Wearable Smart Phone Sensor Fall Detection System

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Abstract—One of the most important measures that developed countries need along with economic success is the provision of contemporary health services for the elderly. Inadequate care for the elderly can put them in danger of falls with serious injury or even death. When an older person falls due to illness, immediate lack of care may lead to death. In this paper, a wearable smart phone sensor fall event detection system is introduced. The proposed system utilizes real-time raw sensory accelerometer, gyroscope and gravity data collected from the AndroSensor App and is then processed and applied to a machine learning classifier. The smart phone is positioned at the waistline to yield the most accurate fall detection results. The system is trained and can detect common activities, like sleeping, walking, sitting, jogging, and events, such as falling in any direction. An full accuracy is almost accomplished using Support Vector Machine classifier in comparison with other classifiers as addressed by other previous research works. Nevertheless, the system requires more validation with elderly people under the supervision of caregivers in a controlled environment.

Keywords—Wearable sensor, AndroSensor app, fall detection, support vector machine (SVM)

1 Introduction

Falls in the elderly are the second most common cause of death from unintentional accidents or injuries [1]. Approximately, more than 400,000 people worldwide died from injuries related to fall. People suffering from fatal falls are usually the elderly, 65 years or older. As the number of elderly increases, the percentage of those who suffer falls during the year increases, especially the group older than 70 years, according to the World Health Organization [2]. It has also been reported that there are approximately 12 million older people living in the United States alone who are at increased risk of falls.

The factors that cause people to experience fall may be intrinsic (health problems) or extrinsic (environmental condition). As for intrinsic cases, some elderly has some chronic health problems and illnesses or disability that may result in high the incidence of falls. Besides, environmental conditions are the other fall factor such as slippery surfaces, dangerous activities, etc. Moreover, frequent falls can cause psychological and physiological impairment and lead to serious injury or even death if there is no immediate health care assistance.

To eliminate falls cases among older people, it is necessary to develop a reliable fall detection system that helps many people, especially the elderly. The fall detection system has drawn the attention of researchers to conduct more studies and surveys and has always been a major research topic in the daily healthcare of the elderly for the past twenty years. Having a fall event detection system is important if it is an automated gadget that is able to send immediate alarm to the caregivers when elderly needs help.

Fall detection systems are primarily being developed for use with most of the elderly. Thus, it's vital that the system design is not intrusive. In any developed system, there are still many drawbacks that need to be improved. As the device should be always attached to the user wherever he/she goes. Designing a user-friendly fall detection system is an essential element. Such a device should be an easily attached mobile gadget. Moreover, it would like to be sensor-based wearable devices which are mostly not heavy. In addition, it should be available at an affordable price.

Another important aspect which needs to be considered during the design of fall detection system is power consumption. Fall detection systems usually contain a high number of sensors which normally require continuous power supply to remain sensors ON all time. Therefore, the power consumption model for all sensors and networks of fall detection systems should be carefully designed. Other than that, the use of any camera based design will only destroy the user's privacy as it will be constantly monitored. Developing a fall detection system seems to be the best approach to reduce the fall cases count and reduce the burden on healthcare workers [3].

2 Literature review

2.1 Background of fall detection system

Figure 1 outlines a standard device used in detecting falls. The device will start sending real time data to a processing unit. It causes triggering/warning when the algorithm catches a fall. It may be in the form of a warning sound (to get attention and seek help from surrounding people), quick action (e.g., airbag inflation), or sending messages to caregivers. The data can also include the time of unconsciousness of the faller's accident, place, status, and direction.

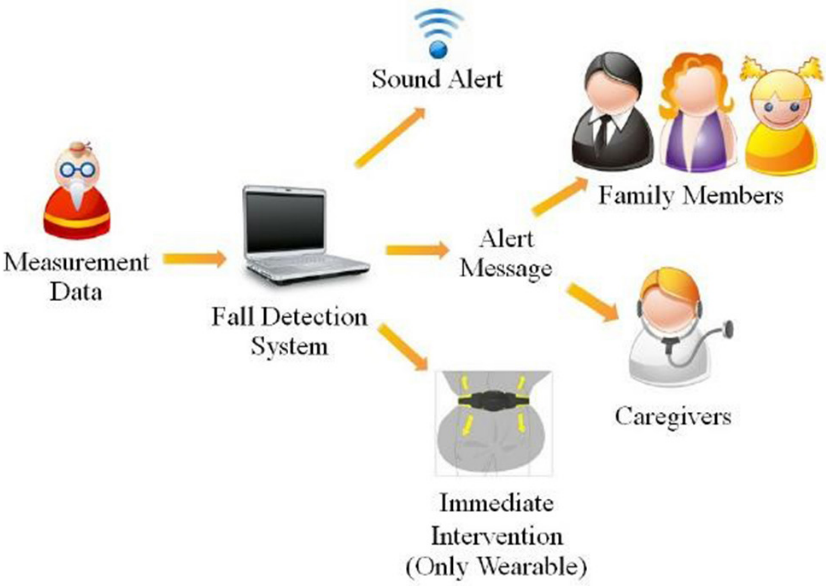

Fig. 1. Fall detection system mechanism

Fall detection system has become an interesting research area for many researchers, the system is an assistive gadget that functions automatically and gives warning or messages to caregivers to assist when it is necessary. Besides, the system should be user-friendly where allow elderly people can freely walk around and their movements are not limited. As an example, a camera-based system may limit the person to move around as they wish to which the subject matter to be in a particular Region of Interest (ROI); whereas wearable based-sensor methods give more freedom for the subject to move around. The difference between falling events and the 'activities of daily life' (ADL) or even almost fall situations are the most critical need in designing the system to detect falls [8].

