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To What Extent is the Motion Sensor of a Phone Accurate for Fall Detection?

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Abstract

Falling is a major problem world-wide, and its impact on health services will become increasingly predominant as the population increases. This paper investigates whether a phone can accurately detect falls based on its sensor readings, to act as an effective and affordable implementation of fall detection. Accelerometer and gyroscope readings were collected from the phone's built-in sensor via a specially built application. Mathematical and computational approaches (thresholds and machine learning respectively) were applied to the data to classify whether it was fall or not fall. Experimental results found that phones produced relatively high accuracy rates but could not match that of competing fall detection methods such as IMU devices and smart watches. This paper concludes by expressing phones have the potential to be an alternative method of fall detection and suggests optimizing algorithms and applying it to more data to better represent its performance.

1 Introduction

1.1 Problem

According to the World Health Organization, falling is the second leading cause of 'unintentional injury deaths' worldwide [1]. It is estimated that every year, 684000 people die from falling over (globally), with adults aged 60 and above being at a significantly greater risk. Around one-fifth of the UK's population is aged 65 and over [2], putting it on the forefront of the problem. Although not all falls are fatal, many are still life-threatening, with a plethora of reasons why this may be the case. Falling can lead to broken bones, damaged ligaments and tendons which may take time to heal, or potentially, leave the person with a permanent disability. It can also lead to brain injuries or damage vital internal organs. The person may also be affected psychologically; they may lose confidence or feel as if they can no longer live independently.

Similarly, falling can come with financial issues, especially in cases where individuals must pay for their healthcare (in countries such as Canada or USA). They must pay for any medications, equipment or surgery needed to prevent a fall as well as those that came as a result. In 2015, the total medical costs associated with falls came to a total of more than $50 million in the United States alone [3].

With the total population expected to continue rising by 1.0% per year [4], and the elderly population to double by 2050 [5], this problem will become ever more prominent and therefore pose a greater stress on health services internationally.

1.2 Literature Review

There are many ways of preventing a fall, ranging from developing daily habits such as tying shoelaces, and mopping up spillages, to strength and balance training. However, as advancements are being made, many people turn to technology.

The phone is the most commonly used and owned piece of technology with desktop Personal Computers coming in second. 53.5 million people in the UK own a smartphone, making it roughly 80% of the population [6]. Globally, the number of people who own a phone is expected to rise as the younger generations age and lower income countries become more developed. Therefore, it may be an easy-to-use, inexpensive way to implement fall detection.

That is not to say, the phone is the only possible method. Other technologies can be used, for example, watches or wearable IMU (Inertial Movement Unit) devices. Like the phone, these use gyroscopes, and accelerometers to measure movement and likely uses a machine learning algorithm to detect when/if a person has fallen over. Fitbit and Apple watches are commonly used. However, the fall detection feature on these have mixed reviews, with Apple stating that their watches 'cannot detect all falls' [7]. Moreover, there is the case of False Positives, where the watch reports a fall that never occurred. This mistake could be due to sudden movements of a person's hand (or elsewhere on the body in the case of IMUs). With time, the effectiveness of fall detection features will improve, as technological advancements are made in both the sensors as well as the detection methods.

Similarly, cameras can be used to track movement and detect if a person has fallen over based on its visual input. It can also record what caused the fall and how the person fell. Because cameras are not portable, this method is mostly implemented in areas where there is a high concentration of people who are likely to fall, for example, an elderly home or a hospital.

The main drawback to the mentioned options is the cost. A (sometimes large) financial investment is needed, which many cannot afford – a smart watch can cost hundreds of pounds. Since most people already own a phone, little to no investment is needed making it the much more affordable alternative.

A technological approach will be the most effective and efficient method for data analysis. This could mean using a program to visualize the data in the form of a graph or chart and proceeding to analyse it using code. There is a wide variety of programming languages capable of this. However, it is widely accepted that Python is the go-to language, as it has many libraries and extensions such as Pandas and NumPy (among many others), specifically built for the task. It also has a strong background in machine learning and artificial intelligence, with over 60% of developers using and prioritising it for development [8].

There are many papers dedicated to fall detection, exploring different areas of the subject, as it is a prominent problem [9] [10] [11]. For example, existing 'pre-impact' apparatus, indicators and algorithms has been reviewed by Hu and Qu for their performance and sensitivity [9], to help prevent a fall or minimize the effect. These can help activate 'on-demand fall injury prevention systems' such as inflatable hips as suggested by the paper. Before proposing future research directions, the writers also summarized the limitations of current designs. One such limitation is current technology – wearable sensors are susceptible to noise, context-aware systems (such as cameras or a device which tracked fluctuation of radiofrequency) are expensive and requires high computational power. Another is limited external validity – actual fall data is hard to acquire so most fall data are collected from simulations, potentially making them inaccurate, unrealistic.

