# A Multifactorial Falls Risk Prediction Model for Hospitalized Older Adults

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*Abstract*— **Ageing population worldwide has grown fast with more cases of chronic illnesses and co-morbidity, involving higher healthcare costs. Falls are one of the leading causes of unintentional injury-related deaths in older adults. The aim of this study was to develop a robust multifactorial model toward the falls risk prediction. The proposed model employs real-time vital signs, motion data, falls history and muscle strength. Moreover, it identifies high-risk individuals for the development falls in their activity of daily living (ADL). The falls risk prediction model has been tested at a controlled-environment in hospital with 30 patients and compared with the results from the Morse fall scale. The simulated results show the proposed algorithm achieved an accuracy of 98%, sensitivity of 96% and specificity of 100% among a total of 80 intentional falls and 40 ADLs. The ultimate aim of this study is to extend the application to elderly home care and monitoring.**

## I. INTRODUCTION

The rapid increase in older adult population (65+) during the last two decades has ascertained to be a major challenge in healthcare worldwide. Consequently, the number of patients requiring continuous monitoring has risen. It is estimated that, by 2025, this group will number approximately 1.2 billion and expand to 2 billion by 2050, with 80% of them living in the developed countries [1]. Falls are a major public health problem among older adults and this incidence increases with age. The possibility of having falls (at least one fall) in 65+ age group can be up to 35 % and in the 75+ age group can increase up to 42%, with 15 % of older adults falling at least twice a year [2]. Falls incidence rate in hospitals are much higher (approximately 30%-50%) which is the current concern for hospitals, especially in long term care settings [2].

Stevens et al. [3] reported that in 2000, direct medical costs related to falls among 65+ age group in US was totaling 0.2 billion dollars for fatal and 19 billion dollars for non-fatal injuries. In New Zealand, hospital related falls incidences are more serious and needs immediate attention. According to the Accident Compensation Corporation New Zealand (ACC), "If you are over 65, you have a one in three chance of falling this year and, if you are over 80, you have a one in two (50%) chance of falling this year" [4].

Moreover, it is reported that Sweden has one of the highest older adult population, nine out of ten fall-related injuries in Sweden are observed for the age group of 65+. For older women (over 80) in Sweden, the risk of fall-related injury (for e.g. trauma) is approximately 50% [5].

According to the Health Quality and Safety Commission's report "Serious and Sentinel Events Report 2010/2011" falls accounted for 52% of all serious and sentinel events reported in hospitals in 2010/2011 compared to 35% in 2009/2010 [6]. Hence, there is a clear need for a falls detection, prediction and avoidance system to be in place, particularly in hospitals to avoid these incidents and reduce the consequences.

Hauer et al. [7] provide a comprehensive, non-exclusive fall definition that identifies a fall as 'an unexpected event in which the participant comes to rest on the ground, floor, or lower level'. Injuries sustained from falls to older adults include fractured bones (hip fracture is common), subdural hematoma ('brain' haemorrhage), soft tissue damage, cuts and also serious wounds [8].

In order to predict falls, it is important to incorporate falls risk factors, related contributors, 'complete' and patient-specific approach. Moreover, there are important factors which need to be considered such as: person's medical condition, social circumstances and psychological factors [9]. Among four types of successful fall prevention trials it was found that three trials of multifactorial interventions had higher success rates in residential care facilities in Europe [10].

Several falls prevention and intervention factors have been identified and reported in the literature such as providing safe environment, technological aid (sensors or equipment), educating and training staff on fall prevention, reviewing prescription drugs and providing free hip protectors. Moreover, it is reported that there is three folds increase in the hospital related falls incidences when compared with general community settings [11, 12].

## II. PROPOSED MODEL

Falls risk factors can be classified into intrinsic (such as age-related physiologic changes, diseases and medications) and extrinsic (such as environmental hazards). The proposed model is a multifactorial falls risk prediction tool based on vital signs, motion data and patient health record. Real-time vital signs recording, monitoring and interpretation followed by an appropriate medical assessment/treatment is the main component of the proposed model. The other risk factors included in the proposed model are:

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- Possibility of chronic diseases (such as Hypotension or Pyrexia), confusion and cognitive impairment
- Age, gender, falls history (Multiple falls, recent falls or injurious fall) and muscle strength,
- Medication (for example Antiarrhythmics, antidepressants, antihypertensives, diuretics, hypoglycemics, neuroleptics, psychotrophics, sedatives and vasodilators) or alcohol
- Performing high-risk individuals for the development falls in activity of daily living (ADL) [13]

Fig. 1 shows the overall architectural of the proposed model representing key modules and their linkage as explained below:

*A. Motion data analysis*

To best extract the motion activity from a tri-axial accelerometer, a number of methods and algorithms have been proposed in the literature [14].