There is a method that has been made to ease the subject when calling for help after fall happens which is 'Personal Emergency Response Systems (PERS)' or automatic fall detection systems [9]. However, some individuals cannot activate the PERS devices at a certain amount of time in some cases of emergency such as after falling or fainting or unconsciousness, etc. Due to some shock or loss of consciousness, it has been reported that more than 80 percent of the elderly were unfamiliar with the use of the device to seek help.

Based on the existing studies and research, three main methods have been developed for fall detection systems that are a camera-based method, a wearable sensor-based method, and an ambient sensor-based method. To be explained more, sensors like pressure, passive infrared sensors, etc. are used to detect falls within an area for ambient sensor-based methods. The good thing about this method where it is not expensive and non-intrusive. Nevertheless, with limited distance and other environmental factors that will result in inaccuracy and specificity. The next method is a camera-based method that involves a camera and a computer to track and monitor the movement of a person. The benefit of this system is that more than one event can be detected and monitored simultaneously and also it is a non-wearable device that gives comfort to the subject involved. Nonetheless, the system is only within a small and specific area and more expensive than the other two methods. Other than that, wearable-based approaches are where most of the studies and research are about this method in detecting falls. This method has a device attached to the user with some sensors such as an accelerometer and gyroscope. On top of that, this method is one of the cheapest and easy to use among all methods that had been mentioned before. However, the cons of using this device are that sometimes the user carelessly gives false alarm/warning to the caregivers.

2.2 Wearable sensor-based device

The wearable-based system is when the devices are attached to users with embedded sensors to get available data like acceleration and orientation then the system processes data by algorithms to recognize whether the users are experiencing fall or not. In addition, most wearable device systems are in the form of accelerometer devices and usually link with gyroscope sensors to obtain the position of the users. Wearable devices provide the best system and have the cheapest sensors to provide self-dependence for the old people.

The most critical part in the design of wearable sensor-based fall detection system is the place of the sensor. The frequent positions that are usually used for experiments are waist, thigh, foot, and head. The waist is almost the centre of the human body mass, also the neck that will support the head and the balance of the body when humans are performing ADL. When the body hits the ground, sensors attached will detect larger accelerations and positions of the humans. Hence, the method that will be focused on this paper is wearable sensor device based. There are two main techniques to detect fall with this system: 'Machine Learning-Based' systems and 'Threshold-Based' systems as illustrated in Figure 2.

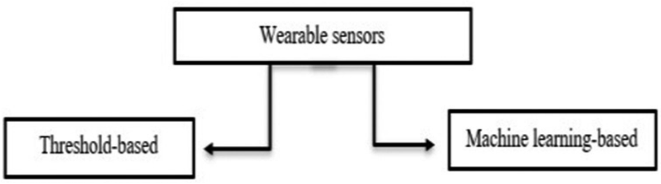

Fig. 2. Wearable sensors device-based system

In a threshold-based system, fall is reported when the acceleration reaches pre-defined thresholds. In addition, this approach has been focused on the capability in detecting and recognizing fall from ADL, and the reading of sensors from single or multiple threshold values. Besides, the approaches are simpler and also computationally low in cost. On the other hand, the machine learning approach is where different features of fall and the ADL patterns can be detected with the use of labelled data to train a classifier using its algorithms such as 'Decision Tree', 'Support Vector Machine' (SVM), 'Hidden Markov Model' (HMM), and 'Neural Network'.

3 Related works

3.1 Threshold-based wearable system method

A threshold-based algorithm is where the fall can be recognized when one or multiple features of sensor readings exceeds a predefined threshold. For example, authors in paper [10], made threshold-based fall detection algorithms with the use of bi-axial gyroscope sensors and three threshold values have been identified by them. In addition, Wu et al. had proposed a tri-axial accelerometer system and came up with an algorithm that is based on sum acceleration thresholds and information about the angles of rotation [11]. Therefore, this algorithm had reported a good sensitivity and specificity of the system when the threshold values merged with the quaternion rotation. For past works, countless systems for fall detection have been developed using various kinds of sensors. In [12], accelerometer and gyroscope sensors integrated had been used by Rakhman et al. into a smartphone and had verified some threshold-based algorithm and sensor data to detect the fall. The same goes for [13] where Huynh et al. made a device with built-in triaxial accelerometers and gyroscopes for detecting falls and making use of the threshold-based algorithm. Basically, this type of algorithm has values that are lesser acceleration, higher acceleration, lesser angular velocity to check whether the subject has fallen or not. The results had shown high sensitivity and specificity with not less than 96 percent.

Under certain conditions in systems, the precision of threshold-based fall detection may not be correct since only the accelerometer is used. For instance, Habaebi et al. had suggested an efficient and affordable fall detection system by using an accelerometer with the help of ZigBee as a wireless connection that will benefit patients and caregivers alike [14]. The results in this article verified the specificity, sensitivity, and accuracy of the system for fall recognition. Other than that, in Shahiduzzaman's paper in 2015, by using more than one sensor, he combined the accelerometer with the 'Heart Rate Variability (HRV)' sensor [15]. Messages from the HRV sensor will check the abnormalities in the heart rates due to the anxiety at the time someone is falling. Based on the data collected, the accuracy with the means for distinguishing falls from ADL is more than 96 percent. Nevertheless, Wang et al. made a fall detection system by applying tri-axial accelerometers and wireless sensor networks [16]. False positives occurred when only one sensor is used which is an accelerometer. As an example, sitting down faster only will develop similar vertical acceleration. Hence, it is important to combine a triaxial accelerometer with a gyroscope to detect falls for every working paper. On the other hand, Casilari et al. (2016) compared different threshold-based algorithms that use data collected from a smartphone. This method is very simple where the fall is detected when the acceleration magnitude surpasses a threshold within a 1-second interval of time [17]. The results had shown low in performance in terms of sensitivity and specificity with 90 percent and 91.7 percent respectively. This can be acceptable but not that good since the movement of the arm maybe not associated with the measured activity.

