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Original Article

Application of Decision Tree to Classify Fall Risk Using Inertial Measurement Unit Sensor Data and Clinical Measurements

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Background: While efforts have been made to differentiate fall risk in older adults using wearable devices and clinical methodologies, technologies are still infancy. We applied a decision tree (DT) algorithm using inertial measurement unit (IMU) sensor data and clinical measurements to generate high performance classification models of fall risk of older adults.

Objects: This study aims to develop a classification model of fall risk using IMU data and clinical measurements in older adults.

Methods: Twenty-six older adults were assessed and categorized into high and low fall risk groups. IMU sensor data were obtained while walking from each group, and features were extracted to be used for a DT algorithm with the Gini index (DT1) and the Entropy index (DT2), which generated classification models to differentiate high and low fall risk groups. Model's performance was compared and presented with accuracy, sensitivity, and specificity.

Results: Accuracy, sensitivity and specificity were 77.8%, 80.0%, and 66.7%, respectively, for DT1; and 72.2%, 91.7%, and 33.3%, respectively, for DT2.

Conclusion: Our results suggest that the fall risk classification using IMU sensor data obtained during gait has potentials to be developed for practical use. Different machine learning techniques involving larger data set should be warranted for future research and development.

INTRODUCTION

With the global increase in the elderly population, falls are a major health concern for older adults. Over 30% of community-dwelling older adults and approximately 60% of the residents in nursing and old peoples' homes fall every year [1]. Furthermore, about one-quarter of injury-related deaths in older adults over 65 years and 34% of those over 85 years occur due to falls [2,3]. According to the Centers for Disease Control and Prevention (CDC), 2.8 million patients were treated for fall-related injuries in the emergency room in 2014, and about 1 million of these patients were hospitalized [4].

Falls in older adults commonly occur during dynamic movements (gait and weight shift) in their daily living activities. According to the video capture analysis of falls in long-term care, Robinovitch et al. [5] found that forward walking was the most common activity (24%) at the time of a fall. Overstall et al. [6,7] found that the increasing sway of gait in older adults correlated with a history of falls. Furthermore, individuals with impaired gait are 1.65 times more likely to experience a fall than individuals with no impairments [8]. Gait abnormalities (i.e., lower gait speed) also indicate possible sarcopenia, which causes serious problems in older adults [9-11].

Many studies utilize various fall risk assessment methods to assess older adults' fall risk. Some research studies classify fall risk based on a history of falls [12,13]. However, it is a proxy measure for fall risk because a faller has a higher risk of falling again [12]. Some research studies utilize fall risk scores from various functional tests such as the Berg Balance Scale (BBS), Timed Up and Go (TUG), and Tinetti tests [14-16]. These studies have clinical use advantages, but these tests have some limitations regarding the diversity of their testing factors. Generic fall risk measurements like St Thomas's risk assessment tool in falling elderly inpatients (STRATIFY) are also used for assessing fall risk, but this tool also has limitations, including a low sensitivity to predict future falls [17-19]. However, the Physiological Profile Assessment (PPA) presents some advantages in assessing fall risk [20]. The primary advantage for PPA is the diversity of testing factors including physiological factors like vision, proprioception, and lower limb strength. However, PPA is also limited, as it is not suitable for clinical use because of the testing time [21]. Short-form PPA (S-PPA) has been developed, which tests only five factors (the Melbourne Edge Test, proprioception test, knee extension muscle strength test, postural sway test, and reaction time test) to address this limitation. Although there is a significant correlation between clinical measurements and the PPA score, most studies have measured fall risk using the selected method [22]. Therefore, identifying clinical measurement scores in each fall risk group may help to comprehensively understand fall risk. Furthermore, Brodie et al. [23] found a significant correlation between PPA score and gait analysis features (total steps per day).

To analyze human movements, such as quantitative gait abnormality, three dimensional motion capture system camera is classified as the gold standard, but it has limitations: it is too expensive and impractical to analyze in clinical settings [24,25]. Various wearable devices, including accelerometers, gyroscopes, magnetometers, foot pressure sensors, inclinometers, and goniometers, were utilized in previous studies to compensate for these limitations [26-29]. Specifically, inertial measurement unit (IMU) sensors have been used commonly in gait analysis instead of expensive and impractical motion capture systems [30]. Furthermore, IMU shows high accuracy for extracting features during gait compared to the gold standard (three dimensional motion analysis camera) [31,32].