Similarly, Khan and Hoey surveyed the availability of data [10] used to train supervised machine learning algorithms. They produced a taxonomy, which categorised distinct types of accessible data, independent of sensors used or selection methods. Their paper explained different techniques which may be used for different types of data – labelled, semi-labelled and unlabelled data, or when there is an insufficient amount. For example, an algorithm may detect a fall by sensing anomalies instead of looking at sensor reading patterns, in the case of training data absence. It also notes that implementing thresholds on sensor readings may be inexpensive but is hard to generalize across different people and is therefore inaccurate. Like the previous article, it agreed that realistic fall data is hard to acquire, thus has reduced availability or incomplete datasets (semi/unlabelled) making it hard to process. Moreover, the paper concluded by discussing open research problems and potential future research such as a 'standard framework to evaluate different detection methods.'

D. Miguel et al looked at making a low-cost, 'camera-based fall detection system' [11]. A camera is used to track a person, modelling their movement data in real-time and applying it to a machine learning algorithm. The system can potentially have an alert feature, which will notify a user via a text message if a fall is detected and whether the subject has recovered. Their product had success, with a detection rate of 'greater than 96%'.

Huynh et al [12] optimized a fall detection algorithm that used both accelerometer and gyroscope readings from an IMU. According to their paper, when using accelerometer alone, algorithms had to trade sensitivity for specificity. This means although algorithms could correctly detect a fall with high accuracy, they were not very sensitive so larger movements were needed for the detection to trigger. Specificity of accelerometer-only algorithms ranged from 88% to 94% but had sensitivity of around 85%. Their algorithm implemented the gyroscope which contributed to detecting falls and resulted in both high specificity and high sensitivity, of 96.3% and 96.2% respectively.

Ge and Xu [13], compared the result between using static and adaptive thresholds. Thresholds define a region where a specific type of data should be, for example, walking. If the data exceeds the region, it is classified as something else, for example, falling. Static thresholds stay constant regardless of the pattern of data, while adaptive thresholds change in accordance with the data. Their study found (using data from a mobile phone) that adaptive thresholds had a higher performance, with an accuracy increase of around 2% to 5%. Another paper, by Ren and Shi [14], proposed static thresholds were inflexible, and also implemented adaptive thresholds in their study, concluding with similar results.

This paper will be trying to determine how effective a mobile phone is at fall detection, based on readings from the device's built-in sensors: gyroscope (measures orientation and angular velocity) and accelerometer (measures acceleration). The primary data will be collected by a mobile application that can both access and record the reading from the sensors. Then, a mathematical and technological approach will be used for analysis. This will be further detailed in the next section of the paper.

2 Methodology

In order to perform this study, experiments will be carried out to collect the accelerometer and gyroscope data. Then, various methods were employed to differentiate between motions based on the pattern of the data.

2.1 Application Used

A mobile application was developed for participants to easily collect fall data. Figure 1 displays how the application looked on the phone used for the experiment

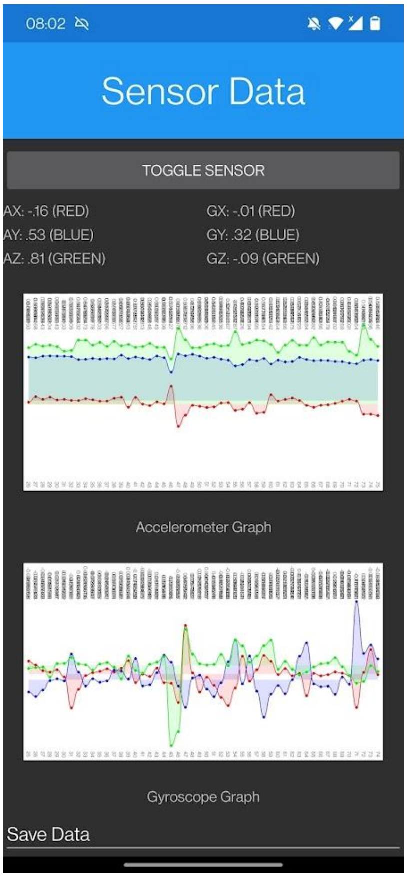

Figure 1

A button at the top will allow participants to turn the sensors on and off. Accelerometer and gyroscope readings were shown beneath the button to two decimal places. There were also graphs visualizing the sensor data in real-time. This gave the participants a rough idea of how the data looked. It also indicated whether the sensors had been turned on, if there was no change in the graphs or the sensor readings, then the sensor had not yet been turned on. The very bottom part of the app allowed participants to change the name of the file that data was saved to – a new file was created for each new file name.

Sampling rate of the application was 14Hz.

2.2 Experimental Setup

The environment was fixed, and the phone position was kept constant throughout, so only the motion performed affected the sensor readings.

There were two participants, with initials BD and TV, performing the experiments, independent from one another. They were both male, aged 16 and 13 respectively, and both came from Leeds. Participants performed a set of five motions – normal walking, falling forwards, backwards, to the side and dropping the phone.

Each motion was repeated three times producing a total of 30 datasets. Before starting, participants were given a briefing about what they were required to do, what and how the data was collected, how it was going to be used and the precautions taken place to ensure their safety and confidentiality. The full procedure is attached in the appendix.

