Ooi Jia Hui

Title: XGBoost based machine learning approach to predict/detect fall events in older adults.

Introduction

Fall is defined as “an event which results in a person coming to rest inadvertently on the ground or other lower level” and it often occurs indoor and are associated to activities of daily living (ADLs). According to the statistics reported by World Health Organization (WHO), approximate 30 % of people above 65 are victims of accidental falls annually and the fall rate is at the alarming rate (about 50%) for people above 85 [1]. As people get older, they become more fragile and their senses such as vision deteriorates. Due to their diminishing sensing ability, elder people are more prone to fall, which is the most common causes of injury and death among them.

Nowadays, various fall detection algorithms have been proposed using different machine learning techniques, in order to increase the accuracy of fall prediction or to reduce the probability of false positive in a fall detection system. However, these proposed fall detection systems shared the same limitation since they are not trained and validated with the objective population (elderly people), thus, reducing their accuracy in real-life applications [2].

In this study, XGBoost algorithm by Chen and Guestrin [3], a decision tree based ensemble learning technique was used to model a fall prediction system (binary classification model). SisFall: (Sistemic research group fall and movement dataset) [4] dataset was chosen to train the model as it includes both young adults and elderly performing a wide variety of ADLs and falls. Meanwhile, the open-source public datasets such as MobiFall and tFall only involved young adults and their performed activities were limited. The XGBoost model was created in the Python programming language using Jupyter notebook, to predict if a fall has occurred or not.

A robust fall detection system permits the accurate fall detection among the target population, as well as minimizing the negative consequences of a fall allowing elderly people to live an active and independent life. Hence, the objective of this study is to design and model an accurate and reliable fall detection system (XGBoost classifier) with a high sensitivity and low false positive rate, based on the dataset with falls and activities of daily living (ADLs) acquired with an accelerometer. To predict the occurrence of falls or normal daily activities based on the kinematics analysis (acceleration).

Dataset

SisFall dataset consists of 4500 text files of which 1798 are related to 15 types of falls and 2702 files are related to 19 types of ADL, performed by 23 young adults and 14 elderlies. In the original SisFall dataset, the movement data was measured and collected at a sample frequency of 200 Hz using two triaxle accelerometers (ADXL345 and ITG3200) and gyroscope (MMA8451Q). The details of the related performed and simulated activities can be referred to [4].

For the fall detection algorithm in this study, SisFall dataset was used as a labelled dataset, so the output was in numerical format, either 0 or 1. All the ADLs were classified as 0 (non-fall events) while all the data related falls were classified as 1. For the simplicity of the system in this work, only the data collected using ADXL345 accelerometer was used to build the model and were converted into csv format.

The data obtained from the accelerometer was pre-processed, followed by features extraction to maximize the separation between falls and non-fall events. Down-sampling of the data from 200Hz to 100Hz was performed to reduce the computational burden. According to the studies [5] [6], mean, standard deviation, variance, sum vector magnitude, and tilt angles are the most commonly used features in existing fall detection systems. Therefore, 3 main parameters were computed from the data: sum vector magnitude (SVM), SVM on horizontal plane and angle between z-axis and vertical plane, using the formula:

$$SVM = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2}$$

$$SVM\ on\ horizontal\ plane = \sqrt{{a_x}^2 + {a_z}^2}$$

$$Angle\ between\ z - axis\ and\ vertical\ plane = atan2\sqrt{{a_x}^2 + {a_y}^2}, a_z$$

In the above equations, a_x , a_y and a_z refer to x-axis, y-axis and z-axis accelerometer readings.

Changing of body movement in a pre-fall state causes alternation in the acceleration [7]. In most studies, the highest peak during the sudden change of SVM was used to indicate a fall event. Hence, in this study, a window of 3s was selected to extract 300 data points from each sample so that it can clearly depict the process of pre-fall, fall and post fall events.

Mean, standard deviation, variance and range were calculated along each of the three axes (x, y, and z) and the three parameters. Thus, a total of 24 features for each sample were extracted to model the system.

Statistical analysis of the data was performed at the significance level of 0.05, using IBM SPSS Statistics (version 23, IBM). The features were not normally distributed after performing Kolmogorov-Smirnov test ($p<0.05$). Kruskal-Wallis test was performed, indicating a significant difference ($p<0.05$) between the events of fall and ADLs.

Result and Discussions

Part 1: Tuning the hyperparameter

In order to optimize the model, XGBoost was initally trained and tested with some estimates of the hyperparameters. The model should be tuned to ensure the best performance of the system is achieved and is not overfitting. For the computational simplicity, the dataset was split into 80% of the training set and 20% of the test set.