In practice, most fall-related reports are collected through subjective data such as patient interviews and questionnaires [33]. Therefore, these quantitative data from wearable sensors can provide more accurate information about falls, which may help provide a more effective fall prevention strategy. From this perspective, many studies suggest various fall prevention strategies using machine learning algorithms and these quantitative data [12,34,35]. Aziz and Robinovitch [35] suggested that the accuracy of classification models of falls and non-falls using waist-mounted tri-axial accelerometer data is up to 96.0%. Santhiranayagam et al. [34] suggested that the accuracy of a support vector machine-based classification model that analyzes the gait of young and older adults using IMU is 92.1%. Drover et al. [36] suggested that the accuracy of faller classification models using a wearable sensor is up to 77.3%. However, to the best of our knowledge, there is no study classifying the fall risk assessed by S-PPA using IMU data and clinical measurements for gait. Therefore, this study aims to develop a classification model for the fall risk assessed by S-PPA using IMU data and clinical measurements in older adults. We hypothesize that the accuracy of our classification model is up to 80.0%.

MATERIALS AND METHODS

1. Subjects

This study had 26 older adult participants (3 males and 23 females). Average age, weight, and height were 79.6 ± 6.2 years, 57.8 ± 7.5 kg, and 155 ± 6.8 cm, respectively. Exclusion criteria included subjects who used gait assistance methods (walker, cane, etc.). Experimental protocols have been reviewed and approved by the Institutional Review Board at Yonsei University Mirae campus (IRB no. 1041849-202301-BM-004-03), and all participants provided an informed consent form before the experiment.

2. Experimental Protocol

During the experiment, the investigator took clinical measurements for each participant. In this experiment, we measured muscle mass, number of falls in the past year, fear of fall (ranging from 1 to 5, where 1 means the subject is not afraid to fall at all.), education level, drinking and smoking history, PPA, bilateral hand grip strength, BBS, TUG, five times sit to stand (5STS), and Fall Efficacy Scale-International (FES-I). After clinical measurements, subjects wore 10 IMU sensors (Xsens DOT; Xsens Technologies) to measure gait for 10 m at a sampling rate of 60 Hz. The IMU sensors were placed on the head, sacrum, bilateral upper arm, forearm, thigh, and shin of each subject.

3. Input Features

1) Physiological Profile Assessment

S-PPA is the modified version of PPA, a common measure of fall risk, which includes five physiological factors. The following test were performed to test these factors.

(1) Melbourne Edge Test

The Melbourne Edge Test was used in the study to evaluate the participants' visual contrast sensitivity. The test involved identifying the directions of contrast edges of circular patches on a chart. The patches were presented at different angles, including horizontal, vertical, and diagonal. The participants were provided with a keycard that contained four possible directions of contrasting edges. The test recorded the correct identification of the lowest contrasting edge in decibels. The Melbourne Edge Test was found to have good reliability in measuring visual contrast sensitivity in older adults who live in the community [17,20].

(2) Proprioception test

The proprioception test was designed to evaluate participants' sense of proprioception. Participants were instructed to sit in the S-PPA proprioception char with their eyes closed and align their great toes on either side of a vertical acrylic-plastic plate (60 × 60 × 1 cm). Any differences in the alignment of their great toes were measured and recorded in degrees. The test was found to have moderate test-retest reliability in older adults, with an intraclass correlation coefficient (ICC) of 0.50 and a 95% confidence interval (CI) of 0.15–0.74 [17,20].

(3) Hand reaction time test

The hand reaction time test was used to assess response time. In this test, participants were instructed to press a response switch on a modified computer mouse when a red light next to the switch was activated. The time taken to react was measured in milliseconds using a built-in timer. The test showed moderate test-retest reliability, with an ICC of 0.69 and a 95% CI of 0.45–0.84 [17,20].

(4) Knee extension muscle strength test

The knee extension strength test was used to evaluate the quadriceps muscle strength in the dominant leg. All subjects in our experiment were dominant on the right side. The participants were instructed to sit while a strap connected to a spring gauge was placed around their legs to measure the force applied during knee extension. The measurement was recorded in kilograms. This test demonstrated excellent test-retest reliability with an ICC of 0.97 and 95% CI of 0.93–0.98 [17,20].

