A pilot study for development of a novel tool for clinical decision making to identify fallers among ophthalmic patients

P Melillo1,2†, A Orrico1,2†, M Attanasio1,2, S Rossi2, L Pecchia3, F Chirico2, F Testa2, F Simonelli2

Abstract

Background: Falls in the elderly is a major problem. Although falls have a multifactorial etiology, a commonly cited cause of falls in older people is poor vision. This study proposes a method to discriminate fallers and non-fallers among ophthalmic patients, based on data-mining algorithms applied to health and socio-demographic information.

Methods: A group of 150 subjects aged 55 years and older, recruited at the Eye Clinic of the Second University of Naples, underwent a baseline ophthalmic examination and a standardized questionnaire, including lifestyles, general health, social engagement and eyesight problems. A subject who reported at least one fall within one year was considered as faller, otherwise as non-faller. Different tree-based data-mining algorithms (i.e., C4.5, Adaboost and Random Forest) were used to develop automatic classifiers and their performances were evaluated by assessing the receiver-operator characteristics curve estimated with the 10-fold-crossvalidation approach.

Results: The best predictive model, based on Random Forest, enabled to identify fallers with a sensitivity and specificity rate of 72.6% and 77.9%, respectively. The most informative variables were: intraocular pressure, best corrected visual acuity and the answers to the total difficulty score of the Activities of Daily Vision Scale (a questionnaire for the measurement of visual disability).

Conclusions: The current study confirmed that some ophthalmic features (i.e. cataract surgery, lower intraocular pressure values) could be associated with a lower fall risk among visually impaired subjects. Finally, automatic analysis of a combination of visual function parameters (either self-evaluated either by ophthalmological tests) and other health information, by data-mining algorithms, could be a feasible tool for identifying fallers among ophthalmic patients.
multifactorial with several unrelated to mobility, e.g., poor vision, cardiovascular conditions.

The current paper proposes a novel tool to identify fallers among ophthalmic patients by using data-mining methods applied to vision assessment and questionnaire to achieve information about participants’ lifestyle, eye symptoms, use of glasses, systemic medical and ocular surgical history, and current medications.

Methods
Study population and ethical approval
This study was conducted on a group of subjects aged 55 years and over, enrolled among the patients visited at the Eye Clinic of the Second University of Naples from February to July 2014. The research followed the tenets of the Declaration of Helsinki and each subject gave informed consent to participate in the study. Ethics approval was obtained from the Institutional Review Board of the Second University of Naples.

Socio-demographic and medical data were recorded with a standardized questionnaire that was developed ad hoc, including the variables summarized in Table 1 Table 2 and Table 3. Selected variables, which have been considered in previous studies investigating risk factors for falls, included but were not limited to those on visual impaired subjects [13-23]. In particular, information about lifestyle (e.g., cigarette smoking habit, alcohol consumption, job activity, social engagement, etc), systemic medical history (e.g., history of cancer), and general physical health (e.g., sleep problems, walking aid use, depression, hypertension, diabetes, urinary incontinence, arthritis, Parkinson disease, number and type of prescribed drugs, etc) were recorded. Moreover, a global rating of subjective health was also assessed.

All participants attended a baseline assessment where they underwent an eye examination, including assessment of the presence and severity of lens opacities, test of the best-corrected visual acuity (BCVA) by Snellen chart and measurement of the intraocular pressure (IOP). IOP was measured by using Goldmann applanation tonometry and in case of IOP than higher than 20 mmHg the ocular medical records of the patients were reviewed in order to find previous diagnosis of glaucoma, slit-lamp biomicroscopy of anterior segment, fundus examination and computerized visual field were performed to assess if the optic nerve is damaged in order to pose diagnosis of glaucoma. Moreover, if assessed by medical record, recent worsening in the visual acuity or change in the manifested refraction were recorded. Finally, vision problems (e.g. blinding effect when exit from indoor environment, or when entering indoor environment), use of multifocal glasses and of eye drops were asked to each participant.