There are some recent studies that combined Machine learning algorithms with threshold-based sensors such as Koshmak et al. [18] which acceleration of subject, pulse are observed through a smartphone, combined with the context that is incorporated by 'Passive Infrared sensor' (PIR), pressure mats, etc. With the help of the Bayesian Networks classifier, fall detection can be performed by all of the sources.

To lessen overhead computation, threshold-based algorithms are designed. However, the values of the threshold may be varied due to the position of sensors and activity pattern of the individual. Based on the article by Mao et al., they stated that the position of sensors and the threshold value are the factors that will affect the accuracy of fall detection. In their experiments, the sensors are placed on the shoulder, waist, and foot [19]. By varying both acceleration of the threshold and the position of the sensor will improve the capability of the systems. The results had shown that the waist attached to the sensor has the best performance, among others. In an article where the numerical threshold is set on acceleration along with a threshold-based study of accelerometer data, Kostopoulos et al. had focused on the rebound of the subject and the remaining movement in the post-fall phase for the detection system. The largest and the lowest threshold value of acceleration over the minimum amount of time are used to detect the fall circumstances [20]. The difference between maximum and minimum thresholds are calculated to determine the rebound of the subject. Afterward, fall is classified subsequently by relying on the values of the acceleration. Basically, a post-fall study is conducted to observe the impacts of the fall event which then decide if an alarm sent to the caregiver to be cancelled or not.

Several recent papers where the proposed system had worked based on sensors that were embedded in the smartphone. However, the problem of this system is that the mobile phone needs to be carried all the time and to be changed frequently to detect a fall. Another difficulty is that not all phones have specific sensors that are already provided in it. Also, phone drops will cause false results in detecting falls. For example, these authors had developed a threshold-based method for detecting falls and phone drops using the G-force value that is from accelerometer readings [21]. There are 3 levels in checking the algorithm which are during dropping the phone, detecting fall, and confirming the fall.

3.2 Machine-learning based wearable system method

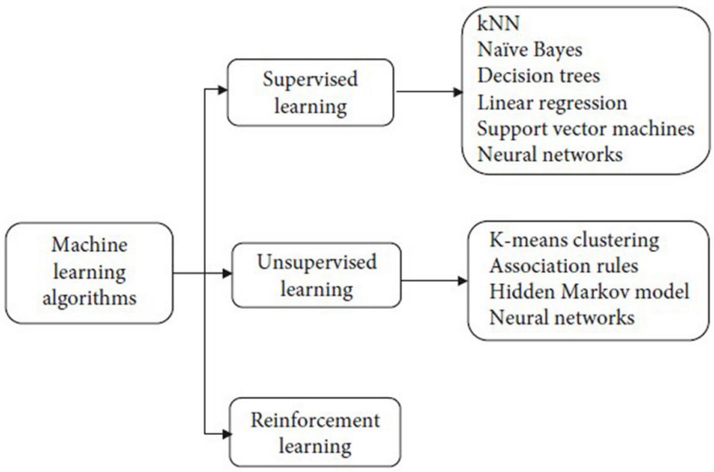

Fig. 3. Taxonomy of machine learning algorithms

Figure 3 depicts that machine learning algorithms can be divided into three parts. The most used one is supervised learning among others. Basically, it is true that threshold-based systems have been in recent studies and surveys due to their low computational overhead, but still, it could lead to false results in the performance obtained that different factors can affect the thresholds themselves.

Therefore, the machine learning method is the new possible way to increase the accuracy and specificity of the system compared to threshold based. The study on the efficiencies of various methods of machine learning has been made for fall detection systems. For instance, De Quadros et al. (2018) making a comparison between threshold-based and machine learning methods for fall detection appealed to data collected by accelerometers, gyroscopes, and magnetometers [22]. The study had finalized that the ML-based had better performance than threshold-based methods. Similarly, in other papers, five various threshold-based methods and five machine learning methods by using tri-axial accelerometer data from a device attached at the subject's waist are examinated to see the performance. Based on the observation, the best accuracy achieved by machine learning with 96 percent whereas threshold-based got 94 percent only.

Machine learning-based has different techniques in terms of the set of features used, sensors used, sensors placement, applied algorithms, the dataset used, monitoring of parameters, and so on. Some research is mainly focused on supervised learning with strong results of the performance of wearable-based fall detection systems. The authors in [23] focused on the features of acceleration and the strength of magnetic fields of earths along the perpendicular-axes to detect the fall. By using different techniques of ML in the paper, performance of some various methods had been compared and it is shown that 'k Nearest Neighbour' and 'Least Square Method' (LSM) did not miss any fall which was considered as the best classifiers among other techniques. Besides, Choi et al. had used a single node and two nodes to compare the machine-learning algorithm [24]. The results had shown that the accuracy of 99.4 percent achieved in a single node where the accelerometer and gyroscope sensors attached to chest level while the accuracy of 99.8 percent has been achieved when using two nodes that are placed on the thigh. In both cases, it can be concluded that the NaiveBayes classifier worked really well.

Furthermore, Jefiza et al. [25] used the Back Propagation Neural Network (BPNN) to detect fall with 3-axis accelerometers and gyroscopes data and recorded 98.182 percent accuracy, 98.33 percent accuracy, 95.161 percent sensitivity, and 99.367 percent specificity. Other than that, these authors [26] made a comparison on the performance of machine-learning algorithms with various kinds of falls that are forward, backward, right and left. Among three of the algorithms tested, 'Support Vector Machine (SVM)' has the highest accuracy and precision.

Machine learning algorithms were also used sensors consolidated with mobile phones, much like thresholdbased techniques. An article on a method for the detection of falls is proposed as an example, a machine learning classification using mobile phones. Accelerations with other machine learning algorithms have been used as features for making comparisons [27]. The results had shown that both 'SVM' and 'Sparse Multinomial Logistic Regression (SMLR)' could make a 98 percent accuracy of the fall event using mobile phones.