2.3 Ethics

2.3.1 Participants

Although this experiment tried not to target participants from a single demographic, it was important that they could withstand the impact of falling over multiple times. Therefore, only those who have had at least 6 months experience in Judo was to partake in this experiment. They would have thoroughly practiced ‘Ukemi’ or ‘breakfalls’ – this included forward, backward and side breakfalls. These techniques were utilized throughout each process to minimize the impact of falling over and ensured participants remain physically unharmed. Moreover, they fell onto gymnastics mats for the same reasons previously mentioned. Participants were able to take a break of up to 10 minutes between each motion and could stop the experiment before completion if they wished (if this was the case, their data would be deleted as it was not fit for analysis).

Participants’ parents were given details about the experiment and permission for it to be carried out was granted.

2.3.2 Process

During Motion 4, falling to the side, participants placed the phone in the opposite pocket to the side that they were falling on. This was so the phone does not bridge between their body and the mat, potentially harming the participant or breaking. To keep the results consistent, participants needed to keep the phone on this same side throughout all motions, so they declared which side they were going to fall onto before conducting the first process.

2.3.3 Confidentiality and Consent

To be involved in the experiment, participants needed to fill in a Consent Form on Google Forms, sent to them via email. They needed to state their age, gender, and the city they lived in. They also needed to confirm that they have read the information sheet about the experiment and understood the risks associated with it, as well as provide consent.

The identity of each participant was kept anonymous throughout the experiment and analysis. To do this, they were only addressed by their initials, and their data was/will not be shared. At the end of the experiment, participants were given a debrief explaining how their data was going to be used and informed them that they had the right to withdraw their data at any time.

2.4 Data Analysis

The collected data was initially studied by manually visualizing it. After this, two methods of fall detection were developed. The first was to implement thresholds. If the data exceeded a region or set of regions, it was to be detected as a fall.

Another method was using a classifier, a machine learning algorithm which categorized data into groups depending on their structure and characteristics, for example, grouping the data into 'fall' or 'not fall'. The proposed algorithm was a Convolution Neural Network (CNN) – a Deep Learning algorithm based on a model of the visual cortex [15]. The purpose of the algorithm was to differentiate images of distinct topics from one another. It took the image as an input, assigned weights, or biases to different parts, and classified the image based on its features.

3 Results

The accelerometer measures the acceleration of the phone with respect to gravity, so the Earth's gravitational pull is always influencing the phone's sensors. Values are usually represented in terms of g in three axes (x, y, z), fixed with the phone. As the phone's orientation change, the measured data will be changed accordingly.

The gyroscope measures the rate of rotation around a particular axis of the phone. Gyroscope sensors are not affected by the Earth's gravitational pull since gravity does not act at an angle.

There were two participants, TV and BD, producing a total of 30 datasets from 5 different motions.

Section 3.1 shows the results of acceleration data only, while Section 3.2 shows both data.

3.1 Accelerometer Only

3.1.1 Visualization

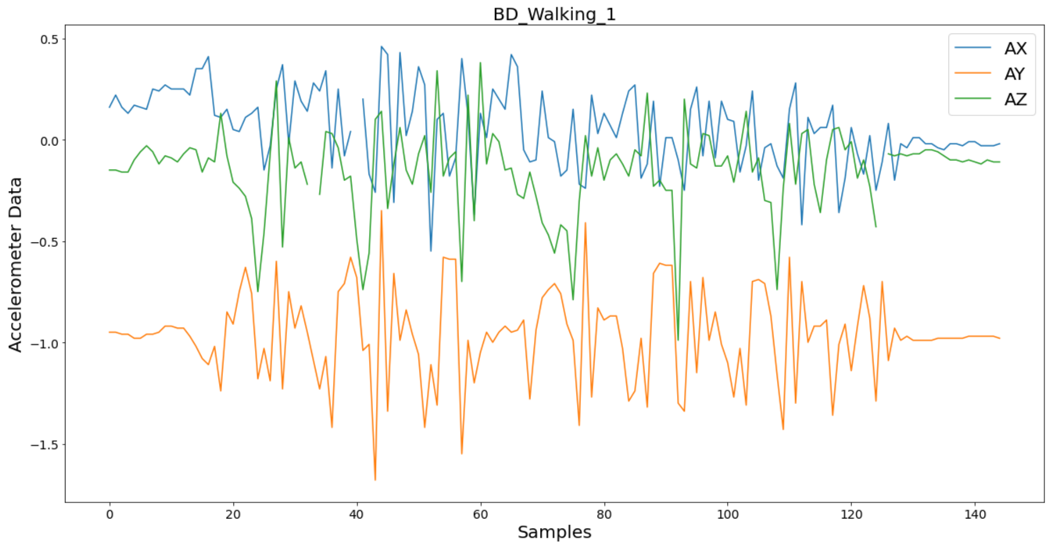

Figure 2

Figure 2 shows the three-axis accelerometer data of Participant BD walking. The x-axis represents the sample index. The walk took approximately 10 seconds, at a sampling rate of 14Hz, which resulted in approximately 140 samples. The line AY fluctuated around -1 rather than 0 because the phone's y-

component was aligned with the force of gravity but facing the opposite way. As the participant moved their leg to walk, the acceleration changed accordingly.