Initially normal motion data activity from older adults (with no falls history or walking issues) were collected during walking, sitting, stumbling, falling (right, left, backward and forward) and their ADLs. Data were captured from the three axes of accelerometer and a classifier calculated the time of change in trajectory of motion. The falls have faster changes than sitting on the chair. Therefore the speed, change and diversion from normal trajectory are the unique features incorporated into the classifiers when detecting various activity-based events. The classifiers also accurately identified the direction of falls or stumbles (forward, backward, left or right) from the X, Y and Z axis. This database serves as a framework for the proposed model. A unique two-way classification model was adopted based on the collected information.

Firstly, threshold based detection is adopted, where threshold limits are set by analyzing the collected motion activity. For example, gait speed, step length, sway and asymmetry of gait data points exceeding those set threshold limits for each activity were considered ‘not normal activity’ and can be further elaborated into low, medium or high risk depending upon the mean or standard deviation values of exceeded limits.

Secondly, motion data from the accelerometer was compared against the already collected database in a moving window analysis (5sec, 10sec or 15sec window) in each particular activity (sitting, walking, standing, etc.).

The falls prediction model uses both methods; in the case of incomplete information the earlier method (standalone) works well and if the information is complete (at the end of each time window), then both methods will contribute towards the falls prediction.

*B. Vital sign analysis*

We integrated vital signs into the proposed falls prediction model to combine physiological parameter with motion activity and patient health record to capture most of the patient’s activities and changes in life style or health conditions (Fig. 1). This multifactorial model provides better identification, detection and classification of falls risk. The integration of vital signs to falls prediction systems has not been given much attention in the literature and there is room for further research [15, 16].

Dropping of blood pressure is one of the expert rules/conditions adopted as one of the contribution factors to the risk of falls where:

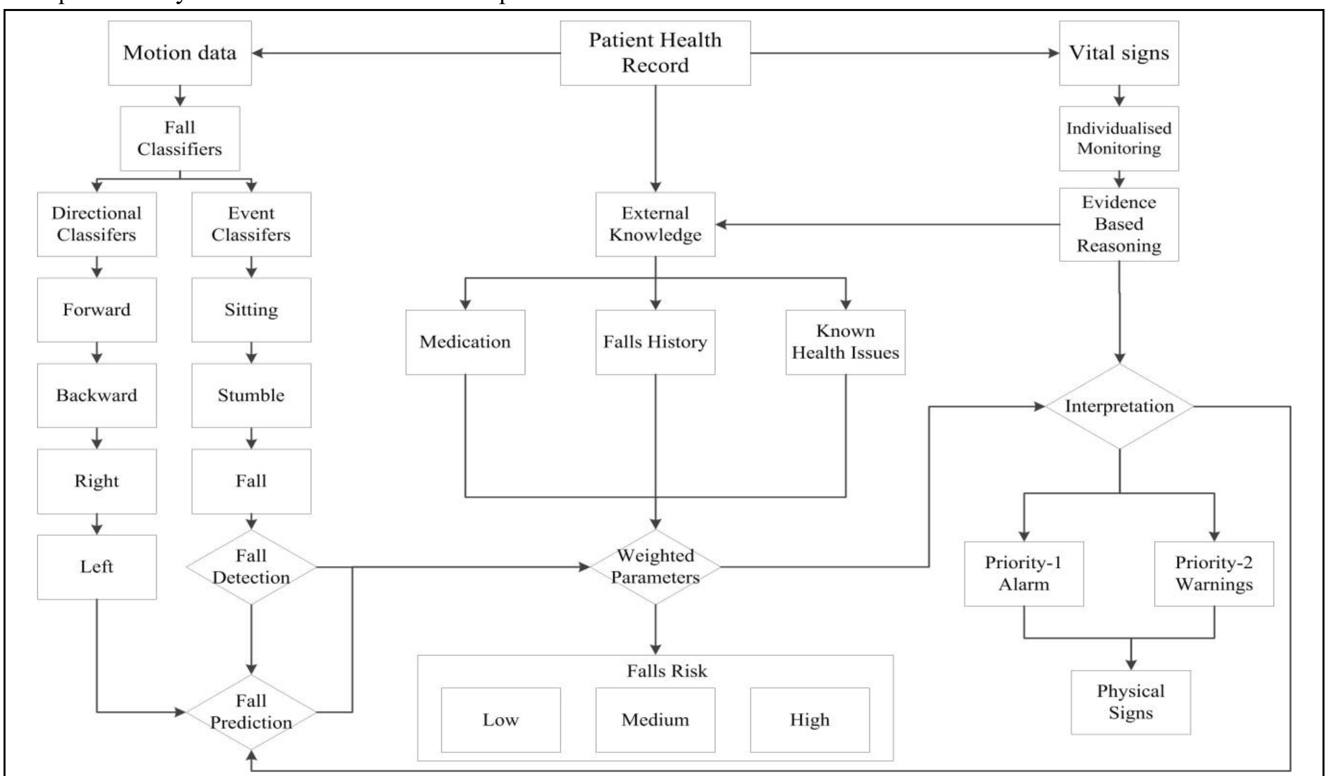

Fig 1. Architectural data model of the proposed system representing key modules and their linkage.

*'A fall of more than 20 mmHg in systolic blood pressure and/or more than 10 mmHg in diastolic blood pressure when standing (compared to the sitting blood pressure) indicates risk of fall'* [16].

The relation between vital signs and overall weighted parameters with respect to the falls risk has been maintained due to the fact that the clinical situation, particularly of hospitalized patients, is often subject to changes (unstable).

### C. History of falls and muscle strength

Information about the previous falls is another contributing factor to the prediction of falls [5, 15, 17]. In the proposed model, past history, current status and any ongoing falls-related illness as well as the type (if any) of injury due to the previous fall(s) are considered.

A study was conducted to underpin the relationship between the falls and lower limbs (strength) and reported that isometric and concentric muscular strength which start to decline in men from the age of about 50 and up to 15% per decade may contribute to functional performance in older adults [18]. However, there is no strong evidence that shows a clear association between balance and strength of lower limbs and therefore, the contribution of these two functional aspects in decreasing risk of falls.

### D. Medications

Another important factor that has been widely adopted in the majority of falls risk assessment tools is the effect of taking different types of medications. It is reported an association between falls and medication, which indicates that falls risk increases with the increase in the number and types of medication. Some studies have classified the drugs into low, medium and high risk for falls [19]. The proposed model gives the weight of low for 0 to 4, medium for 4 to 6 and high for 6+ different types of medications [20]. The number of different types and number of medications will be entered by the clinicians into the system.

## III. Experimental Results

### A. Data collection

Data collection has been started after obtaining an ethical approval from local and national ethics committees (NTX/12/EXP/073, WDHB 0980712176, AUTEC 12/117) and with written informed patient consents. This research project involves 30 hospitalized patients (mean age 82Y 4M) and monitored for more than 200 hours. We employed VitelMed which provides connectivity with a wide variety of medical devices to collect vital signs. A special feature of VitelMed is the one touch button, for automatically connecting to a call center or medical professionals. It has also two way video/audio tele-visiting (conferencing) feature. The collected data can be stored or transferred for emergency care (or ambulance), secondary care (hospital) primary care (medical centers) and homes or aged care facilities [21].

A tri-axial accelerometer (8XM-3 mini, tri-axial accelerometer from Gulf Coast Data Concepts [22]) was also employed for motion activity data and attached to the patient's chest for 24 hours. The falls detection accuracy has been evaluated using four healthy male individuals (aged 62Y7M, 69Y9M, 72Y3M and 75Y9M respectively), performed intentional falls and normal ADLs. The data was stored and saved in the device with real-time-stamp for further analysis.

### B. Accuracy evaluation of falls classifiers

In order to evaluate the falls prediction of the proposed model, we employed market-available clinically proven medical devices incorporated into the VitelMed. The system is able to collect multiple data simultaneously from multiple patients and transmit the data in real-time to the laptop/PC for interpretation and then to a clinician's remote device. We have previously piloted this equipment with in-patients in the hospital setting for vital signs monitoring and interpretation [21].