Visual disability was assessed by the Activity of Daily Vision Scale (ADVS) in the 15-item version proposed by Pesudovs et al.[24]. For each item, the patient was asked whether if he/she engaged in the activity (if not it is “Not Applicable” which is treated as missing data), and then the level of difficulties in doing the activity: no difficulty (5), a little difficulty (4), moderate difficulty (3), extreme difficulty (2), unable to perform the activity because of poor vision (1). Finally, the average score for the 15 items was computed.

A fall was defined as unintentionally coming to the ground or some lower level not as a result of a major

| Table 1 Socio-demographic information assessed with the structured questionnaire. |
|-----------------------------|-----------------|---------------- |
| Variables                   | Categories or unit of measures                      | References      |
| Gender                      | male; female                                           | [15-17,21]      |
| Age                         | Years                                                    |                |
| Independent life            | Yes; no                                                  | [21]            |
| Health compared with that of age group | Much more healthy; More healthy; About as healthy; Less healthy; Much less healthy | [15]            |
| Living alone                | Yes; no                                                  | [21]            |
| Type of house               | Condominium; single apartment                         | [21]            |
| Jobs                        | merchant or craftsman; worker; employed; freelancer; other | [21]            |
| Retired                     | Yes; no                                                  | [13,21]         |
| Frequency pushing/dragging heavy loads | Never; Occasionally; 1-2 per week; Daily; Several times per day | [14]            |
| Attendance at religious service in previous month | Yes; no                                         | [14]            |
| Attendance at club meeting in previous month | Yes; no                                         | [14]            |
| Owns or cares for a pet     | Yes; no                                                  | [14]            |
| Sufficient contact with family/friends | Sufficient; insufficient                       | [14]            |
| Ability to raise €350 in an emergency | No difficulty; A little difficulty; Lot of difficulty Impossible to raise €350 | [14]            |
intrinsic event (e.g., stroke) or overwhelming hazard; participants were asked to report any fall in the previous year and, consequently, they were classified as fallers or non-fallers for the purposes of the current study. Moreover, after the baseline assessment, participants were contacted by telephone in order to record any falls experienced over a prospective 12-month follow-up.

### Table 2 Medical history information assessed with the structured questionnaire.

| Variables                                   | Categories or unit of measures | References |
|---------------------------------------------|-------------------------------|------------|
| Weight                                      | Kg                            | [15,16]    |
| Body mass index                             | Kg / m²                       | [17,18,21] |
| Smoking habit                               | yes, no, ex                   | [15-17,21] |
| Alcohol consumption                         | Never, occasionally, usually  | [15,21]    |
| Depression                                  | Yes, no                       | [21,22]    |
| Anxiety                                     | Yes, no                       | [17]       |
| Urinary incontinency                        | Yes, no                       | [21,22]    |
| Osteoarthitis                               | Yes, no                       | [16,21,22] |
| Hypertension                                | Yes, no                       | [17]       |
| Diabetes                                    | Yes, no                       | [16-18]    |
| Hearing loss and/or vestibular problems     | Yes, no                       | [18,21]    |
| Cancer history                              | Yes, no                       | [17]       |
| Parkinson disease                           | Yes, no                       | [17]       |
| Alzheimer disease                           | Yes, no                       | [17]       |
| Asthma                                      | Yes, no                       | [17]       |
| Cardiovascular disease                      | Yes, no                       | [17,18]    |
| Shortage of breath                          | No; yes; only if going uphill/hurrying | [14] |
| Problems with headaches                    | Yes, no                       | [14]       |
| Problems with Walking                       | No problem; Uses walking aid; Gait problem (no aid); Nonambulant | [23] |
| Sleeping hours                              | Hours                         | [14]       |
| Nocturnal awakenings                        | Never, often, every night     | [14]       |
| Waking hour overnight                       | Hours                         | [14]       |
| Number of prescribed drugs and types        | Antidepressants; antipsychotics; antiemetic; sedatives and hypnotics; medicines for Parkinson’s disease; antihypertensive or antiarrhythmic; analgesics; antiepileptic | [15-17,21-23] |

### Data-mining methods

Three different data-mining approaches were used to develop classifier for faller identification, i.e. the C4.5 decision tree induction algorithm, the Random Forest (RF), and the boosting meta-learning approach Ada-boostM1 (AB).