While supervised learning approaches can see more use in fall detection as have been raised just now, unsupervised learning is also not an uncommon thing. For example, Lim et al. (2018) stated that supervised-based learning has some restrictions regarding detecting flaws and classifying behaviour and therefore they tried unsupervised learning instead [28]. The algorithm created a model of the probability using previous activity information from accelerometer readings of a subject. After that, the model was used to evaluate if there is an abnormal activity or not. Advantage of this method is that it achieved a qualified degree of personalization in fall event detection. Certain observations on wearable sensors gave some disadvantages where the position of sensors give effects to the accuracy of the fall detection. Yu et al. (2018) used the Hidden Markov Model (HMM) algorithm to reduce the errors of wrong sensor positions [29]. The orientation of the sensors is applied to the algorithm classifier to avoid misaligned position and orientation of the sensors. The article had reported 99.2 to 100 percent sensitivity on the dataset.

Some studies focusing on energy efficiency in fall detection. Guvensan et al. (2017) combined both threshold and machine learning algorithms. The classifiers were applied to the data that had been generated from the 3D accelerometer that was attached to the mobile phone [30]. The algorithm had applied three tiers which are pre-elimination tier, double thresholding tier, and machine learning tier. Each of these tiers has its task to do. The energy-saving was reported to be more than 62 percent compared to machine-learning only methods.

Figure 4 below shows the flow diagram for the machine-learning mechanism. There are many ways for improving the algorithm performance used for fall event detection systems, improving data pre-processing, influencing the extraction of features, and applying sets to fall detection. The purpose was to differentiate falls from ADL. The wearable fall event detection system here in this study consists of a wearable sensor and a mobile phone [31]. The system operates by applying windows sliding to analyse data streams instead of analysing instantaneous acceleration values and angular velocities. It used the 'Kalman filter' to pre-process the raw noise reduction data and for fall detection, the 'Bayes network' classifier was used. The algorithm was capable of differentiating simulated falls from ADL with 95.67 percent accuracy, 99.0 percent sensitivity, and 95.0 percent specificity.

Fig. 4. Flow diagram of machine-learning method

In addition, Zhao et al. (2015) applied a windowing technique by obtaining real time data from a tri-axial gyroscope [32]. The data are categorized into an overlapping set of windows. The time domain features which are the replace of maximum resultant and it's angular acceleration, and also the fluctuation frequency were taken out from the data windows. Then, a classifier called decision tree was used to classify every window as a fall event or not. The results gave 99.52 percent for accuracy and 99.3 percent for the precision.

Besides, authors in [33] had suggested a 'hybrid' method between the fall event detection based on thresholds and ML algorithms. In this paper, a threshold-based algorithm is developed to detect fall events when classifying ADL using a supervised machine learning algorithm. In the smartphone, data was collected from sensors called Inertial Measurement Unit (IMU). For detection and classification, there are four different classifiers used which are 'kNN', 'SVM', 'decision tree', and 'discriminant analyses. A field of recent research was the development of deep learning methods for the detection of falls using wearable-device based. Fakhrulddin et al. (2017) used the 'Convolutional Neural Network' (CNN) to the streaming time series of the accelerometer data from 'Body Sensor Networks (BSN)' for fall and non-fall circumstances [34]. Other than that, Torti et al. also detailed the implementation of 'Recurrent Neural Network (RNN)' algorithms for regulated devices on a Microcontroller Unit, with the help of a tri-axial accelerometer for detecting fall [35]. For a comprehensive review, readers are advised to consult [37, 38].

4 Methodology

4.1 Design

The fall detection system model is shown in Figure 5 and mainly comprise of five parts which are: acquiring data, pre-processing, training, and classifying of data, and evaluation classifier. Figure 6 elaborate more for the proposed fall detection system. In the event of a fall event, gravity, accelerometer, and gyroscope sensory data are gathered on a smartphone using the "AndroSensor" application. This data is processed by the machine learning algorithm with the use of MATLAB toolbox. The classifier is trained and then tested.

Fig. 5. Components of fall detection system model

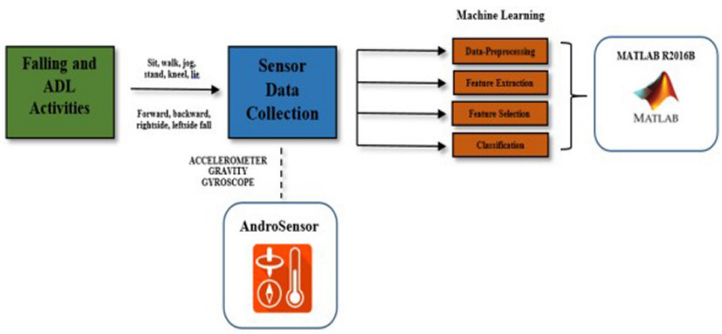

Fig. 6. Proposed block diagram of fall detection system

4.2 Acquiring data

The beginning of the methodology proposed is to collect data which will be used in data preprocessing stage. The proposed system uses the "AndroSensor" application of a smartphone that collects data from gyroscopes, accelerometers, and gravity sensors to produce them according to fall events or human activities daily life (ADL). The typical position of the phone sensor is shown in Figure 7 below.