For testing and evaluating of the motion activity, four individuals excluding any impaired vision, imbalance, walking with any support or cognitive impairment were selected. Activities performed included forward, backward, right-side and left-side intentional falls as well as ADLs as suggested by Noury et al. [23]. A total of 80 intentional falls and 40 ADLs were simulated and the falls detection algorithm achieved an accuracy of 98%, sensitivity of 96% and specificity of 100%, as shown in Table I. This test was performed on classification of different falls in order to evaluate the accuracy of this algorithm and integrate it to the predication model.

### C. Testing of falls risk prediction model

The falls risk prediction results are categorises into high, medium and low risks and compared with the results obtained from the Morse falls scale (MFS), by medical staff using the same 30 patients (10 patient data for training and 20 patient data for testing).

The proposed falls risk predication model which includes motion data, number of medications, history of falls and vital signs achieved an accuracy of 74%, sensitivity of 85% and predictability of 85% (Table II). In this table, there are 17 true positives (TP) instances when the system and the MFS were positive (System (+ve) and MFS (+ve)) and three false positive (FP) instances when the system was positive (System (+ve)) but the MFS was negative (MFS (-ve)).The best available option for the evaluation of the proposed model results is comparing them with MFS risk assessment scores. The MFS uses falls history, confusion, aid and IV infusion to categorise the falls risk with scoring as: everyone (0-24), medium (25-44) and high (45+).

TABLE I
ACCURACY EVALUATION OF FALLS DETECTION

| Category | Test | TP | TN | FP | FN | Accuracy % |
|---|---|---|---|---|---|---|
| ADL | 40 | 0 | 40 | 0 | 0 | 100 |
| Forward Fall | 20 | 20 | 20 | 0 | 0 | 100 |
| Backward Fall | 20 | 18 | 18 | 0 | 2 | 94.7 |
| Left-side Fall | 20 | 20 | 20 | 0 | 0 | 100 |
| Right-side Fall | 20 | 19 | 19 | 0 | 1 | 97.4 |
| Total Falls | 80 | 77 | 77 | 0 | 3 | 98 |

ADL is activity of daily life, TP=alerts on falls, TN=no alert no fall, FP=alert on no fall and FN=no alert on fall

TABLE II
ACCURACY EVALUATION OF THE MODEL AS FALLS CLASSIFIERS

| System/MFS | MFS (+ve) | MFS* (-ve) | Total |
|---|---|---|---|
| System (+ve) | 17 (TP) | 3 (FP) | 20 |
| System (-ve) | 3 (FN) | 0 (TN) | 0 |
| Total | 17 | 3 | 20 |

*MFS is Morse Falls Scale, TP is true positive, TN is true negative, FP is false positive and FN is false negative.

## IV. DISCUSSION AND CONCLUSION

The proposed multifactorial falls prediction model showed that individuals who are at high risk of falls could be identified. The model was developed to establish an efficient falls prediction so that it can be used to minimise the personal and financial cost of associated injuries in older adults. It was also aimed at minimising false alarms which are a nuisance for patients and caregivers or can compromise effectiveness of care [21]. Users' need and clinicians' preferences were taken into account and non-invasive, wireless and body-worn sensors were employed in the design of the proposed model [24]. In the hospital or residential aged care facility, there would be value in an alarm type system that sends a nurse urgently to the patient to check their immediate status – hopefully they can then prevent a fall that may be due to 'feeling faint', 'weak knees' or because the person is confused and gets up when they shouldn't. In the community as operating as a slower alarm system – alerting on duty physicians that this person is deteriorating in terms of vital signs/mobility and needs to be semi-urgently reassessed.

The further prospective validation of the proposed model (i.e. its ability vs. the MFS to predict actual falls) is underway as it requires a bigger sample size and a longer monitoring time. The model will be tested on two groups of patients with a history of falls, and some without any previous falls. It is important to have ongoing monitoring of the selected patients to check for rates of successful diagnoses, as well as FPs and FNs.

The ultimate goal of the project is to extend the application into a broader monitoring system on which the data not only use for falls detection and falls prevention but also for diagnosing of specific diseases based on the ongoing monitoring of vital signs.

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