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Home-based Self-health Management Strategies of COVID-19 for the Elderly in Applied Economics

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Abstract

At this moment of the COVID-19 epidemic, it is difficult for caregivers to be fully aware of the elderly by closing care to prevent accidents at home. Existing research, home-based self-health management strategies, by using contextual tools and a lack of empirical procedures or technological components in internet monitoring, home accidents from individualized patterns has not been achieved. We use vision detecting through the internet monitoring method in a smart lighting materials house to fill this research gap. We examined the impact of physical transitions and visibility on fall detection and compared the accuracies of fall prediction based on combinations of related factors. The results indicated that including both physical transitions and visibility would enable older people to avoid falls. We evaluated the impact of physical transitions and visibility on fall detection and compared the accuracy of falls based on combinations of related factors. The accuracy of predictions using both physical transition and visibility was higher than 81%, which is a high forecasting accuracy rate. Those are significant contributions to the elderly in applied economics.

Keywords: COVID-19, Home-based, Physical transition, Visibility, Fall detection.

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1. Introduction

The elderly are kept at home for a long time because of the COVID-19 epidemic, according to a report by the World Health Organization, every year, approximately 28% of people aged 65 years and approximately 32% of people aged 70 years suffer from accidents such as falls (Luque, Casilari et al. 2014, De La Concepcio'n, Morillo et al. 2017). The United Nations has projected an increase of more than 30% in the elderly population by 2050 in 64 countries (De La Concepcio'n, Morillo et al. 2017). Injuries resulting from house accidents can reduce the activities and socialization of the elderly and lead to further physical decline, depression, social isolation, and feelings of helplessness (Haralambous, Haines et al. 2010, Burland, Martens et al. 2013, Lea, Andrews et al. 2015). In the pass, the elderly with chronic diseases in nursing places are safeguarded by doctors or caregivers, most elderly live alone and frequently go outside as part of their daily routines (Garripoli, Mercuri et al. 2015). For outside care purposes, existing research on internet monitoring could be optimized. Examples of such factors are physical symptoms, impairment records, and demographic details (Boardman and Sasse 2004, Vieira, Freund-Heritage et al. 2011). For this moment of COVID-19, it is difficult for caregivers to be fully aware of the real-time for the elderly to prevent accidents (Lee, Park et al. 2016). Internet monitoring with materials communications about accidents involve information about an entity (e.g., smart home-connected light appliances) that is relevant to the relationship between accidents and the elderly and may help induce preferred behavior of the elderly in these internet monitoring materials contexts (Zhang, Adipat et al. 2009).

Dynamic and extrinsic materials context factors, such as smart home-connected light appliances, are usually used because the behavior variability of the elderly is higher with respect to such factors compared to outside care factors such as demography, for example (Ozdemir and Barshan 2014, De Backere, Ongenae et al. 2015, Yang, Ren et al. 2015, Lee, Park et al. 2016). Owing to time pressures, it is difficult for caregivers to judge whether there has been a change in a factor within a short timeframe (Ozcan and Velipasalar 2016, Ozcan, Velipasalar et al. 2017, Pannurat, Thiemjarus et al. 2017). Accordingly, our first research question for this study was: What are the features of internet monitoring materials contexts relevant to accidents? The elderly may have different preferences and change their behaviors frequently even under the same conditions, which affects the effectiveness of internet monitoring materials contexts (Delahoz and Labrador 2014, Wannenburg and Malekian 2016, Yang, Ren et al. 2016). Accordingly, our second research question for this study was: Based on the features identified in addressing the first research questions, how can we dynamically distinguish the elderly with different preferences?

2. Literature Review

Many studies in various fields have used the data science technique of mutual help such as Collaborative Filtering (CF). Mutual help needs trust and touch for each other and mutual trust is the bedrock of a relationship (Bongue, Dupré et al. 2011, Virginia 2012, Jeon, Jeong et al. 2014, Reay, Collier et al. 2017). However, during the COVID-19 epidemic, people need to keep away from each other. Several studies use smart materials or tools such as sensors within wearables, which have used accelerometers to generate measurable times and observable behaviors (Fuentes, Gonzalez-Abril et al. 2012). However, people must fasten sensors around their waist or on their shoes, for otherwise there would be too many angles to track owing to the device's orientation to the human frame (Chon and Cha 2011). Because of these limitations, it is difficult to accurately measure physical transitions. Alternatively, accelerometer sensors could be embedded in smartphones to detect the physical transition from holding the phone to putting it down (Iqbal and Bailey 2010, Salvucci and Bogunovich 2010, Bogunovich and Salvucci 2011). Light and materials are mutually dependent on each other. Materials are key to understanding light in architecture because they directly affect the quantity and the quality of the light. Some studies in recent years have considered light intensity in the internet monitoring because it can be used to detect smart home-connected light appliances and changes in real time (Winterboer, Cramer et al. 2009, Chou, Zhang et al. 2017). A light sensor with an illuminance unit can detect light and measure its intensity. For example, an illuminance lower than 119 lux could indicate a dark room. In residential aged care (RAC), illuminance could help understand the likelihood of falls. The Illuminating Engineering Society of North America, which is the recognized technical authority on illumination, has established standard levels for lights in terms of lux units (Wahl, Kantermann et al. 2014). Lights can be categorized into five levels as shown in Table 1 (Wahl, Kantermann et al. 2014).