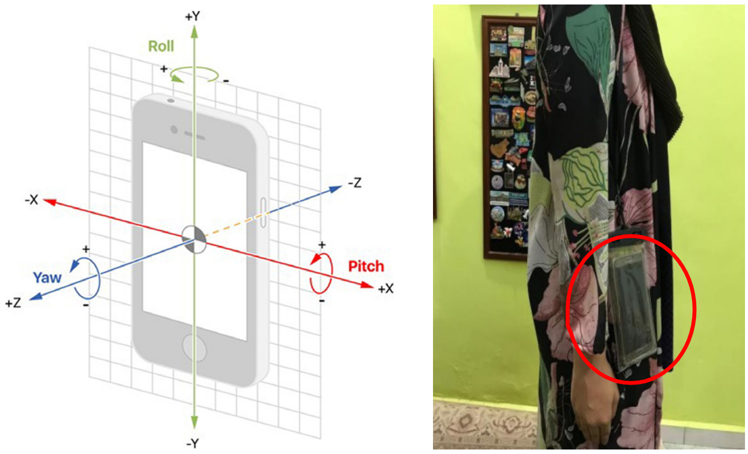

Fig. 7. Position of phone sensor at waist

Every axis on the sensor has different functions on the smartphone [35]. The X-axis is to measure the lateral movement of the user. The value of the X-axis will increase if it moves to the left and the value will be decreased if it is moved to the right. For the Y-axis, the movement is measured upward and downward. It has a gravity value of 9.81 for this case as the phone is placed vertically. The value will be decreased if the smartphone is moved towards the sky and increased if it is moved towards the ground. On the other hand, Z-axis is to measure the movement to the front and rear. The value will decrease if it moves to the front and increase if it moves to the rear.

The accelerometer used is an electromechanical instrument for calculating acceleration performance. In addition, a dynamic sensor is used to detect movements or vibrations. The gyroscope sensor, on the other hand, detects the angular velocity while the gravity sensor is used to calculate the orientation of user behaviour. The gravity sensor gives a 3-D vector that indicates the magnitude and direction of the force of gravity.

A middle-aged female volunteered for fall and other AVD events. The sensor is brought to the position of the waist, which according to previous researchers has the highest precision. All sensors are sample-read in the time interval to generate the raw data. The readings are collected based on common activities such as sleeping, walking, sitting, kneeling, and jogging. Different types of events were also examined, including falling forward, falling backward, falling to the left, and falling to the right. The data is analysed and visualized in MATLAB software using a machine learning algorithm. Snapshot samples of the jogging activity and forward and backward fall events, captured by the different sensors, are shown in Figure 8 below.