(5) Postural sway test

The postural sway test measured the displacement of the body and was conducted by tying a belt to the waist of each participant for 30 seconds. A rod connected to the belt was used to record body movement on graph paper in mm^2, with a pen attached to the end of the rod. This test showed moderate test-retest reliability, with an ICC of 0.68 and a 95% CI of 0.45–0.82 [17,20].

Scores from the five tests were the input data for the S-PPA software program, and these scores were converted into individual fall risk scores ranging from –2 to 4. Furthermore, the S-PPA software indicated a normal range for each subject's age; therefore, we inferred that the high fall risk group is out of the normal range group, while the low fall risk group is in the normal range group (Figure 1).

2) Berg Balance Scale

BBS was a measurement for assessing balance and fall risk in older adults. It consisted of 14 tasks ranging from 0 to 4. A maximum score of 56 indicated good balance and low fall risk. BBS was found to have excellent test-retest reliability (ICC = 0.98) [37,38].

3) Timed Up and Go test

The TUG test was a simple and quick assessment of functional mobility and fall risk. It measured the time required for a person to stand up from a chair, walk 3 m, turn around, walk back to the chair, and sit down again. The TUG test was found

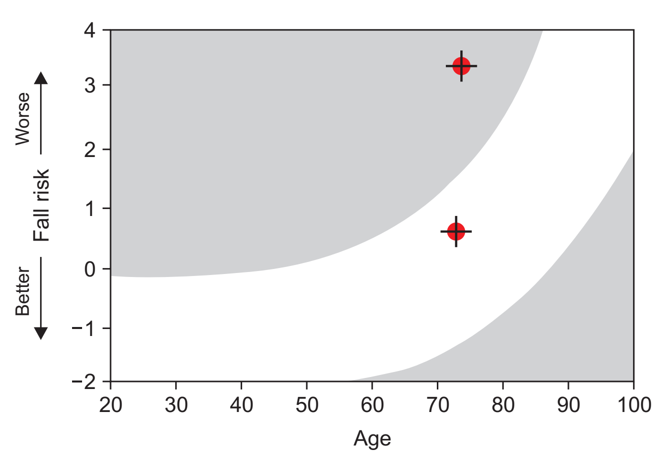

Figure 1. Example data (red cross point) in each group. The white range in this figure is the average normal population fall-risk score for each age group. Subjects with S-PPA scores outside this white range were classified into the high fall-risk group.

to have excellent test-retest reliability (ICC = 0.99) [39].

4) Fall Efficacy Scale-International

FES-I was a self-report questionnaire used to assess an individual's fear of falling. It consisted of 16 items that measure the level of concern about falling during various activities, such as walking on uneven surfaces, climbing stairs, or getting in and out of the bathtub. FES-I was found to have excellent internal and test-retest reliability (Cronbach's alpha = 0.96, ICC = 0.96) [40].

5) Hand grip strength

Handgrip strength was assessed using digital hand grip dynamometer (PGF-1000; Ls Networks Co.). It was commonly used in older adult studies, especially to assess possible sarcopenia [9]. The participants were assessed for bilateral hand grip strength while standing with full elbow extension according to the recommendations of the Asian Working Group for Sarcopenia (AWGS) 2019.

6) Five times sit to stand test

The 5STS test was used in assessing older adults' possible sarcopenia. According to the AWGS 2019, over 12 seconds for 5STS is treated as the cutoff for low physical performance [9].

7) IMU features during gait

To determine each gait cycle from the IMU data, we used the angular velocity in the Y-axis data from bilateral shins (Figure 2) [31,41]. We extracted features, including the mean and variance of accelerations, linear and angular velocities, and magnetic field data, from the left-side mid-swing to the next mid-swing during gait.

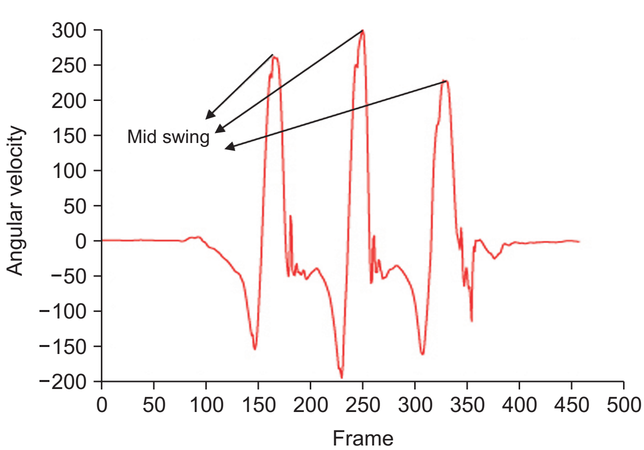

Figure 2. Definition method from angular velocity in Y-axis data using shin inertial measurement unit sensor data.