Table 1: Light levels by luminosity

Category	Min (Lux)	Max (Lux)	Description	Bright/Dark
1	0	119	Dark Room	Dark
2	120	249	Dimmed Room	Dark
3	250	999	Bright Room	Bright
4	1000	4999	Cloudy	Bright
5	5000	∞	Sunny	Bright

The idea behind the use of internet monitoring context such as lights for fall prevention in RAC is that older people cannot concentrate on their smart home-connected light appliances sufficiently if the visibility is low (Kwolek and Kepski 2015, Kwolek and Kepski 2016). Therefore, low visibility or reduced internet monitoring could be considered a risk signal.

To increase the accuracy of fall prediction, we use machine learning to dynamically evaluate different proven features used in fall prevention. To our knowledge, this is the first empirical machine learning study that examines features of falls in RAC. This research provides several new theoretical and practical insights on adapting physical transitions and lighting for effective forecasting of falls in RAC.

3. Proposed Framework and Research Model

A previously proposed framework consists of a server, user interface, remote base station, and community cloud (Aslam 2014). It has numerous sensors (e.g., time and location sensors) and incorporates personal information. However, it does not adequately focus on the factors relevant to falls. The main measurement methods of fall factors include Hidden Markov Models and machine learning. Prevailing methods mainly use Hidden Markov Models to calculate the probability of state transitions following a single step. The limitations of this approach are the inability to build prediction models and the requirement of many parameters because of the static nature of the method (Popescu, Hotrabhavananda et al. 2012, Pannurat, Thiemjarus et al. 2017). An ideal approach should identify fall processes and construct a self-learning framework (Figure 1).

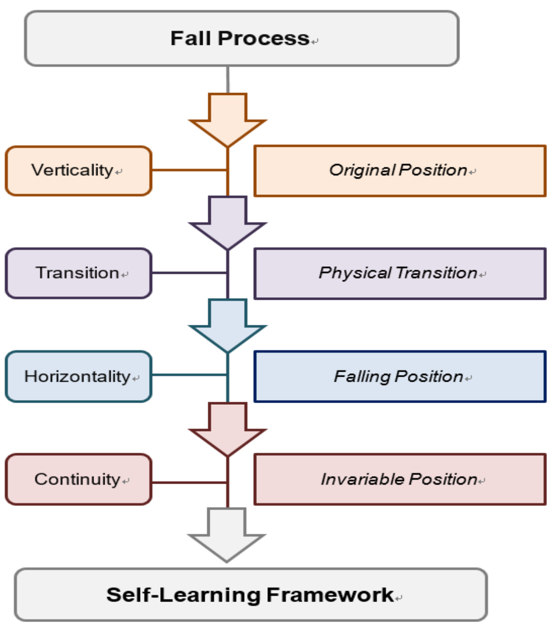

Figure 1: Self-learning framework

Our proposed comprehensive fall framework (Figure 2) includes the relevant features (including the self-learning framework in Figure 1), sensor detection, context awareness, and an application service that would interact with cloud computing and caregiving. A fall prevention model should consider the entire process of a fall to identify relevant features and physical transitions. Invariable position after horizontality indicates the position of the fall from verticality and serves to define the duration of the fall process in RAC. A component of context awareness must be included. The framework should be representable in a structured, uniform, and interchangeable format for implementation on different system architectures. Figure 2 shows our proposed framework. Later, we propose an experimental process based on this framework.

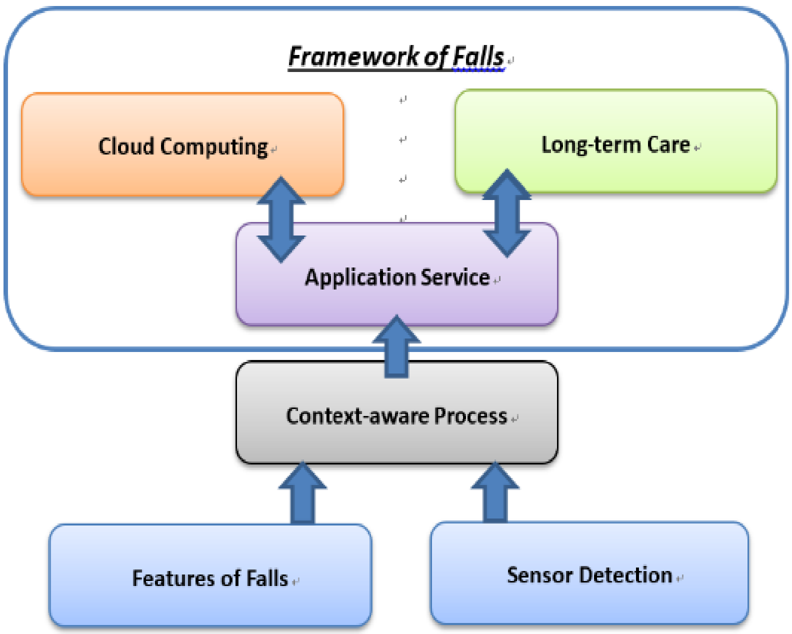

Figure 2: Fall prevention framework.