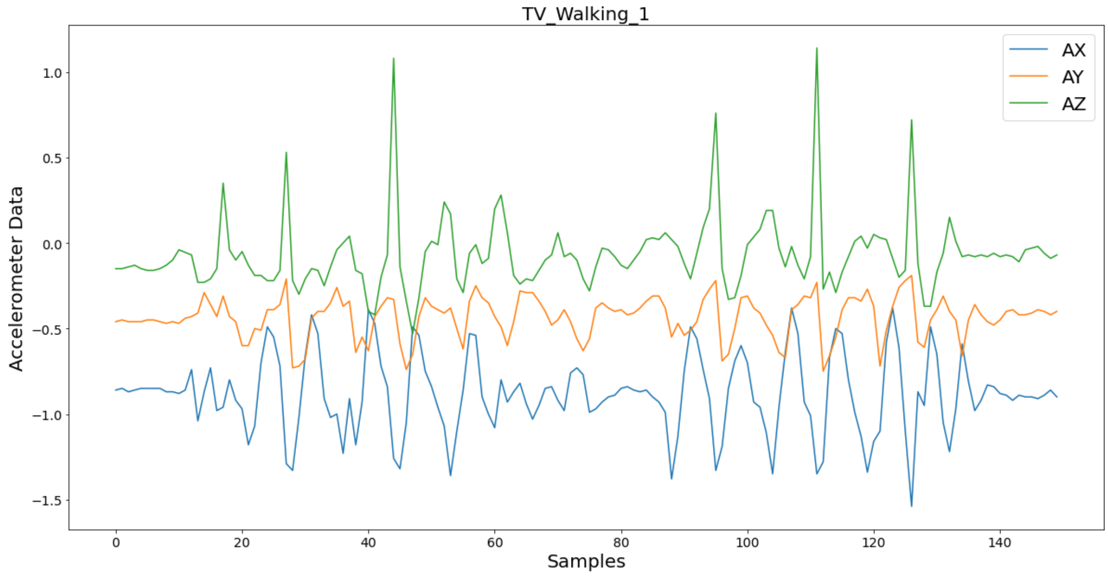

Figure 3

Figure 3 displays the walking data from Participant TV. The data was linearly interpolated at several locations due to gaps in the original data. Between Figure 2 and Figure 3, the walking patterns of the two participants were different. This may have been due to a combination of the size difference between the participants, their walking habits and/or their clothing, participant TV wore looser clothing.