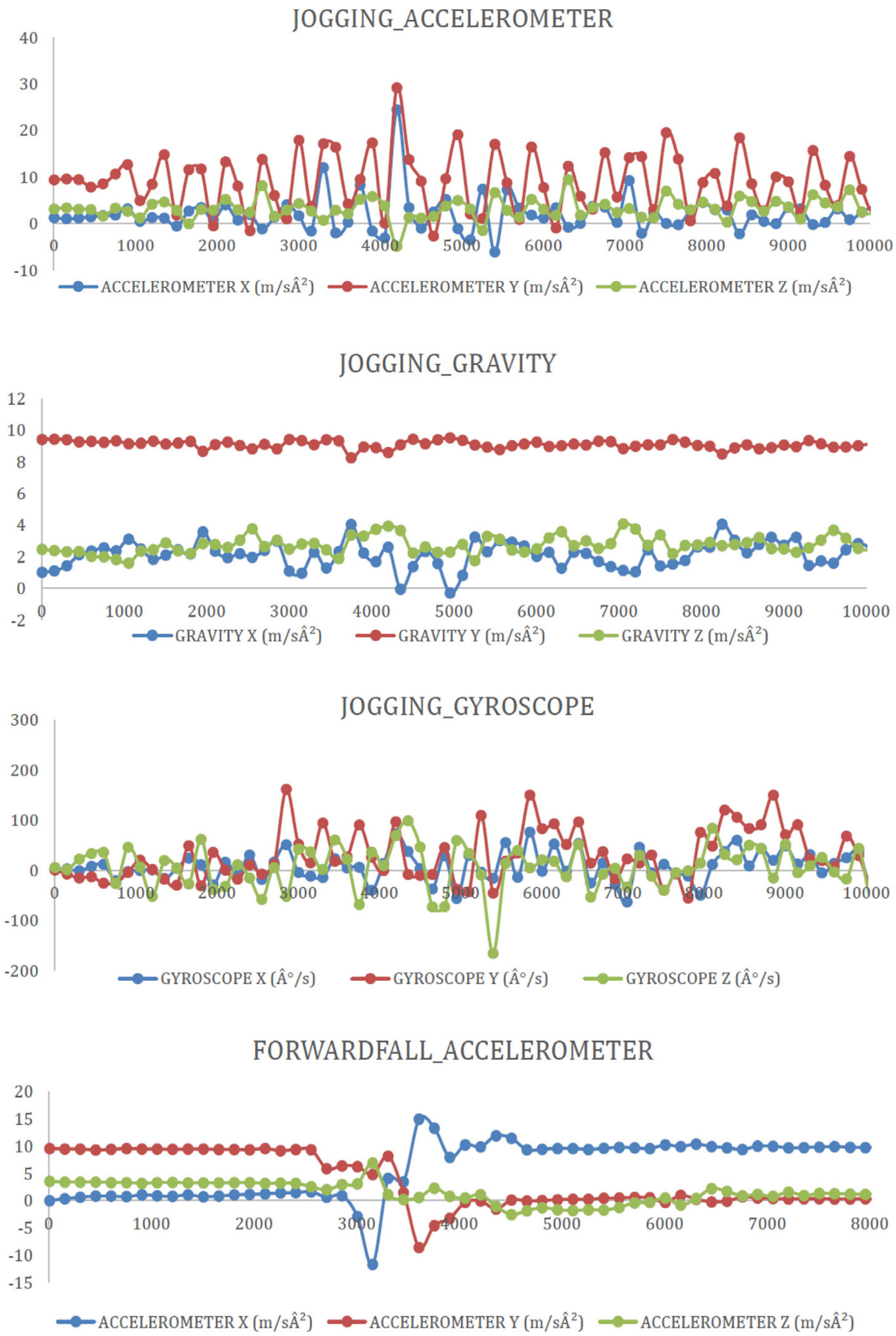

Fig. 8. *(Continued)*

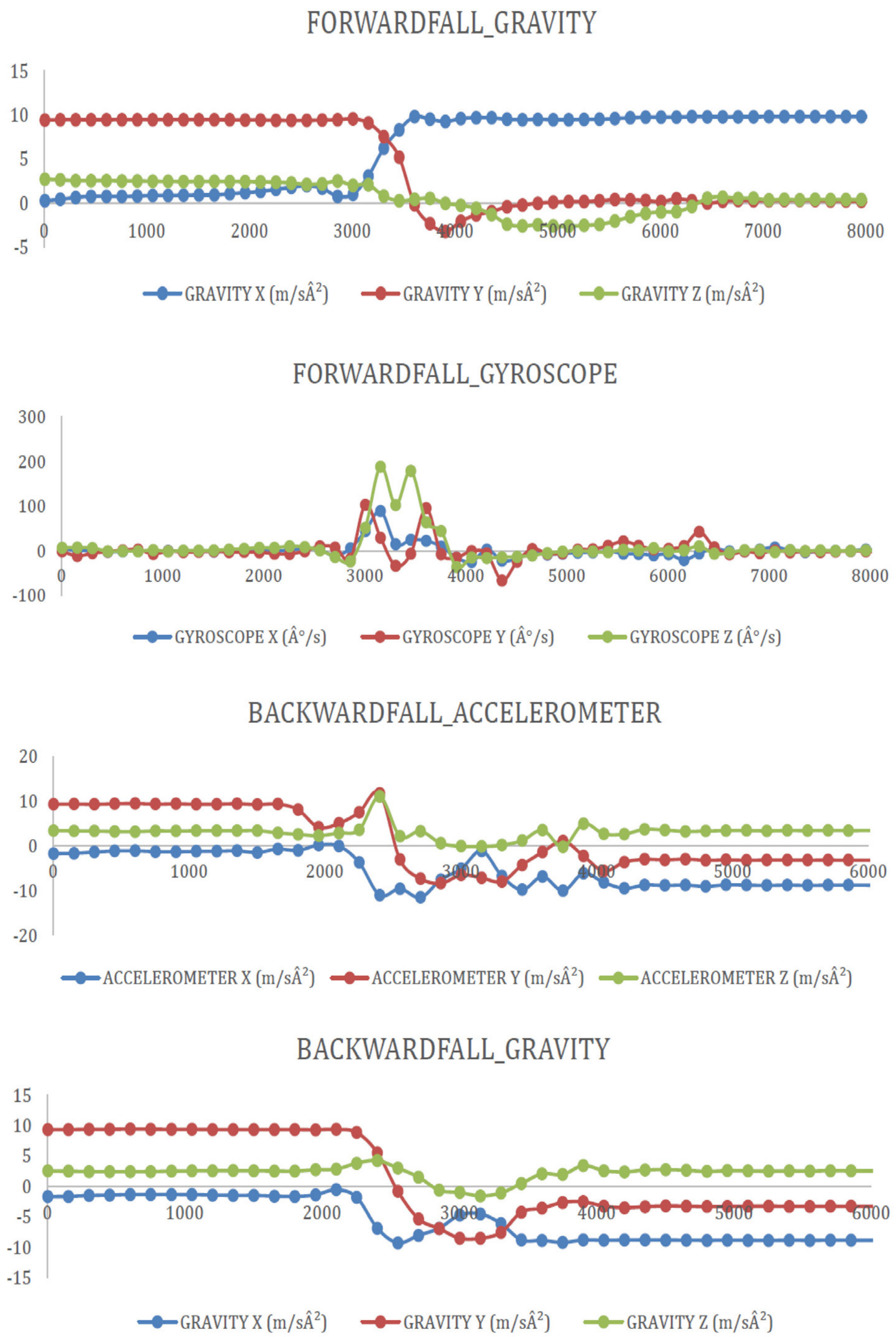

Fig. 8. *(Continued)*

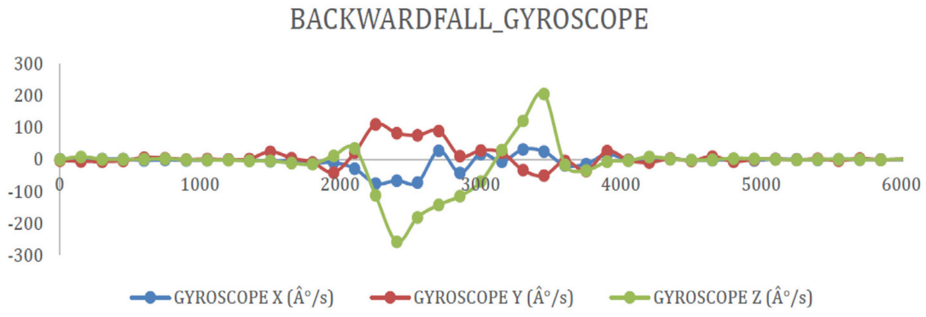

Fig. 8. Snapshots of jogging activity and forward and backward fall events captured by different sensors

4.3 Preprocessing data

When data collection is completed, the pre-processing of data follows. Data preprocessing is an indispensable process performed prior to analysing sensor data. In fact, it is vital to identify or even replace missing values in the data set. This process is used to eradicate undesirable noise from the signal so that machine learning algorithms can perform a better classification. In addition to the classification, existence of noise may impact the precision and accuracy of the algorithms.

Several kinds of filters that are used as described in previous research. At present work, to reduce the complexity with less computational cost, the Butterworth low pass filter with fourth order infinite impulse response (IIR) is used with the cut-off frequency Fc = 5 Hz.