Body inclination can be measured by accelerometer sensors fastened around the waist, on the shoes, or embedded in mobile devices. However, they still cannot address the issue of physical transitions when falling. We aimed to find a way to measure various angles to calculate the shift of the barycenter. The accelerometer *z*-axis sensor can measure the acceleration of gravity to read the body inclination in the horizontal angle for certain durations (Figure 3).

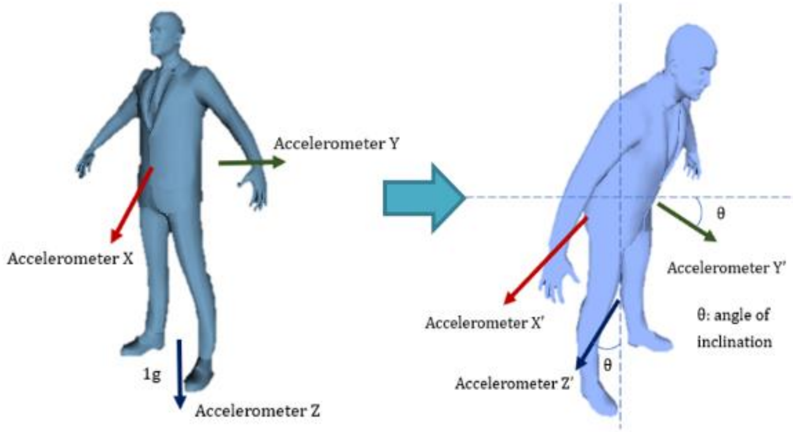

Figure 3: Detection of physical transitions

In Equation (1) below, *Acc_Z* represents the accelerometer *z*-axis in a certain period from the vertical to the inclination *Acc_Z′* variable, and θ indicates the inclination angle of the shift of the barycenter in that period.

Theorem 3.1 *This is the inclination angle of the shift of the barycenter in that period.*

$$Acc\_Z' = |Acc\_Z| * \sin(\theta) \tag{1}$$

The accelerometer *z*-axis sensor is useful for detecting physical transitions because it is near the surface of the earth around 9.8 m/s^2, which is used as G (that is, 1 G = 9.8 m/s^2). If the value of the barycenter is greater than a certain threshold on θ, we can conclude that a physical transition toward a fall is occurring. Conversely, if an individual is using a support device such as crutches by holding them, the value of the acceleration will be lower than the θ as the barycenter is still in the horizontal plane. An algorithm for applying this inclination detection approach is presented below. The algorithm initializes the parameters (e.g., accelerometer *X*, *Y*, and *Z* values), sets up logic functions (e.g., *Angle_X12* represents the dynamic angle based on initial *X1* and *X2*), computes the initial inclination, and verifies the final conditions to enable dynamic detection of the barycenter shift to assess whether the conditions of not falling are met.

Algorithm 1: Detecting inclination

```
Algorithm : Inclination detection
Initialization of parameters:
  Acc_X1, Acc_Y1, Acc_Z1, Acc_X2, Acc_Y2, Acc_Z2, Acc_X3, Acc_Y3, Acc_Z3
Set up logic functions:
  Angle_X12 (Acc_X1, Acc_X2)
  Angle_Y12 (Acc_Y1, Acc_Y2)
  Angle_Z12 (Acc_Z1, Acc_Z2)
  Angle_X23 (Acc_Z2, Acc_Z3)
  Angle_Y23 (Acc_Z2, Acc_Z3)
  Angle_Z23 (Acc_Z2, Acc_Z3)
Compute initial inclination:
    If Angle_X12 && Angle_Y12 && Angle_Z12 >= 30 then alarm = yes
    Else if Angle_Y12 && Angle_Z12 >= 45 then alarm = yes
    Else if Angle_Z12 >= 60 then alarm = yes
    Else alarm = no
    End if
Verify final inclination:
    If Angle_X23 && Angle_Y23 && Angle_Z23 >= 30 then fall = yes
    Else if Angle_Y23 && Angle_Z23 >= 45 then fall = yes
    Else if Angle_Z23 >= 60 then fall = yes
    Else fall = no
    End if
```

The RAC facilities would consist of some combination of dark, dimmed, and bright rooms. Light intensity is a internet monitoring context factor in this scenario. Mobile light sensors and Internet of Things can help dynamically capture and modulate light intensity and visibility. For example, an illuminance lower than 120 lux could indicate dark conditions and a higher probability of falling. Therefore, to decrease the probability of falls, the illuminance should be increased to a bright level (Figure 4).