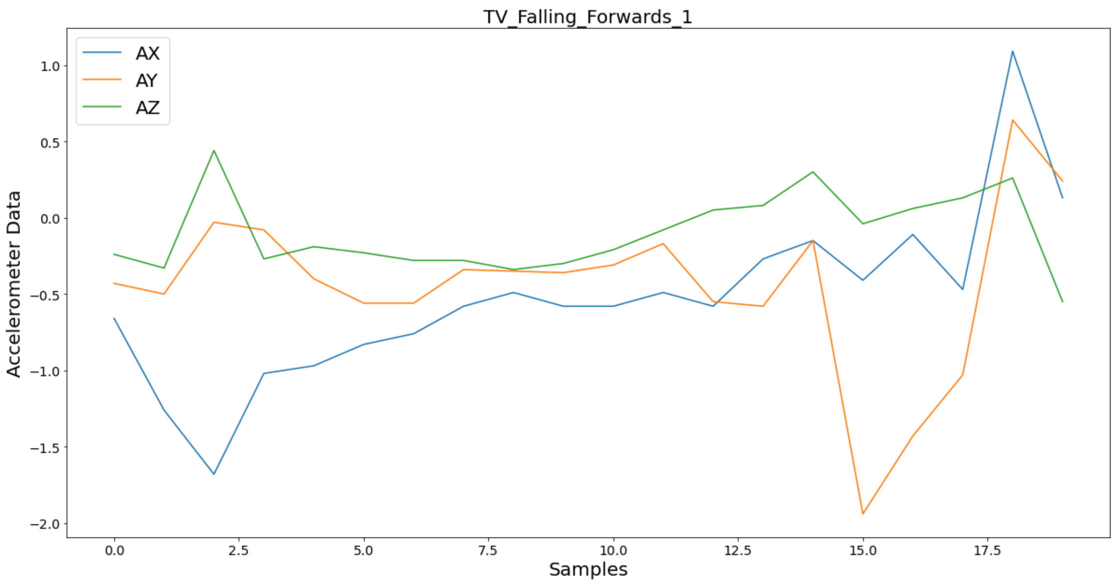

Figure 4

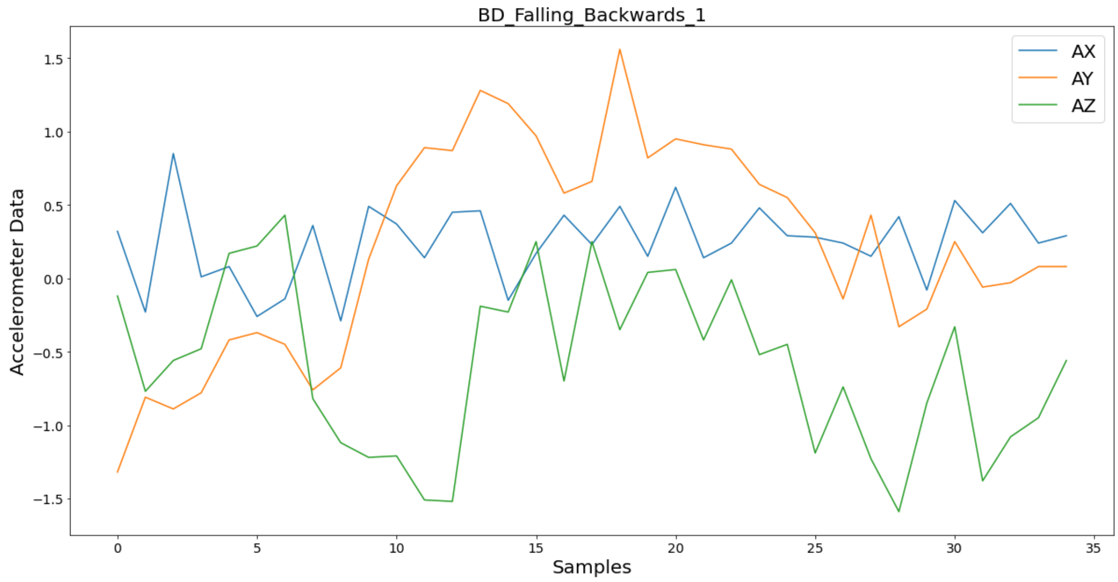

Figure 5

Figure 4 shows the data of Participant TV falling forwards. The motion lasted around 1.2 seconds so approximately 20 samples were produced. Different ways of falling produced different accelerometer patterns but they followed the general trend of staying relatively flat before spiking suddenly. For example, Figure 5 shows participant BD falling backwards. It obeyed the observation, but its peak was wider than Figure 4's and AY had a positive change rather than negative. Spikes were to be expected since the participant would accelerate quickly before hitting the ground when they fall over.