### Table 3 Variables related to eye condition and visual function assessed with the structured questionnaire.

| Variables                                      | Categories or unit of measures | References |
|------------------------------------------------|-------------------------------|------------|
| Ocular conditions                             | Cataract; pseudophakic; glaucoma; age-related macular degeneration; other retinal degeneration | [20,23]    |
| Use of bifocal / multifocal eyeglasses         | Yes, no                       | [15,23]    |
| Use of eye drops                              | Yes, no                       | [15,23]    |
| Best corrected visual acuity in each eye      | Decimals                      | [17,18,20] |
| Visual acuity loss                            | Decimals                      | [23]       |
| Recent refraction change                      | Yes, no                       | [23]       |
| Intraocular pressure                          | mmHg (average both eyes)      |            |
| Better vision                                 | Sunny day; rainy day; indifferent |        |
| Blindness effects                             | No, entering indoor; exit indor |            |
The choice of the algorithm parameters was based on the performances (i.e. accuracy, then sensitivity and finally specificity) estimated by 10-fold cross-validation: one with 90% subjects for training and the other with 10% subjects for validation. Repeating the test 10 times, the classification performance were then calculated by averaging the values obtained from the 10 validation subsets.

C4.5 is the landmark decision tree algorithm developed by Quinlan et al.\[25\]. The feature of each node is selected in order to divide input samples effectively and information gain is used as a measure of effectiveness. After the induction of the decision tree, a pruning method was applied to reduce the tree’s size and complexity.

RF is the state-of-the-art classifier developed by Breiman[26]. It is composed of a number of decision trees that choose their splitting attributes from a random subset of $k$ attributes at each internal node. The best split is taken among these randomly chosen attributes and the trees are built without pruning, as opposed to C4.5. One of the most relevant downsides of using RF, particularly in medical domain data-mining, is that its model is not easily understandable as a single tree. Moreover, we computed the feature importance measures based on Random Forests (RF)[26].

AB is a meta-learning algorithm which works by incrementally running classifiers on samples of data instances and combining them into an aggregate model[27]. Each individual or weak classifier contributes to the aggregate model in proportion to its accuracy. After each iteration, data instances are reweighted based on incorrect aggregate classifications. This boosts the emphasis of misclassified instances, refining the construction of weak classifiers in future iterations. In the current study, C4.5 was adopted as weak classifier in the AB algorithm.

AB classifiers were developed by varying the number of iteration from 20 to 400 and C4.5 trees (both as single classifier and as base classifier in AB) were developed by varying confidence factor for pruning from 0.05 to 0.5, minimum number of instances per leaf from 5 to 20. MLP were trained by varying the learning rate from 0.3 to 0.9, the momentum from 0.2 to 1 and the number of epoch form 100 to 2000. RF was constructed using an ensemble of random trees from 20 to 400 with no depth limit and varying the number of randomly chosen features from $\log_2(n)+1$ to $n$, where $n$ is the number of feature. As regards SVM, we used radial basis function kernel, varying gamma from $10^{-5}$ to 10.

**Results**

The study sample consisted of 150 participants (mean age ± standard deviation: 73.0 ± 9.6 years; range: 55-99 years) including 60 males (40%) and 90 females (60%). Participants had a range of severity of visual impairment, for example, BCVA ranging from no light perception to 20/20. 109 participants (72.7%) suffered from cataract in at least one eye, whereas 42 participants (28.0%) were pseudophakic in at least one eye.

The most informative variables, according to the values of feature importance estimated by RF, were: the answer to the item “Read writing on television” of the ADVS, IOP and BCVA in right eye. As shown in Figure 1, among the ten most relevant variables, five were obtained by the ADVS, i.e. the difficulty score, and the following items: “See television”; “Thread a needle”; “Read writing on television”; “Read newspapers”.