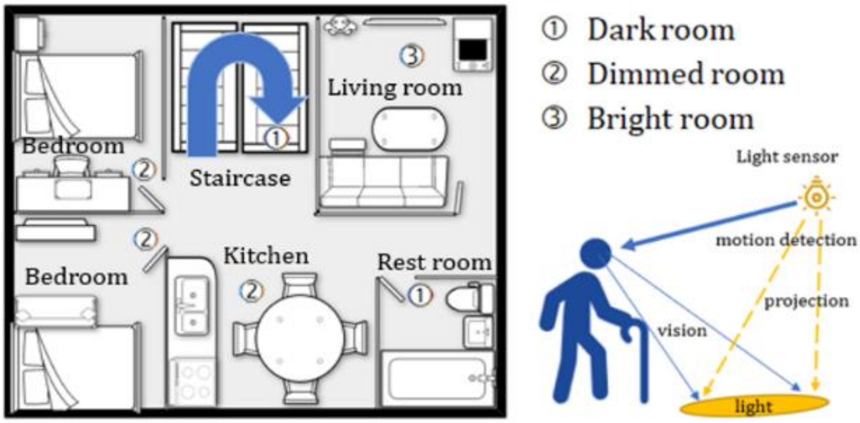

Figure 4: Internet monitoring detection with light intensity sensors

An algorithm for applying this internet monitoring detection approach is presented below. The algorithm initializes the parameters for motion and light detection and initial values, sets up logic functions (e.g., the motion function represents whether dynamic motion is occurring based on the initial *Motion_Y* and *Motion_N* values), and dynamically computes parameters to assess whether the physical internet monitoring is a dark room (represented by one), dimmed room (represented by two), or bright room (represented by three) following from the categorization guidelines of the Illuminating Engineering Society of North America.

Algorithm 2: Internet monitoring detection

Algorithm : Motion & light detection

Initialization of parameters:

```
Motion_Y, Motion_N, getLight, projectionLight
```

Set up logic functions:

```
Motion (Motion_Y, Motion_N)
LightIn (getLight)
LightOut (projectionLight)
```

Compute dynamic detection:

```
  If Motion == Yes then LightIn
    Switch
      Case LightIn == 1 : LightOut = 2 ; break
      Case LightIn == 2 : LightOut = 1 ; break
      Case LightIn == 3 : LightOut = 0 ; break
  Else
    LightIn = 0
    LightOut = 0
  End if
```

Next, we describe our proposed research model, which is a novel idea that incorporates relevant factors into a dynamic self-learning method. For our problem area, the main challenges faced by classification methods is the existence of many unclear physical transitions and the varied features of the contextual internet monitoring.

We reflect the different combinations of fall factors as follows. The factors for falls are restricted to light levels and accelerometer *X Y Z* readings, light levels and accelerometer *X Y* readings, light levels and accelerometer *X* readings, accelerometer *X Y Z* readings, accelerometer *X Y* readings, and accelerometer *X* readings. Accordingly, we evaluate the different combinations of falls at six levels. Figure 5 illustrates this research model.

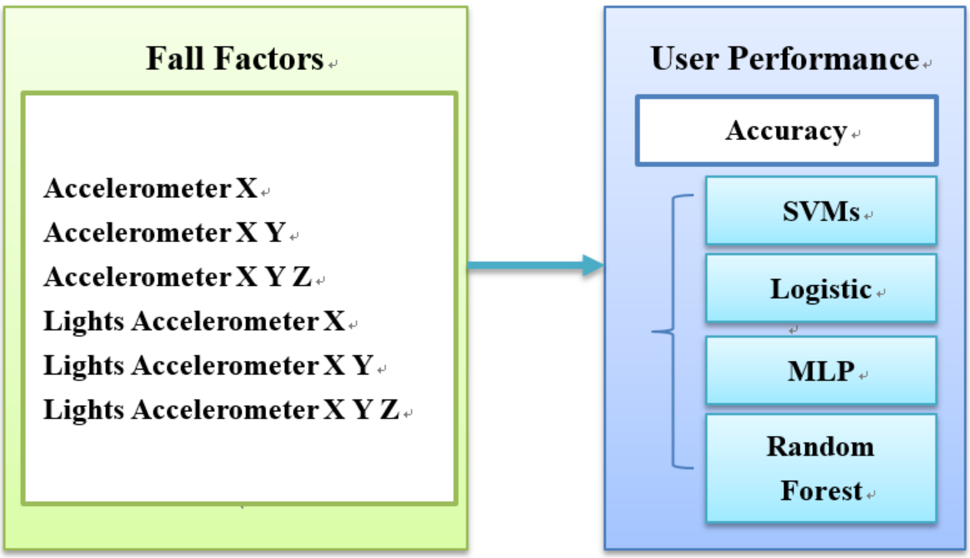

Figure 5: The research model

We include the following machine learning algorithms: support vector machines (SVM)(Chou, Li et al. 2019, Chou 2020, Chou and Cho 2020, Chou and Hung 2021, Chung, Chou et al. 2021, Chou 2022, Chou, Lee et al. 2022), logistic regression, multi-layer perceptron (MLP), and random forests. These algorithms were chosen because they are popular machine learning algorithms and have been widely used (Jahangiri and Rakha 2015, Kremic and Subasi 2016, Chou, Zhang et al. 2017). SVM can handle multidimensional time series with a high level of noise and make coordinated multi-resolution forecasts (Huang, Nakamori et al. 2005, Bogle and Potter. 2015).