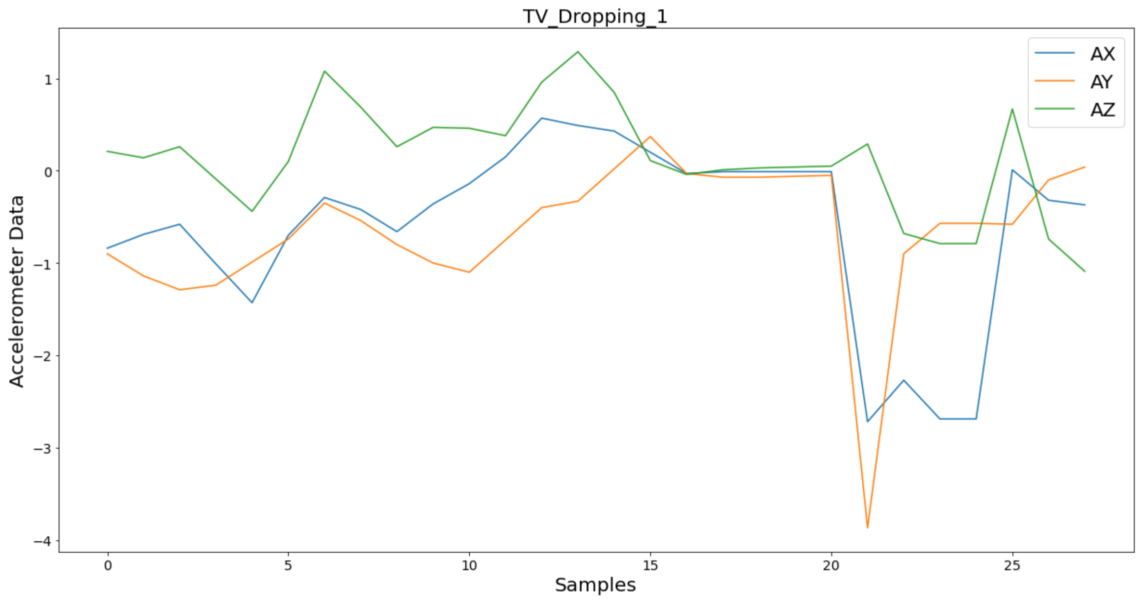

Figure 6

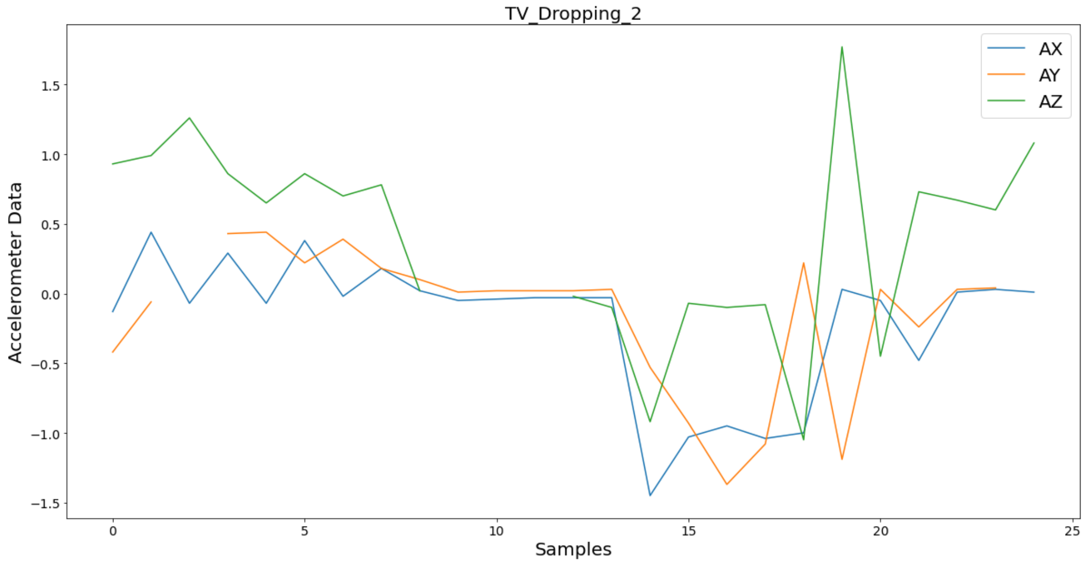

Figure 7

Figure 6 shows Participant TV dropping the phone, which had a similar pattern to Figure 4 – lines staying flat before spiking. This motion lasted roughly 1.5 seconds so approximately 30 samples were collected. The way the phone was dropped and the way it bounced greatly influenced the accelerometer reading. For example, Figure 7 shows another dropping pattern by the same participant. The pattern was mostly similar to Figure 6, besides the AZ spike, suggesting the phone had bounced.

3.1.2 Thresholding Method

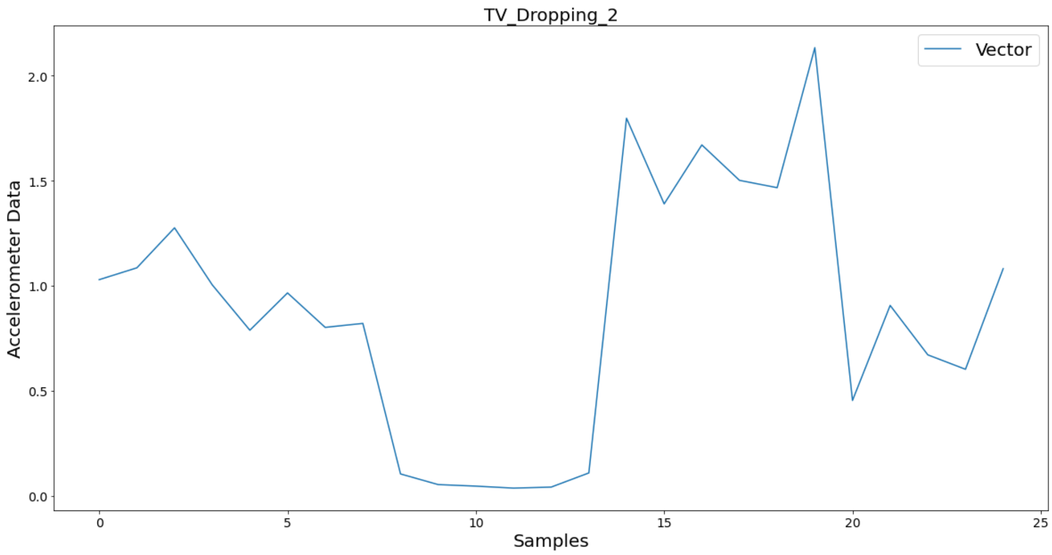

Figure 8

The three axes were combined to find the magnitude of the acceleration vector by using the equation below:

$$|R| = \sqrt{(AX)^2 + (AY)^2 + (AZ)^2}$$

Figure 8 shows the absolute magnitude of acceleration of Figure 7. Based on studying the data, a threshold of $1.8g$ was set. This value was found by trial-and-error and chosen because it returned the greatest accuracy rate. If the data exceeded the threshold, it would be categorized as a fall. Not all detections were correct, so the results will be shown on a confusion matrix.

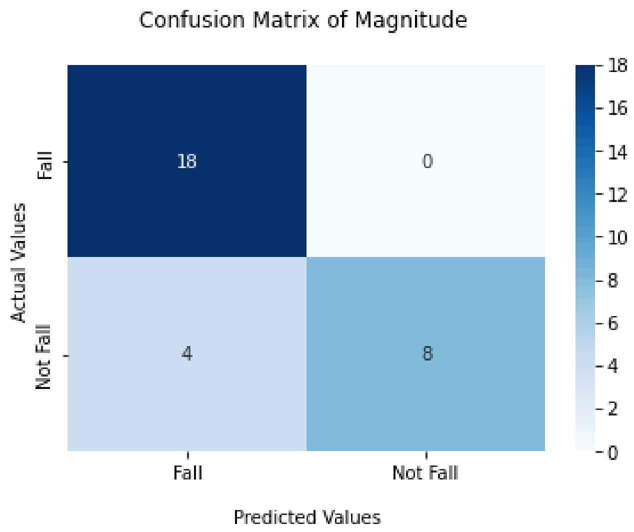

Figure 9

Figure 9 is a confusion matrix made using the threshold value. It shows the matches between detections and the actual motion. The best accuracy rate (falls detected as falls and not falls detected as not falls) was approximately 87%. In all 4 incorrect detections, dropping the phone was classified as falling.

