setting (Fig. 1A). Beyond the high classification accuracy of the current prediction model of the first fall, further analyses are needed to increase the visibility of these rules because of limited sample size associated with those nodes. Thus further statistic validity of the current prediction model on a larger and truly independent cohort is still required to guarantee the clinical relevance of the current prediction model. One of the key results is indeed relatively moderate accuracy rate for non-fallers in the test set (61%) compared to the accuracy rate of 96% in the training dataset. The possibility that this drop is a sign of impaired robustness of the model needs to be considered as a limitation of the present study. However, we assume that the accuracy of this prediction model for *future fallers* may help medical professional prescribe an intervention early enough to effectively prevent the first fall onset. From a clinical viewpoint, although this new guide reliably identifies older adults at high risk for fall, diagnosing older individuals who are really not at risk as being at high risk is much less dramatic.

To conclude, using few routine clinical, anthropometric, and metrologic measurements, this pilot study tested a reliable prognostic model to predict the first fall onset in older adults. The model may offer a simple and easy tool to use in the clinical settings and medical field."

Conflict of interest

The authors report no conflicts of interest.

Author contribution

Conception and design of the cohort study: GB.

Collection, assembly, analysis and interpretation of data: CLG, JBM, TD.

Drafting the article or revising it critically for important intellectual content: TD, CLG, JBM, CC, GB.

Sponsor's role

The study was sponsored by grants from the Region of Pays de la Loire (#2011-05457 & #2011-05455), France, for the projects "RP3AP" and "LMA". The sponsors had no role in the design and conduct of the study, in the collection, management, analysis, and interpretation of the data, or in the preparation, review, or approval of the manuscript.

References

Beauchet, O., Allali, G., Annweiler, C., et al., 2008. Does change in gait while counting backward predict the occurrence of a first fall in older adults? Gerontology 54, 217–223.
Bloch, F., Thibaud, M., Tournoux-Facon, C., et al., 2013. Estimation of the risk factors for falls in the elderly: can meta-analysis provide a valid answer? Geriatr. Gerontol. Int. 13, 250–263.
Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., 1984. Classification and Regression Trees. Wadsworth, Belmont, California.
Cattagni, T., Scaglioni, G., Laroche, D., et al., 2014. Ankle muscle strength discriminates fallers from non-fallers. Front. Aging Neurosci. 6, 336.
Dai, B., Ware, W.B., Giuliani, C.A., 2012. A structural equation model relating physical function, pain, impaired mobility (IM), and falls in older adults. Arch. Gerontol. Geriatr. 55, 645–652.
Davis, J.C., Robertson, M.C., Ashe, M.C., et al., 2010. International comparison of cost of falls in older adults living in the community: a systematic review. Osteoporos. Int. 21, 1295–1306.
Davis, J.C., Bryan, S., Best, J.R., et al., 2015. Mobility predicts change in older adults' health-related quality of life: evidence from a Vancouver falls prevention prospective cohort study. Health Qual. Life Outcomes 13, 101.
Gillespie, L.D., Robertson, M.C., Gillespie, W.J., et al., 2012. Interventions for preventing falls in older people living in the community. Cochrane Database Syst. Rev. 9, CD007146.
Ivziku, D., Matarese, M., Pedone, C., 2011. Predictive validity of the Hendrich fall risk model II in an acute geriatric unit. Int. J. Nurs. Stud. 48, 468–474.
Kojima, G., Masud, T., Kendrick, D., et al., 2015. Does the timed up and go test predict future falls among British community-dwelling older people? Prospective cohort study nested within a randomised controlled trial. BMC Geriatr. 3 (15), 38.
Kotsiantis, S.B., 2007. Supervised machine learning: a review of classification techniques. Informatica 31, 249–268.
Mignardot, J.B., Olivier, I., Promayon, E., et al., 2013. Origins of balance disorders during a daily living movement in obese: can biomechanical factors explain everything? PLoS One 8, e60491.
Mignardot, J.-B., Deschamps, T., Barrey, E., et al., 2014. Gait disturbances as specific predictive markers of the first fall onset in elderly people: a two-year prospective observational study. Front. Aging Neurosci. 6, 22.
Perry, S.D., 2006. Evaluation of age-related plantar-surface insensitivity and onset age of advanced insensitivity in older adults using vibratory and touch sensation tests. Neurosci. Lett. 392, 62–67.
Raileanu, L.E., Stoffel, K., 2004. Theoretical comparison between the Gini index and information gain criteria. Ann. Math. Artif. Intell. 41, 77–93.
Rubenstein, L.Z., Harker, J.O., Salvà, A., et al., 2001. Screening for undernutrition in geriatric practice: developing the short-form mini-nutritional assessment (MNA-SF). J. Gerontol. A Biol. Sci. Med. Sci. 56, M366–M372.
Schoene, D., Wu, S.M., Mikolaizak, A.S., et al., 2013. Discriminative ability and predictive validity of the timed up and go test in identifying older people who fall: systematic review and meta-analysis. J. Am. Geriatr. Soc. 61, 202–208.
Stalenhoef, P.A., Diederiks, J.P.M., Knottnerus, J.A., et al., 2002. A risk model for the prediction of recurrent falls in community-dwelling elderly: a prospective cohort study. J. Clin. Epidemiol. 55, 1088–1094.
Tinetti, M., Speechley, M., Ginter, S.F., 1988. Risk factors for falls among elderly persons living in the community. N. Engl. J. Med. 319, 1701–1707.
Verghese, J., Holtzer, R., Lipton, R.B., et al., 2009. Quantitative gait markers and incident fall risk in older adults. J. Gerontol. A Biol. Sci. Med. Sci. 64, 896–901.
Whitney, J., Close, J.C.T., Lord, S.R., et al., 2012. Identification of high risk fallers among older people living in residential care facilities: a simple screen based on easily collectable measures. Arch. Gerontol. Geriatr. 55, 690–695.
WHO, 2007. World Health Organization report/WHO Global Report on Falls Prevention in Older Age (47 pp.).
Yoo, S.H., Kim, S.R., Shin, Y.S., 2015. A prediction model of falls for patients with neurological disorder in acute care hospital. J. Neurol. Sci. 356, 113–117.