Please refer Equations (2) and (3) below. *X* represents the four dimensions of features in the training dataset and *Y* indicates the range of conditions 1, 2, and 3.

As Equation (4) shows, SVM is a supervised learning method with statistical risk minimization to estimate a classified hyperplane. In Equation (5), the boundary between the two categories (2 / ||*w*||) should be maximized to find a decision boundary between the two categories that forms the optimal hyperplane. When the margins are maximized, the two categories are perfectly separated.

Theorem 3.2~3.5 *These are the four dimensions of features and the boundary between the two categories to form the optimal hyperplane.*

$$\{(X_i, Y_i)\}, \forall_i = 1, 2, \ldots, n, X_i \in R^d, Y_i \in \{1, 2, 3\} \tag{2}$$

$$X_i = \begin{bmatrix} light \\ accelerometer\ \ X \\ accelerometer\ \ Y \\ accelerometer\ \ Z \end{bmatrix} \tag{3}$$

$$Y_i(W^T X_i + b) \geq 1, \forall_i = 1, 2, \ldots, n \tag{4}$$

$$\max_W \{2/\|W\|\} \rightarrow \min_W 1/2 W^T W \tag{5}$$

To our knowledge, there is no other existing research work that incorporates physical transitions, visibility, and fall factor combinations into a machine learning system. Compared to younger people, older people sometimes have different preferences for visibility and different patterns of physical behaviors and transitions. We consider physical transitions and visibility to be relevant to fall prediction. Fall frequency in daily activities refers to the total probability of falls during a period of time, which may change depending on the number and type of activities in the period of time. It is important to dynamically distinguish physical transitions and visibility from different combinations. Accordingly, we test two hypotheses, as explained below.

H1: Incorporating both physical transitions and visibility into a fall prediction framework will lead to better performance than incorporating only physical transitions or visibility.

H2: Different combinations of fall factors will cause significant differences in the performance of prediction.

Through these hypotheses and our experimental tests, we aimed to create a novel, high-performing fall prediction framework that incorporates physical transitions and visibility in different combinations.

4. Experiments

We applied SVM, logistic regression, MLP, and random forests to test our hypotheses and quantitatively evaluate our research model for its accuracy in fall prediction. Our training data consisted of data from daily activities from a total of 1294 datasets[4]. This sensor-generated data contained light levels along with accelerometer *x*, accelerometer *y*, and accelerometer *z* readings from the laboratory experiment (Figures 6–9).

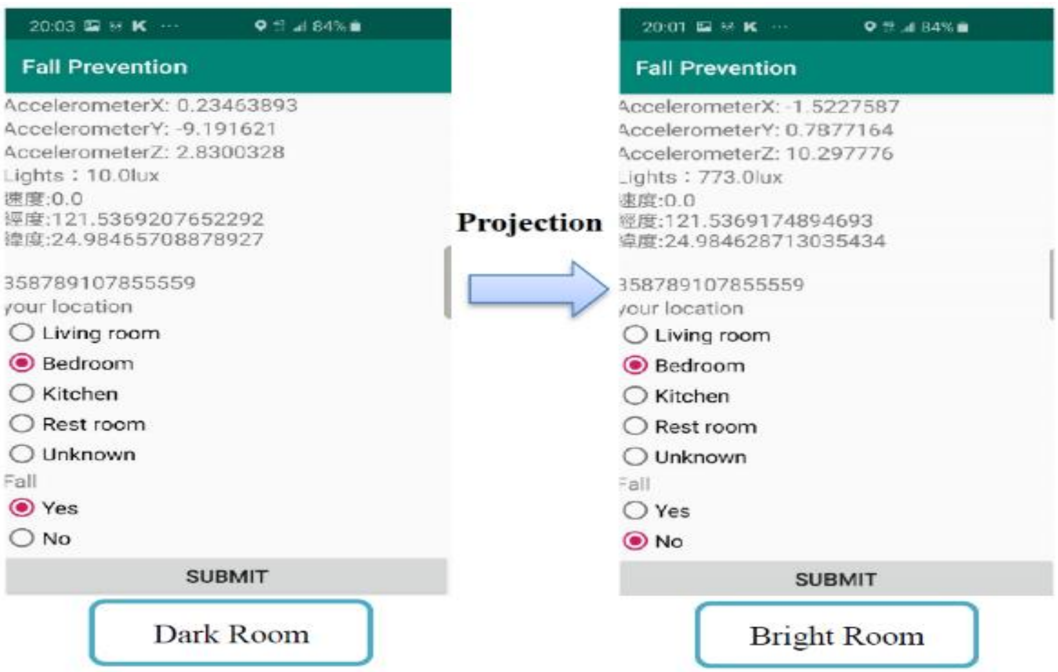

Figure 6: Visibility improvement in the bedroom from dark to bright

[4] https://drive.google.com/file/d/1_Wut8kt_HF0iap0tXtr9TGx1PS_h1b-o/view?usp=sharing