3.1.3 CNN

In this section, a machine learning algorithm was implemented [16]. All datasets were combined with axes still separated and given a label corresponding to their motion. 75% of the data was used for training while 25% for testing, resulting in 7 datasets used for each motion.

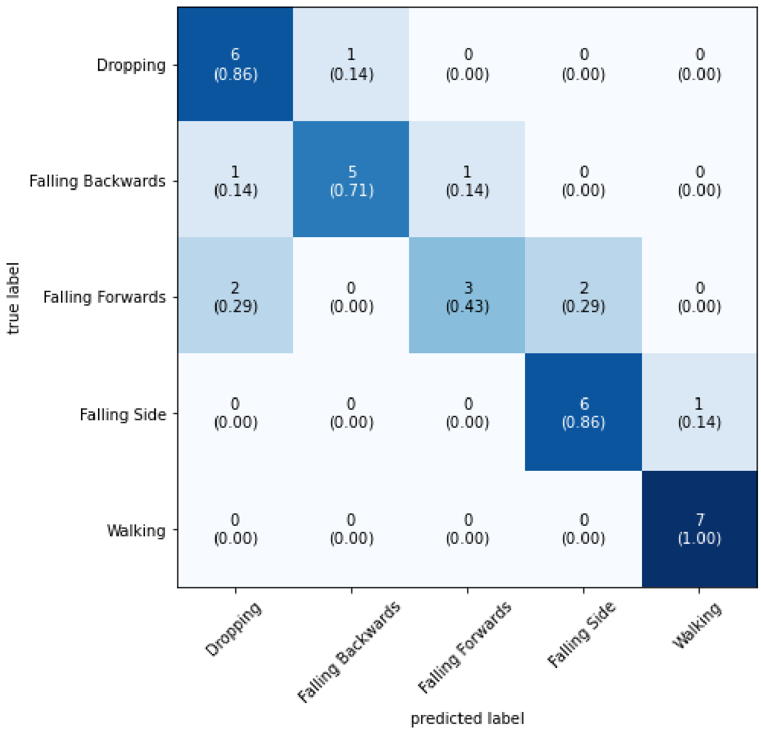

Figure 10

Figure 10 is a confusion matrix showing the results of the machine learning algorithm. The y-axis represents actual values while the x-axis represents detected values. The algorithm correctly detected different types of motions on most occasions. For example, the walking motion was correctly detected every time. However, there was some confusion between falling forwards, dropping the phone, and falling sideways. Overall, the accuracy rate was 86% when differentiating between fall or not fall and 77% when differentiating between types of falls.

3.2 Accelerometer and Gyroscope

3.2.1 Visualization

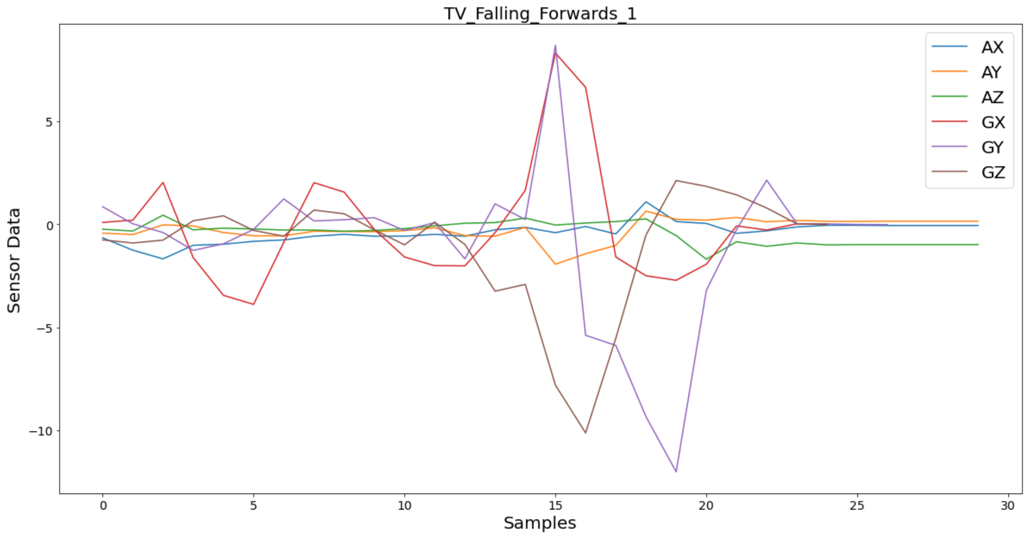

Figure 11

Figure 11 shows the pattern of Participant TV falling forwards, same as Figure 3, but this time, including the readings from the gyroscope. The large spikes indicated when the participant had fallen over. These had a similar timestamp to the spikes of the accelerometer data.

3.2.2 Threshold Method

The same equation was used to combine the gyroscope axes to find the magnitude of the gyroscope vector. Figure 12 shows the absolute vector of the accelerometer and gyroscope data on one graph.