4.4 Extraction feature

Once the raw data is preprocessed, feature extraction is the following step in the classification. At the present work, as shown in Table 1 the six features were extracted from preprocessed dataset. These features include minimum, maximum, mean, variance, skewness, and kurtosis of the dataset. The features can be expressed mathematically as shown in Table 1. Every feature is drawn from the 3 data gravity, accelerometer, and gyroscope sensors, along the 3-D axes. Size of a function or a feature for a sensor along the 3 axes is [1(number of samples) × 1(number of functions) × 1(number of axes)]. In this approach, the size of the 6 features together with the 3 axes from each individual sensor becomes [1(number of samples) × 6(number of features) × 3(number of axes)] = [1(row) × 18(Column)] to get a sample. Therefore, the final size feature vector is [1(row) × 54(column)] for the 3 sensors along the 3 axes in a sample.

Table 1. Extracted features

Features	Equation
Maximum value	$\max\ (a[k])$
Minimum value	$\min\ (a[k])$
Mean value	$\mu = \frac{1}{N}\sum a[k]$
Variance	$\mu = \frac{1}{N}\sum (a[k] - \mu)^2$
Kurtosis	$K = \frac{m^4}{(m^3)^2}$
Skewness	$S = \frac{m^3}{(m^3)^{\frac{2}{3}}}$

4.5 Data training & classification

Once the trait extraction is complete, the next step is important to classify each activity, be it fall vent or any other ADL activity. During the training stage, various types of algorithms are tried in MATLAB to train the developed model using the dataset with a machine learning classification application. The learning algorithm attempts then to find hidden patterns in the dataset that link input data appropriately to one of the used classifications. A classifier is then created that classifies then observes the new pending dataset. Therefore, the entire dataset is divided into 8 classes based on the different types of falls and ADL activities. There are four kinds of different types of falls, i. H. Falls forward, backward, right, and left. Conversely, there are also four classes for Non-falls, that is walking, sitting, lying down and jogging.

Once the sample has been labelled, a ten-fold cross validation technique is applied to the data to make sure that the ML classifier model is the optimum choice to predict, and that bias is reduced. Next, 4 ML algorithms are utilized for evaluating the proposed system performance. Algorithms include support vector machine (SVM), complex tree classifier (CT), nearest neighbour (kNN), and logistic regression (LR).

Most of the machine learning algorithms research works focus on the performance of precision and accuracy where negative false and positives false events can be avoided; whereas this work focuses on how the ML models are used to understand the dataset, during training, and identify new observations based on the learning. New data consists of the values of the gravity, accelerometer, and gyroscope readings that are flowing into the model. Our model classifies whether these new observations fall into the category of sitting, sleeping, walking, jogging, or falling.

The machine learning classifier that this article focuses on and strives for is the SVM classifier, as done in previous research [4], [5] and [36]. This classifier had performed better with respect to sensitivity and accuracy in comparison with other classifiers. The SVM classifier [6] is utilised based on decision levels, which define the decision limits where the decision level separates between a set of objects with different class parts.

4.6 The flowchart

In Figure 9, the system begins the process of using gyroscope, accelerometer, and gravity sensors in an attempt to identify an activity or event using the AndroSensor app running on a smartphone. Sensor data is then analysed and visualised with MATLAB software. The ML model (classifier) built in MATLAB learns and identifies the event of whether the user is walking, sleeping, sitting, or in some other type of fall.

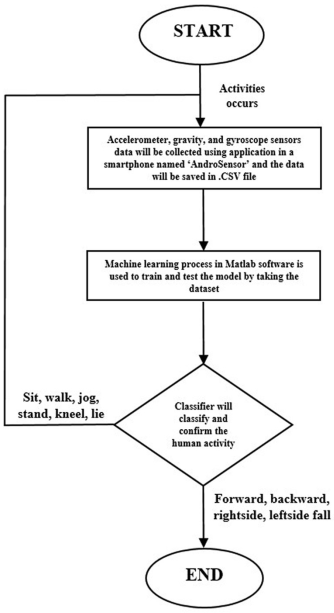

Fig. 9. Fall detection system flowchart

5 Results analysis

5.1 ML-application classifier

As aforementioned, the ML classifier can define the performance capability of the proposed system. The MLA classifier is training and testing the data to predict ADL activity and drop event data after going through each step from data analysis to feature extraction. Figure 10 illustrates the first step in training the data set. After browsing the Application Classifier in MATLAB, the data set saved in Excel was selected for training, specifying the number of columns and rows in the data set. There are 8 fall activity classes and AVDs that are selected as an answer in this case. The sensor data previously extracted would be a predictor. The cross validation with the tenfold scheme is applied for training and testing, so the data set is randomly broken into 10 folds, each time is nine folds for training while one-fold is used for testing. Therefore, the complete dataset from this project is utilized for training and testing processes.

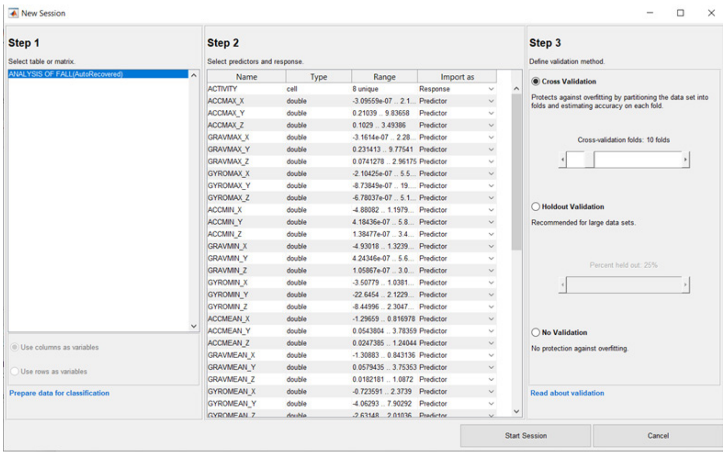

Fig. 10. Selected data set for training and testing

5.2 Classifiers performance

Sensitivity, specificity, and accuracy are considered to analyse the performance metrics of the proposed algorithm. These parameters may define as follow:

1. *Sensitivity (SE). Measures the system ability to detect falls. It's the ratio of the true positive to total count of falls. It can also be expressed mathematically as:*

$$SE = \frac{TP}{TP + FN} \times 100$$

2. *Specificity (SP). It determines the capability of the system to detect a fall only if it occurs. And it is expressed as follow:*

$$SP = \frac{TN}{TN + FP} \times 100$$

3. *Accuracy. It's the system ability to distinguish between falling and non-falling events. Expressed mathematically, it can be quoted as:*

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100$$

Where the TP is defined as True Positive, when a fall happens and the algorithm can detect it, whereas TN defined as True Negative, when no fall occurs, and the algorithm doesn't detect the fall. The FP is a False Positive. That is, no fall occurs, but the algorithm detects a fall. The FN defined as False Negative that occurs when the fall occurs, but the ML algorithm can't detect it.

In this testing experiment, three kinds of ML classifiers were compared, namely; DT, kNN, and SVM. Although the focus of this experiment is on the SVM classifier, we find that all 3 classifiers perform their best with full accuracy, specificity, and sensitivity. The details are shown in Figure 11 using the confusion matrix. The results are based on eight kinds of events, including non-fall and fall events.

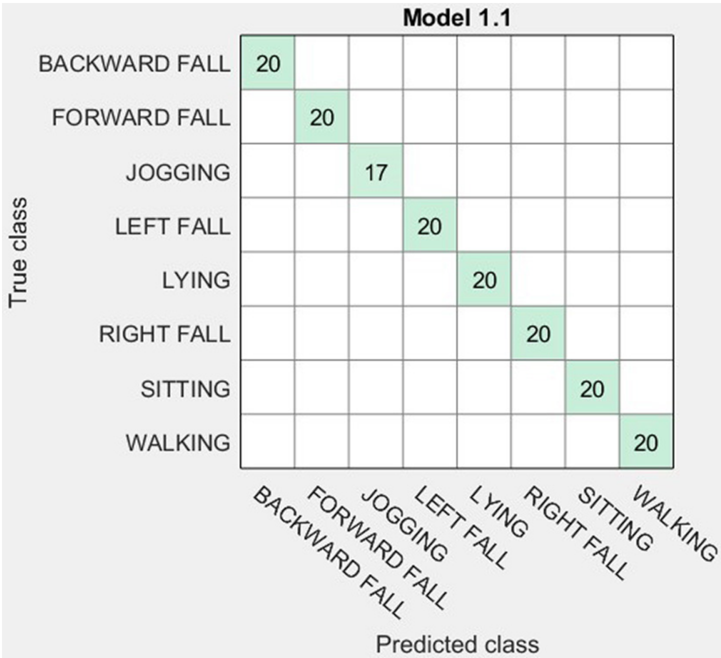

Fig. 11. DT, Knn and SVM confusion matrix

5.3 The test data

Once data training is over, the balance 20% of the entire dataset will be used to test the model. Test data is crucial in making the prediction. The used classifier for the test data is the quadratic SVM classifier. This classifier has the best performances compared to other classifiers. Figure 12 illustrates the confusion matrix which generated from the test and prediction that was simulated in MATLAB. This confusion matrix makes it easy to determine the specificity, sensitivity, and accuracy of test data by coding.

```
cm =

     4     0     0     0     0     0     0     0
     0     5     0     0     0     0     0     0
     0     0     7     0     0     0     0     0
     0     0     0     6     0     0     0     0
     0     0     0     0     5     0     0     0
     0     0     0     0     0     7     0     0
     0     0     0     0     0     0     6     0
     0     0     0     0     0     0     0     7


order =

    'FORWARD FALL'
    'BACKWARD FALL'
    'RIGHT FALL'
    'LEFT FALL'
    'WALKING'
    'JOGGING'
    'SITTING'
    'LYING'
```

Fig. 12. Test data confusion matrix

5.4 Benchmarking against related works

As mentioned in the previous research works, several methods and recommendations were made to ensure the system performance. Such as in [4], they tested datasets with a simple implementation of the most frequently used feature extractions and threshold-based classifications, accomplishing up to 96% accuracy in the case of fall detection. In [5], a Kalman filter-based fall detection method was proposed using a nonlinear classifier and a periodic detector in order to reduce the false positive rate. As a result of this method, a 99.4% accuracy was achieved. In addition, Miguel Pires used a public dataset with a computationally efficient and quite simple feature set to accurately identify a fall accident. Therefore, 99.98% accuracy was achieved using the SVM classifier. In Table 2, the proposed system has performed better with a 100% accuracy, sensitivity, and specificity compared to the other classifiers that were developed.

Table 2. Benchmarking the proposed system against previous research works

Research Paper	MLA	Sensitivity	Specificity	Accuracy
[4]	No	95.5%	95.96%	96.38%
[5]	Yes	99.27%	99.33%	99.37%
[6]	Yes	99.94%	100%	99.98
[36]	Yes	high	NA	NA
Proposed system	Yes	100%	100%	100%

6 Conclusions

Nowadays, every elderly person is carrying a smart phone with them everywhere they go to keep their loved ones and care takers aware of their activities. The combination of available smart phone sensor apps like "AndroSensor" App with Machine Learning serve as a powerful tool for wearable smart phone sensor-based fall event detection system for elderly people. Collected sensory data from Accelerometer, Gravity, Gyroscope are sufficient to lead to an early fall detection and alarm system to save lives. Collected data is pre-processed for unwanted noise elimination and signal smoothing using filters. Extracted features are then used for training and testing on several machine-learning classifiers. Support Vector Machine classifier has proven to be the best in terms of specificity, accuracy, and sensitivity However, its performance can be improved further with larger sized sample and more field-testing using the elderly people under the supervision of medical staff.

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