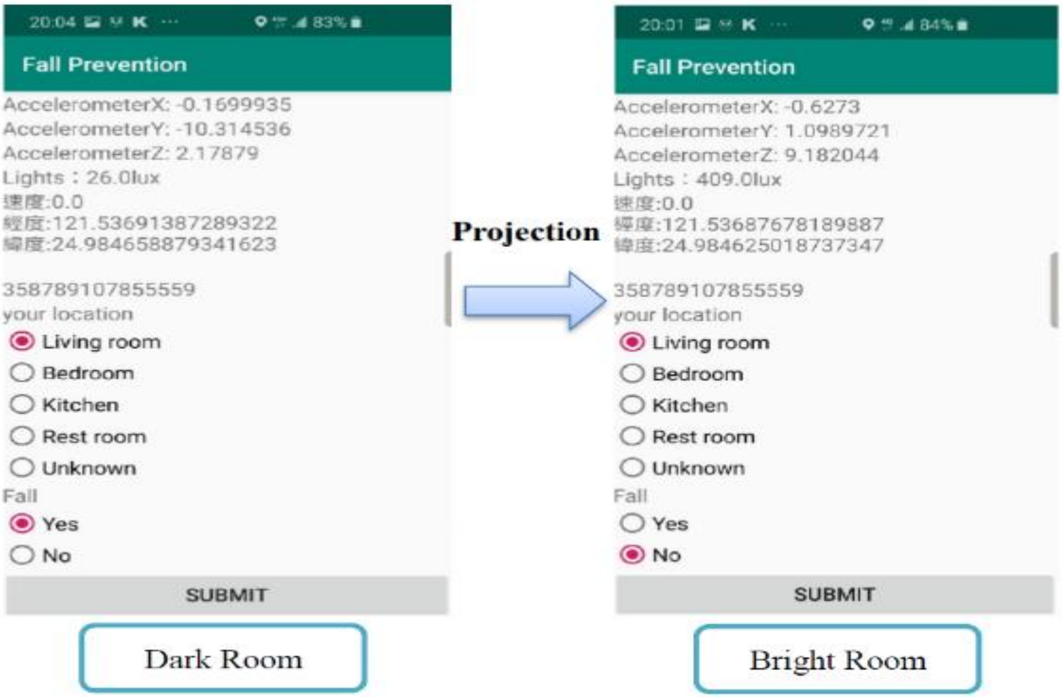

Figure 7: Visibility improvement in the living room from dark to bright

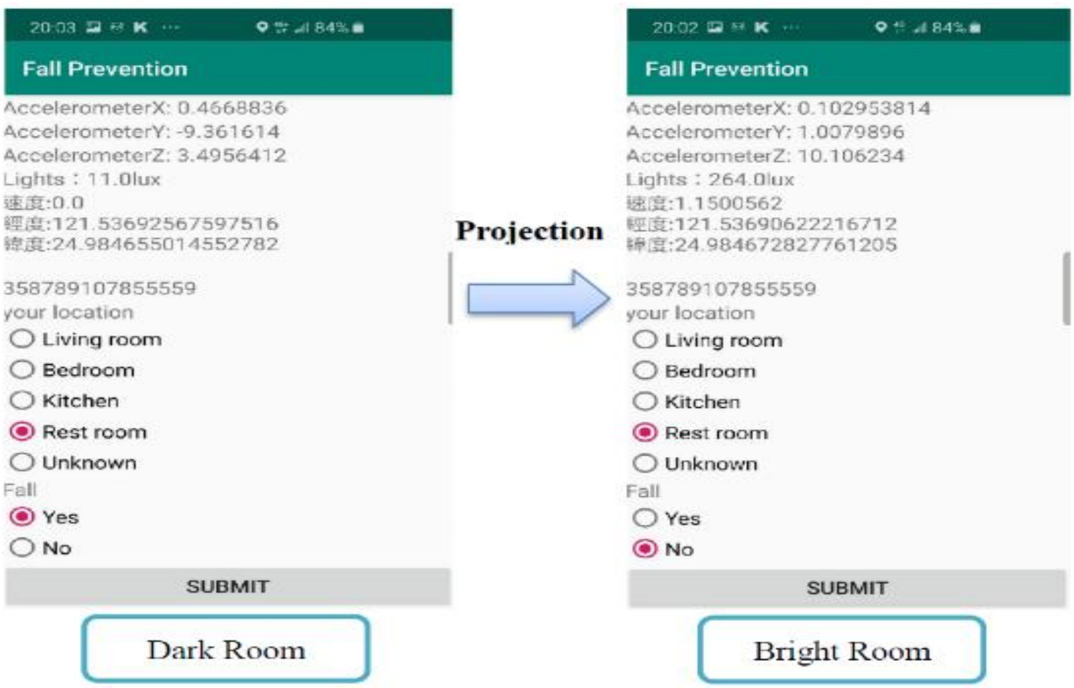

Figure 8: Visibility improvement in the rest room from dark to bright

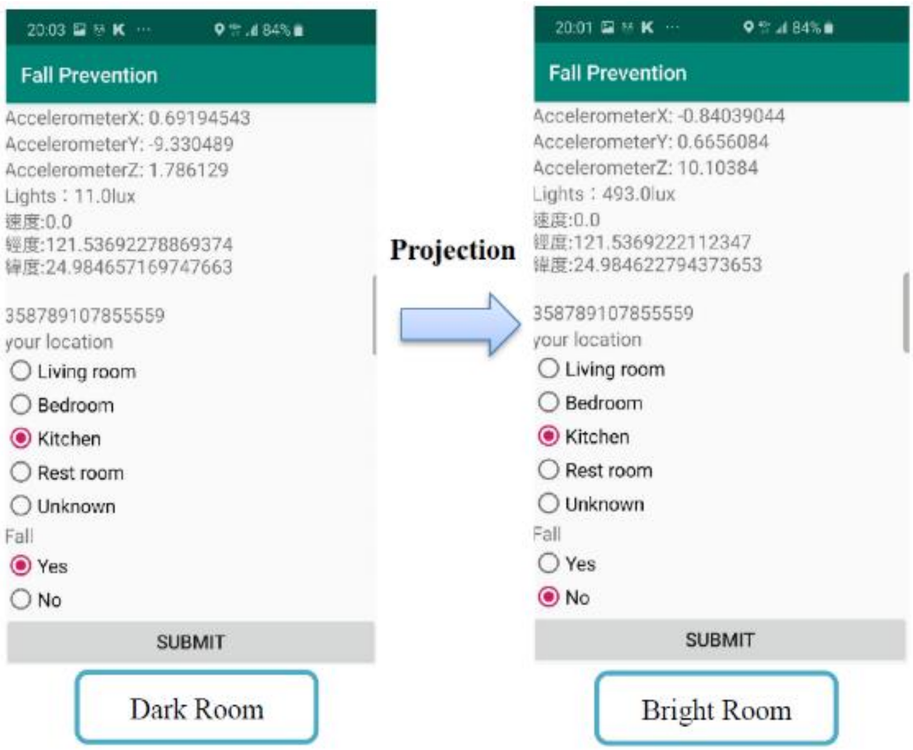

Figure 9: Visibility improvement in the kitchen from dark to bright

We used the R programming language to preprocess and transform the physical transition and visibility data (Table 2).

Table 2: Data processing in R

light[which(light>=0 & light<120)]<-1
light[which(light>=120 & light<250)]<-2
light[which(light>=250 & light<1000)]<-3
light[which(light>=1000 & light<5000)]<-4
light[which(light>=5000)]<-5

We separated our evaluations into two parts: In the first part, we evaluated both physical transitions and visibility related to falls. In the second part, we measure the predictive performance of different combinations of physical transitions and visibility. The independent variable is the level of the factors used for fall prediction, which is operationalized as six levels: 1) lights-accelerometer *x*; 2) lights-accelerometer *x* and *y*; 3) lights-accelerometer *x*, *y*, and *z*; 4) accelerometer *x*; 5) accelerometer *x* and *y*; and, 6) accelerometer *x*, *y*, and *z*. The dependent variable is the performance of fall prediction.

We tested the two hypotheses using all four machine learning algorithms with 10-fold cross validation to obtain the accuracy of fall prediction for all levels of the fall factors. A single subsample was retained as the validation set to test the model, and the remaining nine subsamples were used as training data. All observations were used for both training and validation. Each observation was used exactly once.

We measured the performance by calculating true positive (TP), true negative (TN), false positive (FP), and false negative (FN) rates. The terms positive and negative refer to the classifier's prediction, and the terms true and false refer to whether the prediction corresponds to the real observation. Accuracy is the number of correct predictions divided by the total number of fall predictions (i.e., accuracy = (TP+TN) / (TP+TN+FP+FN)).

5. Results

The performance of the three accelerometer levels is shown in Figure 10. Accelerometer *z* had a clearly higher index distribution than the *x* and *y* levels.