4. Data Analysis

To normalize each gait cycle, we resampled each data to 100 data points. After resampling, the average value of all gait cycle data obtained from each subject was used as input features for the classification model.

We used a decision tree (DT) algorithm, a supervised classifier based on the impurity index (i.e., Gini index [DT1], Entropy index [DT2]) for classification models. Input features in DT were clinical measurements score and IMU sensor data (PPA, bilateral handgrip strength, BBS, TUG, 5STS, FES-I, Fear of fall score, mean and variance of accelerations, linear and angular velocities, and magnetic field data during gait). DT selects the primary features that minimize the DT1. The main advantage of DT is that it is easier to interpret than other methods; therefore, it can be applied in various fields such as healthcare. Other methods might be more accurate but more difficult to understand and interpret than DT [42-44]. We used DT using both the DT1 and DT2 for developing classification models. Among our subjects, 8 subjects (1 male and 7 females) were included in the low fall-risk group and 18 subjects (2 males and 16 females) were included in the high fall-risk group. Therefore, we resampled the low fall-risk group data using the average of the low fall-risk group data and the same number for the high fall-risk group. Then, we randomly divided the datasets into equal sizes for training and testing sets. Subsequently, optimal hyperparameters for each DT were selected automatically. To assess classification model performance, the accuracy, sensitivity, and specificity were computed with the following equations:

$$\text{Accuracy (\%)} = \frac{\text{True positive} + \text{True negative}}{\text{Positives} + \text{Negatives}} \times 100$$

$$\text{Sensitivity (\%)} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}} \times 100$$

$$\text{Specificity (\%)} = \frac{\text{True negative}}{\text{True negative} + \text{False positive}} \times 100$$

All data analyses were conducted using MATLAB routines (R2022B; MathWorks Inc.).

Table 1. Clinical measurements of each group

Variable	High fall risk	Low fall risk
Height (cm)	156.1 ± 7.3	152.3 ± 4.6
Weight (kg)	58.4 ± 7.2	56.7 ± 8.0
Age (y)	79.1 ± 5.1	80.9 ± 8.1
S-PPA	4.2 ± 1.7	2.6 ± 1.9
Muscle mass (kg)	21.0 ± 3.2	19.5 ± 2.4
Left hand grip strength (kg)	19.2 ± 4.1	20.5 ± 4.2
Right hand grip strength (kg)	19.5 ± 6.0	21.2 ± 4.9
BBS	50.3 ± 4.1	51.0 ± 3.8
TUG (s)	13.1 ± 3.7	10.8 ± 2.6
5STS (s)	10.6 ± 3.3	11.4 ± 2.6
FES-I	23.3 ± 9.7	20.8 ± 3.9
Fear of fall	2.4 ± 1.3	2.9 ± 1.6

Values are presented as mean ± standard deviation. S-PPA, Short-form Physiological Profile Assessment; BBS, Berg Balance Scale; TUG, Timed Up and Go; 5STS, five times sit to stand; FES-I, Fall Efficacy Scale-International.

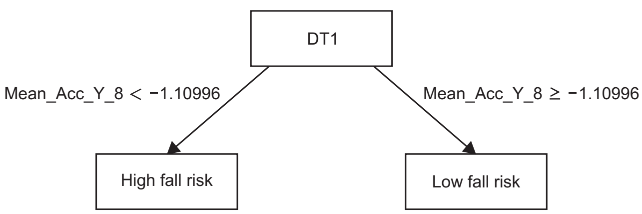

Figure 3. Figure of DT1. Mean_Acc_Y_8, mean of accelerations in the Y-axis data from the right shin inertial measurement unit sensor; DT1, Gini index.

RESULTS

The clinical measurements for each group are described in Table 1. One subject in the high fall-risk group drank alcohol, and one subject in each group smoked daily. In the low fall-risk group, two were uneducated, two graduated from elementary school, one from middle school, two from high school, and one from university. In the high fall-risk group, seven were uneducated, five graduated from elementary school, four from middle school, and two from high school. Two subjects in the low fall risk group experienced falls in the last year, and seven subjects in the high-fall risk group experienced falls in the previous year. All subjects (nine subjects) experienced falls only once in the previous year.

