International Journal of Integrated Care

Sannino, G, De Falco, I, De Pietro, G 2016 Lifestyle-based risk model for fall risk assessment. *International Journal of Integrated Care*, 16(5):S36. DOI: dx.doi.org/10.5334/ijic.2585

CONFERENCE ABSTRACT

Lifestyle-based risk model for fall risk assessment

European Telemedicine Conference 2016, Oslo 15-16 November

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Purpose: The aim of this study was to identify the explicit relationship between life-style and the risk of falling under the form of a mathematical model. Starting from some personal and behavioral information of a subject as, e.g., weight, height, age, data about physical activity habits, and concern about falling, the model would estimate the score of her/his Mini-Balance Evaluation Systems (Mini-BES) test. This score ranges within 0 and 28, and the lower its value the more likely the subject is prone to falling [1]. This would make fall risk assessment much easier, because subjects would not need to undergo the classical Mini-BES test, rather they could estimate it at home by answering some questionnaires.

Context: Falls have been shown to result in increased morbidity and are responsible for over 17 million disability-adjusted life years lost [2]. Many studies have been dedicated to fall detection, as e.g. [3]. An exhaustive review of these studies can be found in [4]. Identification of individuals with a high risk of falling is often an important part of prevention programs. Fall risk assessment is an important and effective prevention tool that identifies intrinsic and extrinsic risk factors that help determine the most appropriate interventions, and ultimately reduce or eliminate falls.

Methods: We decided to avail ourselves of a Genetic Programming (GP) technique for this regression problem because it can automatically find an explicit model for the relationship between the independent variables and a dependent one. Starting from the Human Balance Evaluation database [5], we have conducted an analysis phase by creating a new database composed by 12 items for each of the 156 subjects aged between 18 and 85 (48 ± 22). The parameters taken into account in our study are: age group, gender, Body Mass Index (BMI), foot length, number of falls in the last 12 months, the result of the Falls Efficacy Scale (FES) questionnaire to measure concern of falling (FES-I test score), the International Physical Activity Questionnaire (IPAQ) score, and the total score of the Mini-BES test, which is assumed as the dependent variable. This database has been divided into a training set, a validation set, and a testing set, containing 79, 38, and 39 subjects, respectively.

Results and discussion: The best model found in our experiments has a Root Mean Square Error value equal to 2.74 when estimating the Mini-BES test score that ranges in [0, 28]. This error is related to the items belonging to the test set, i.e. those never examined during the learning phase.

The GP algorithm has also automatically extracted the set of the most meaningful features, which has turned out to contain all of them except gender and foot length. The extracted mathematical model will be integrated in a freely available App developed by using the platform of the eHealthNet project (PON03PE_00128_1) financed within the P.O.N. “Research and Competitiveness” call. So people could assess their risk of falling by themselves through their smartphone by simply answering some questionnaires. This could be seen as a mass screening, and only subjects with a moderate or high estimated fall risk score should undergo physical fall tests.

References:

1. F. Franchignoni, F. Horak, M. Godi, A. Nardone, A. Giordano, Using psychometric techniques to improve the Balance Evaluation System Test: the mini-BESTest, Journal of Rehabilitation Medicine, (323-331) 2010.

2. World Health Organization. Ageing, and Life Course Unit. WHO global report on falls prevention in older age. World Health Organization, 2008.

3. Sannino G, De Falco I, De Pietro G. A supervised approach to automatically extract a set of rules to support fall detection in an mHealth system. Applied Soft Computing 34(205-216), 2015.

4. J. Howcroft, J. Kofman and E.D. Lemaire, Review of fall risk assessment in geriatric populations using inertial sensors, Journal of NeuroEngineering and Rehabilitation, (10:91) 2013.

5. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation 101(23):e215-e220, 2000.

Keywords: fall risk assessment; mathematical model; regression; genetic programming