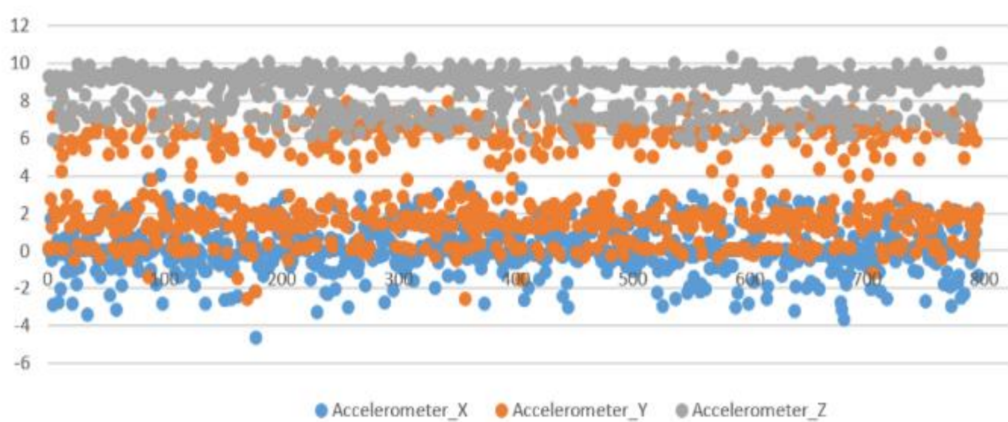

Figure 10: Distributions of accelerometer readings

Table 3 lists the accuracy of factor levels. Considering both physical transition and visibility, the accuracy of SVM is 81.92% for both light levels and accelerometer *x*, *y*, and z; that of logistic regression is 82.15%; that of MLP is 82.15%; and, that of random forests is 82.23%. Without considering visibility, the accuracy of SVM decreases to 71.25%; if only accelerometer *x* readings are used, the accuracy of SVM is 61.44%, which is the lowest value.

Table 3: Accuracy of factor levels

	SVMs	Logistic	MLP	Random Forest
Lights Accelerometer X Y Z	81.92%	82.15%	82.15%	82.23%
Lights Accelerometer X Y	81.84%	81.84%	81.84%	81.84%
Lights Accelerometer X	71.10%	71.10%	71.10%	71.10%
Accelerometer X Y Z	71.25%	70.94%	71.17%	71.02%
Accelerometer X Y	70.48%	70.48%	70.48%	70.48%
Accelerometer X	61.44%	61.44%	61.44%	61.44%

Among all levels, a consideration of accelerometer readings alone yields lower accuracy than using both. We performed ANOVA to examine whether the level used for fall prediction positively influenced the accuracy of predicting direction. To account for multiple comparisons, we conducted an LSD test. The ANOVA test results were statistically significant ($F(5,23) = 39{,}309.932$, $p < 0.01$). Comparisons of all levels showed that both physical transition and visibility were significantly different from others ($p < 0.05$) (Table 4). In summary, the results support the first hypothesis.

Table 4: ANOVA of all p-values

	Lights X Y Z	Lights X Y	Lights X	X Y Z	X Y	X
Lights X Y Z		0.000	0.000	0.000	0.000	0.000
Lights X Y	0.000		0.000	0.000	0.000	0.000
Lights X	0.000	0.000		0.930		
X Y Z	0.000	0.000	0.930		0.000	0.000
X Y	0.000	0.000	0.000	0.000		0.000
X	0.000	0.000	0.000	0.000	0.000	

$p < 0.05$ (The mean difference is significant at the 0.05 level.)

With respect to comparing different combinations, accelerometer *x*, *y*, and *z* were significantly different from accelerometer *x*, and both light levels and accelerometer *x* were significantly different from accelerometer *x*. Therefore, we can state that the results support the second hypothesis too.

6. Discussion

This result suggests that physical transitions and visibility are important factors in fall prevention. Taking into consideration the readings of accelerometer *x*, *y*, and *z* yielded significantly higher accuracy than only accelerometer *x*. This result implies that different combinations of accelerometer readings could have different effects on fall prediction.

Our findings have several implications for fall prevention. First, adding light measurements to RAC smart home-connected light appliances will help in risk detection. Second, effective detection of physical transitions is important for fall prevention. This could be achieved using motion detection methods. Adopting accelerometers in a way that allows older people to detect the position is essential. Lastly, visibility is a vital factor. Older people need to clearly see and understand their internet monitoring before moving at any time. Therefore, RAC smart home-connected light appliances should have sufficient light.

7. Conclusion

In order to find a solution for the issue of the elderly staying alone for home-based self-health management strategies during the COVID-19 epidemic, we evaluated the impact of physical transitions and visibility on fall prediction and compared the accuracy of fall predictions based on combinations of related factors. The accuracy of predictions using both physical transition and visibility was higher than 81%, which is a high forecasting accuracy rate. It was also notably higher than the accuracy obtained from other combinations of factors.

Our study has the following limitations. First, it focuses on dynamic detection for falls. However, a change that is too rapid from body verticality to horizontality is not perfectly reflected in the values of the accelerometer readings because it takes time to record a value in the system for falls. We will endeavor to build a prototype automatic fall system to evaluate the relevant factors and reduce response time. Second, because of high behavior variability, it is likely that the total amount of personal data on patterns is larger than the simulation data in our study. As such, it is necessary to capture additional data on real behavior patterns to improve future research for the elderly in applied economics.

8. Acknowledgments

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