For each data-mining method, the optimal combination of parameters were selected by maximizing the accuracy estimated by 10-fold-crossvalidation as shown in Table 4. The ROC curves for identifying fallers are compared in Figure 2. RF and AB outperformed C4.5 in terms of overall accuracy, sensitivity and specificity rates. RF achieved slightly better performances than AB.

Since AB achieved the highest sensitivity, it was interesting to observe the rules obtained from the decision tree

| Activity of day vision scale: | Items: |
| --- | --- |
| Driving at night | 5 - no difficulty; 4 - little difficulty; 3 - moderate difficulty; 2 - extreme difficulty; 1 - unable because of poor vision; |
| Seeing moving objects with night driving | Not Applicable (considered as missing data) |
| Oncoming headlights | [24] |
| Daytime driving | |
| Drive in unfamiliar areas | |
| Read signs at night | |
| Read signs during the day | |
| See/recognize faces | |
| See television | |
| Read writing on television | |
| Read newspapers | |
| Read medicine bottles | |
| Read food cans | |
| Write checks | |
| Thread a needle | |
with the highest weights, including or not including ophthalmic features, shown in Figure 3. According to the decision tree including ophthalmic features, the subject was labelled as non-faller if pseudophakic, otherwise, in case of headache problems or IOP higher than 15, the subject was classified as faller. According to the model without any ophthalmic feature (Figure 3a), if the subject referred no or little or moderate difficulties in “Seeing moving objects with night driving”, the non-faller label was assigned; otherwise, the classification was based on the presence of anxiety or cardiovascular disease: in case of anxiety and/or any cardiovascular disease, the subject was identified as fallers, whereas the subjects not suffering from anxiety nor any cardiovascular disease were classified as non-fallers.

**Discussion**

This paper presented a pilot study to develop a novel tool to identify fallers among ophthalmic patients, based on a few ophthalmological parameters (such as ocular disease, BCVA, IOP) and a standardized questionnaire (including self-evaluation of visual ability). The system...
has been realized by comparing different approaches for developing decision tree. Each algorithm achieved a satisfactory performance, e.g. the area under the curve is higher than the performance of random choice (i.e. 0.5) and the Random Forest, the state of art classifier based on decision tree, achieved the best performance, with sensitivity and specificity rate of 72.6% and 77.9%, respectively.

The comparison between ROC curve of the proposed method and the performance of several functional mobility tests for predicting falls in community-dwelling older people showed that the proposed method achieved...
higher sensitivity and specificity rates than all the functional tests, which had relative risk (RR) ranging from 1.3 to 2.3 and sensitivity and specificity scores ranging from 11% to 78%, and 28% to 93%[12]. Moreover, these tests need that the subject could perform a mobility action, for that reason, they could be not suitable for all subjects with visual impairment and, finally, they requires materials and expertise, which are not usually available in an eye clinic. On the contrary, the proposed methods required only few ophthalmological parameters, such as IOP and BCVA, which are routinely measured in eye clinics, and the assessment of a questionnaire, which could filled in part by the physician and in part by the patient (under physician supervision) in about 30 minutes. The developed questionnaire strongly relies on a standardized questionnaire (ADVS), which have been developed for the evaluation of outcome of cataract surgery. We adopted a reduced ADVS version, since it has been shown to have an adequate precision, equivalent criterion validity, improved targeting of item difficulty to patient ability with decreased time for filling the questionnaire[24].

The current study has some limitations, in particular, the small sample size. Therefore, the clinical implications of these findings are potentially relevant, since the requested parameters are based on simple and non-invasive measurements, even if an external and further validation on a large dataset is required. For that reason, a further development of the current study could be the test of a reduced questionnaire including only the most significant variables submitted to a large study sample. Finally, the tool for identification of fallers among patients with visual impairment may be essential in the screening tool for assessing the way to the development of a novel tool for assessment of fall risk among patients with visual impairment.

Conclusions

This study proved that visual assessment and a standardized questionnaire, including the ADVS self-evaluation of visual impairment, could be useful for the automatic identification of fallers among the ophthalmic patients. The developed model enabled to identify fallers among ophthalmic patients with sensitivity and specificity rates of 71.4% and 87.8%, respectively. These findings pave the way to the development of a novel tool for assessment of fall risk among patient with visual impairment.

