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

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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.

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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