The Classification model using the DT1 classified the high and low fall-risk groups by mean of accelerations in the Y-axis data from the right shin IMU sensor (Figure 3). Accuracy, sensitivity, and specificity of DT1 were 77.8%, 80.0%, and 66.7%, respectively (Table 2).

The classification model using the DT2 classified the high- and low fall risk groups by mean of accelerations in the X-axis data from the left shin IMU sensor (Figure 4). Accuracy, sensitivity, and specificity of DT2 were 72.2%, 91.7%, and 33.3%, respectively (Table 2).

Table 2. Classification performance of decision tree using DT1 and DT2

Variable	DT1	DT2
Accuracy (%)	77.8	72.2
Sensitivity (%)	80.0	91.7
Specificity (%)	66.7	33.3

DT1, Gini index; DT2, Entropy index.

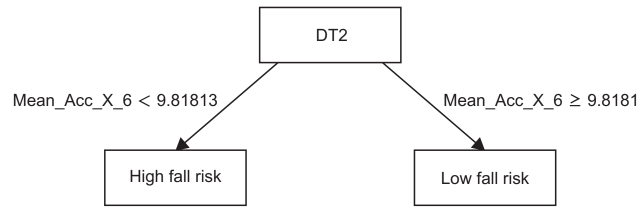

Figure 4. Figure of DT2. Mean_Acc_X_6, mean of accelerations in X-axis data from the left shin inertial measurement unit sensor; DT2, Entropy index.

DISCUSSION

This study aimed to develop classification models for fall risk assessed by the S-PPA using IMU data for gait in older adults. Although the accuracy of our classification models was under 80.0%, which is lower than our hypothesis, we suggest the possibility of developing classification models of fall risk using IMU sensors. Our classification models showed over 70.0% accuracy despite the small dataset (26 subjects) used for machine learning. We suggest that the performance of these classification models can be improved in the following ways.

First, developing classification models based on wider datasets may help improve the performance. Among 26 participants in this study, most were female participants (23 participants) and high fall-risk group subjects. Although falls and fall-related injuries are more common in women [45], matching sex ratios might be more helpful in improving the performance of the classification models. Therefore, future studies with more sex-appropriate number of subjects for each group might be helpful in improving the performance of the classification models. Moreover, our sampling rate (60 Hz) for the IMU sensors might not have been sufficient for our purposes. Previous studies utilized IMU sensors over 100 Hz to develop fall prevention strategies (i.e., fall detection systems) and showed over 95.0%

accuracy [46]. Therefore, a higher sampling rate for IMU sensors may help improve the classification model performance.

Second, although we used impurity criteria in two ways, we used only a DT classifier because DTs have the advantage of being easy to interpret as they present the factors and cutoff values of classification models. Previous studies used various machine learning algorithms to develop classification models [12,34,35]. Aziz et al. [47,48] suggested that a support vector machine (SVM) has superior performance in classifying human movements, which might help improve the performance. Furthermore, Lim and Choi [49] suggested that SVM showed higher accuracy than DT for 2 impurity criteria. Therefore, future studies, including various machine learning algorithms (i.e., Naïve Bayes, K-nearest neighbor, Random Forest, Convolutional Neural Network), might help find optimal algorithms for fall-risk classification models using IMU sensors.

CONCLUSIONS

In conclusion, we developed classification models for fall risk using S-PPA and IMU sensors. Our classification model achieved less than 80.0% accuracy, but if future studies with modified limitations show higher accuracy, it could be helpful in improving effective fall prevention strategies.

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CONFLICTS OF INTEREST

No potential conflicts of interest relevant to this article are reported.

AUTHOR CONTRIBUTION

Conceptualization: JP, JC, SL, KL, WJC. Data curation: JP, JC, SL, WJC. Formal analysis: JP, JC, SL, WJC. Funding acquisition: WJC. Investigation: JP, WJC. Methodology: JP, JC, SL, KL, WJC. Project administration: JP, KL, WJC. Resources: JP, JC, SL, WJC. Software: JP, KL, WJC. Supervision: JP, JC, SL, KL, WJC. Validation: JP, KL, WJC. Visualization: JP, JC, SL, WJC. Writing - original draft: JP, WJC. Writing - review & editing: JP, JC, KL, WJC.

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