Competing interests

The authors declare that they have no competing interests.

Authors’ contributions

PM analyzed the data and wrote part of the manuscript. AO interpreted the data and wrote part of the manuscript. AO and MA contributed to the study design. LP contributed to data analysis. FC performed the electronic data collection. SR, FT, and FS conceived of the study, supervised the study and contributed to data interpretation and critically revised the manuscript for important intellectual content. All the authors read and approved the final version of this paper.

Acknowledgements

This work was supported by the 2007-2013 NOP for Research and Competitiveness for the Convergence Regions (Calabria, Campania, Puglia and Sicilia) with code PON04_3_00139 - Project Smart Health and Artificial intelligence for Risk Estimation.

Declarations

Publication costs were funded by the 2007-2013 NOP for Research and Competitiveness for the Convergence Regions (Calabria, Campania, Puglia and Sicilia) with code PON04_3_00139 - Project Smart Health and Artificial intelligence for Risk Estimation. This article has been published as part of BMC Medical Informatics and Decision Making Volume 15 Supplement 3, 2015: Multidimensional, multidiscipline and shared decision making in healthcare and eHealth. The full contents of the supplement are available online at http://www.biomedcentral.com/bmcmemformdicemak/supplements/15/S3.

Authors’ details

SHARE Project, Italian Ministry of Education, Scientific Research and University, Rome, Italy. Multidisciplinary Department of Medical, Surgical and Dental sciences, Second University of Naples, 80138, Italy. School of Engineering, University of Warwick, CV47AL, UK.

Published: 11 September 2015

References

1. Tinetti ME, Kumar C: The patient who falls: “It’s always a trade-off”. JAMA 2010, 303(3):258-266.
2. Siracuse JL, Odell DD, Gondek SP, Odom SR, Kasper EM, Hauser CJ, Moorman DW: Health care and socioeconomic impact of falls in the elderly. American journal of surgery 2012, 203(3):335-338, discussion 338.
3. Guideline for the prevention of falls in older persons. American Geriatrics Society, British Geriatrics Society, and American Academy of Orthopaedic Surgeons Panel on Falls Prevention. J Am Geriatr Soc 2001, 49(5):654-672.
4. Peel NM: Epidemiology of falls in older age. Can J Aging 2011, 30(1):7-19.
5. Pecchia L, Bath PA, Pendleton N, Bracale M: Analytic Hierarchy Process (AHP) for examining healthcare professionals’ assessments of risk factors. The relative importance of risk factors for falls in community-dwelling older people. Methods Inf Med 2011, 50(5):435-444.
6. Klein BE, Klein R, Lee KE, Cruickshanks KJ: Performance-based and self-assessed measures of visual function as related to history of falls, hip fractures, and measured gait time: the Beaver Dam Eye Study. Ophthalmology 1998, 105(1):160-164.
7. Ivers R, Cumming R, Mitchell P: Poor vision and risk of falls and fractures in older Australians: the Blue Mountains Eye Study. New South Wales public health bulletin 2002, 13(1):28-10.
8. McCarty CA, Fu CL, Taylor HR: Predictors of falls in the Melbourne visual impairment project. Aust N Z J Public Health 2002, 26(2):116-119.
9. Klein BE, Moss SE, Klein R, Lee KE, Cruickshanks KJ. Associations of visual function with physical outcomes and limitations 5 years later in an older population: the Beaver Dam eye study. Ophthalmology 2003, 110(4):644-650.

10. Legood R, Scolfaham P, Coyer C. Are we blind to injuries in the visually impaired? A review of the literature. Injury Prev 2002, 8(2):155-160.

11. Pereil KL, Nelson A, Goldman RL, Luther SL, Prieto-Lewis N, Rubenstein LZ. Fall risk assessment measures: an analytic review. J Gerontol A Biol Sci Med Sci 2001, 56(12):M761-766.

12. Tiedemann A, Shimada H, Sherrington C, Murray S, Lord S. The comparative ability of eight functional mobility tests for predicting falls in community-dwelling older people. Age Ageing 2008, 37(4):430-435.