In this work, the learning rate, lambda, gamma and min_child_weight were fixed throughout the trials and errors. The parameters such as N_estimators, Max_depth, Colsample_bytree and Subsample were adjusted accordingly in each trial. In this proposed XGBoost model, the rate of true positive detection (Recall) is of utmost importance with the least false positive (FPR), to correcly differentiate between ADLs and falls. Hence, the parameter values with the highest sensitivity, specificity and FPR were selected to ensure an optimal model.

Table 1: Hyperparameters and evaluation metrics

Hyperparameter	**Trial 1**			**Trial 2**			**Trial 3**			**Trial 4**		
Learning rate	0.3			0.3			0.3			0.3		
Lambda	1			1			1			1		
Gamma	1			1			1			1		
Max_depth	6			5	8	10	10			10		
Min_child_weight	1			1			1			1		
Colsample_bytree	0.8			0.8			0.6	0.8	1	0.8		
Subsample	0.8			0.8			0.6			0.6	0.8	1
N_estimators	5	10	15	15			15			15		
Sensitivity (TPR) / Recall	0.9722	0.9667	0.9806	0.9750	0.9722	0.9806	0.975	0.9833	0.9778	0.975	0.975	0.9806
False positive rate (FPR)	0.0278	0.0333	0.0194	0.0250	0.0278	0.0194	0.0250	0.0167	0.022	0.025	0.025	0.0194
Specificity	0.9815	0.9778	0.9815	0.9815	0.9778	0.9815	0.9760	0.9778	0.9778	0.9815	0.9796	0.9777

Part 2: Evaluation of the XGBoost model

Based on Table 1, after multiple trial and errors, the XGBoost model was built based on the tuned parameters as specified in Trial 4 with the subsample ratio of 1. Table 2 and Table 3 reported the average results for the 10-fold cross validation of the proposed model.

Table 2: Average Confusion Matrix for 10-fold Cross Validation (Test set)

		Predicted	
		Falls (1)	ADLs (0)
Actual	Fall (1)	TP – 176	FN – 4
	ADLs (0)	FP – 6	TN – 264

Table 3: Performance metrics for 10-fold Cross Validation (Test set)

	Sensitivity	**Specificity**	**Precision**	**F1-Score**	**Accuracy**	**FPR**
Mean ± Std Deviation	0.98 ± 0.01	0.98 ± 0.98	0.97± 0.01	0.97 ± 0.01	0.98 ± 0.01	0.02 ± 0.01

In practical, the fall detection system should not miss a single fall due to the medical implications every fall may carry on which implies a fall detection model with a high recall or sensitivity. Based on the results obtained, the proposed XGBoost model showed a good performance in detecting falls with the average sensitivity of 98% with 4 false negative (FPR about 2%) obtained.

Meanwhile, the average F1-score of about 0.97 indicating the model is having a relatively high precision and recall rate. In general, the proposed fall detection model achieved about 98% accuracy in classifying between fall and non-fall activities, showing a similar sensitivity and specificity. Thus, the XGBoost model indicates a higher potential in detecting the fall events among the elderly in the clinical practice as compared to other previous proposed model such as Decision Tree, SVM, KNN and deep learning [8].

In this study, the dataset used showed an imbalance classification between the fall and non-fall activities. Hence, to overcome this issue, stratified 10-fold cross validation was implemented to ensure the robutness of the model. Each fold had 4000 files for training and 450 for validation. Based on the result obtained, the proposed XGBoost model demonstrated a good performance despite only the measurement data collected from one accelerometer was used. However, to ensure a more robust and realiable fall prediction model, a wide variety of the falls-related factors should be considered such as physiology (i.e., ECG, EMG, blood pressure) and kinematics analysis (i.e., gait pattern, gyroscope), especially target the objective population (elderly) in the future.

Moreover, the current dataset used to train the model in this work may not reflect the actual fall data from elderly people since the fall events were simulated and performed mainly by the young adults. Therefore, a larger dataset with increased numbers of elderly and falls-related events performed by the objective population should be used to model and evaluate the robustness of the current fall prediction system. Meanwhile, the XGBoost model should be validated and tested on the real fall event among the target population.

Apart from that, to achieve the best performance of the model with a better precision and recall, the hyperparameters should be tuned accordingly using grid seach cross validation instead of only conducting a few trials in estimating the optimal parameters and to prevent overfitting of the model.

More features and parameters should be computed and extracted from the dataset in the study and tested for the feature importance. The feature importance is the score result indicating how each variable contributes to the model accuracy when creating the XGBoost model. Thus, the optimal features with higher feature importance can be selected to train the model and predict the fall in older adults at a better performance, resulting in a more reliable and robust model meanwhile reducing the computational and complexity of the system.

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