13. Ahmad R, Bath PA. The use of Cox regression and genetic algorithm (CoRGA) for identifying risk factors for mortality in older people. Health Informatics Journal 2004, 10(3):221-236.

14. Bath PA, Pendleton N, Morgan K, Clague JE, Horan MA, Lucas SB. New approach to risk determination: Development of risk profile for new falls among community-dwelling older people by use of a genetic algorithm neural network (GANN). J Gerontol a-Biol 2000, 55(3):M17-M21.

15. Coleman AL, Stone K, Ewing SK, Nevitt M, Cummings S, Cauley JA, Ensrud KE, Harris EL, Hochberg MC, Mangione CM. Higher risk of multiple falls among elderly women who lose visual acuity. Ophthalmology 2004, 111(5):857-862.

16. de Boer MR, Pluijm SM, Lips P, Moll AC, Völker-Dieben HJ, Deeg DJ, van Rens GH. Different aspects of visual impairment as risk factors for falls and fractures in older men and women. J Bone Miner Res 2004, 19(9):1539-1547.

17. Knudtson MD, Klein BE, Klein R, Lee KE, Cruickshanks KJ. Associations of visual function with falls in older community-dwelling women. J Am Geriatr Soc 2002, 50(11):1765-1768.

18. Parssinen O, Savio A, Siipila S, Rantanen T, Heikkinen E. Lowered vision as a risk factor for injurious accidents in older people. Aging Clin Exp Res 2003, 20(1):25-30.

19. Lord SR, Ward JA, Williams P, Anstey KJ. Physiological factors associated with falls in older community-dwelling women. Journal of the American Geriatrics Society 1994, 42(10):1110-1117.

20. Wood JM, Lacherez P, Black AA, Cole MH, Boon MY, Kerr GK. Risk of falls, injurious falls, and other injuries resulting from visual impairment among older adults with age-related macular degeneration. Invest Ophthal Vis Sci 2011, 52(8):5098-5092.

21. Bonuge B, Dupre C, Beauchet O, Rossat A, Fantino B, Colvez A. A screening tool with five risk factors was developed for fall-risk prediction in community-dwelling elderly. J Clin Epidemiol 2011, 64(10):1152-1160.

22. Tromp AM, Pluijm SM, Smit JH, Deeg DJ, Bouwer LM, Lips P. Fall-risk screening test: a prospective study on predictors for falls in community-dwelling elderly. J Clin Epidemiol 2001, 54(8):837-844.

23. Lord SR, Dayhew J, Howland A. Multifocal glasses impair edge-contrast sensitivity and depth perception and increase the risk of falls in older people. J Am Geriatr Soc 2002, 50(11):1765-1768.

24. Pesudovs K, Garamendi E, Keeves JP, Elliott DB. The Activities of Daily Living Scale for cataract surgery outcomes: re-evaluating validity with Rasch analysis. Invest Ophthal Vis Sci 2003, 44(7):2892-2899.

25. Quinlan JR. C4.5 : programs for machine learning. Morgan Kaufman Publishers; 1993.

26. Freund Y, Schapire RE. Experiments with a new boosting algorithm. ICML: 1996, 1096, 148-156.

27. Freund Y, Schapire RE. A decision-theoretic generalization of on-line learning and an application to boosting. J Comp System Sci 1997, 55(1):119-139.

28. Melillo P, Scala P, Crispino F, Pecchia L. Pupillometric analysis for assessment of gene therapy in Leber Congenital Amaurosis patients. Biomed Eng Online 2012, 11(1):40.

29. Melillo P, Izzo R, Onorio A, Scala P, Attanasio M, Mina M, De Luca N, Pecchia L. Autocorrelation of Heart Rate Variability Analysis. PLoS ONE 2015, 10(3):e0118504.

30. Melillo P, Pecchia L, Testa F, Rossi S, Bennett J, Simonetti F. Pupilometric analysis for assessment of gene therapy in Leber Congenital Amaurosis. Biomed Eng Online 2013, 12(1):40.