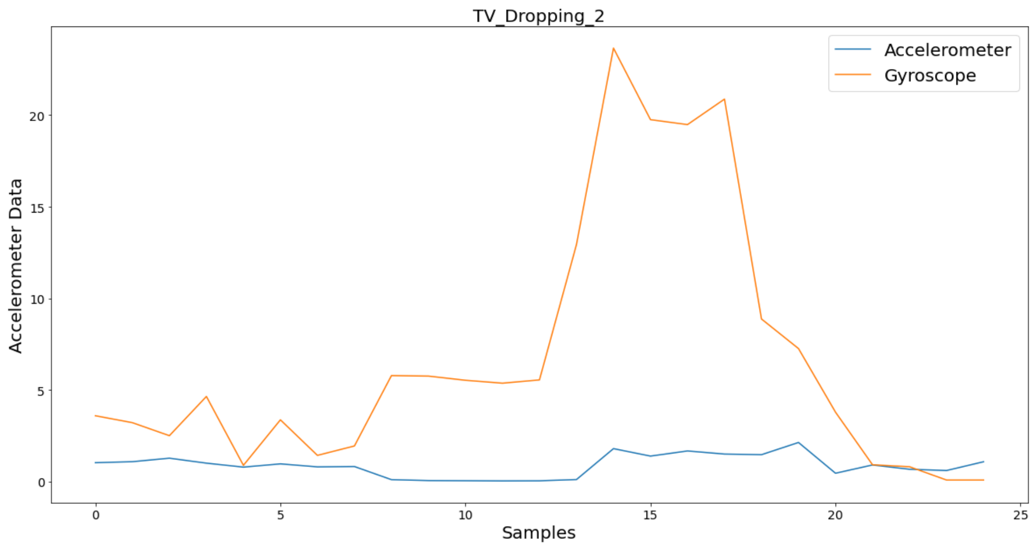

Figure 12

Thresholds of values 1.8g and 8 were set for accelerometer and gyroscope data respectively. These were found by trial and error and were chosen as they gave the highest accuracy rate which stayed constant at 87%. The program made the same wrong detections, with four dropping datasets detected as falling.

3.2.3 CNN

The pre-processing method and machine learning algorithm in Section 3.1.3 was used in this section, but datasets containing both accelerometer and gyroscope data will be used for training and testing, with a 75% to 25% split respectively.

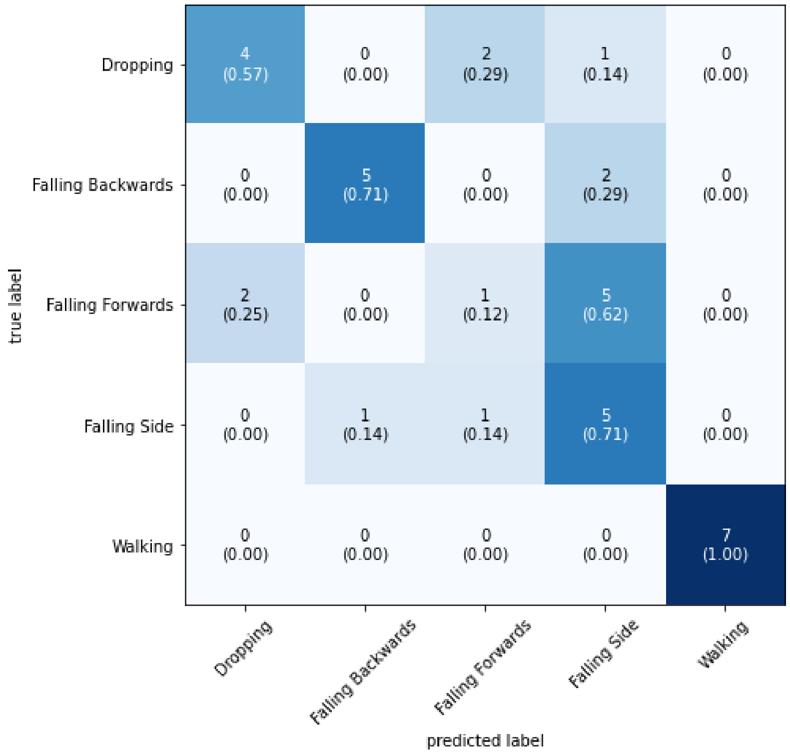

Figure 13

Figure 13 is a confusion matrix showing the results of the machine learning algorithm with both sensor data as input. The algorithm detected most motions with relative success but struggled to differentiate between different types of falls. In particular, falling forwards was consistently thought to be falling sideways. Overall, the accuracy rate of detecting fall or not fall remained at 86% but when required to detect the type of fall, accuracy fell to 61%.

4 Discussion

This study investigates whether the accelerometer and gyroscope data of a phone can be used for fall detection. In this study, two participants carried out experiments to collect the data which was analysed to see how well a computer program could differentiate between fall and not fall.

4.1 Data Processing

The data collected consisted of accelerometer and gyroscope readings in terms of g, plotted against time. Before being analysed, unnecessary data such as the 5 second start/finish indicators, where the axes stayed flat, and any data before and after this region were removed, as to not affect the detections made by the threshold and/or confuse the learning algorithm. There are other methods of indicating when the collection process had stopped. One way would be to do it remotely and allow the experiment conductor to remotely start and stop the sensors from another device. Doing this would save time since data would not need to be removed manually.

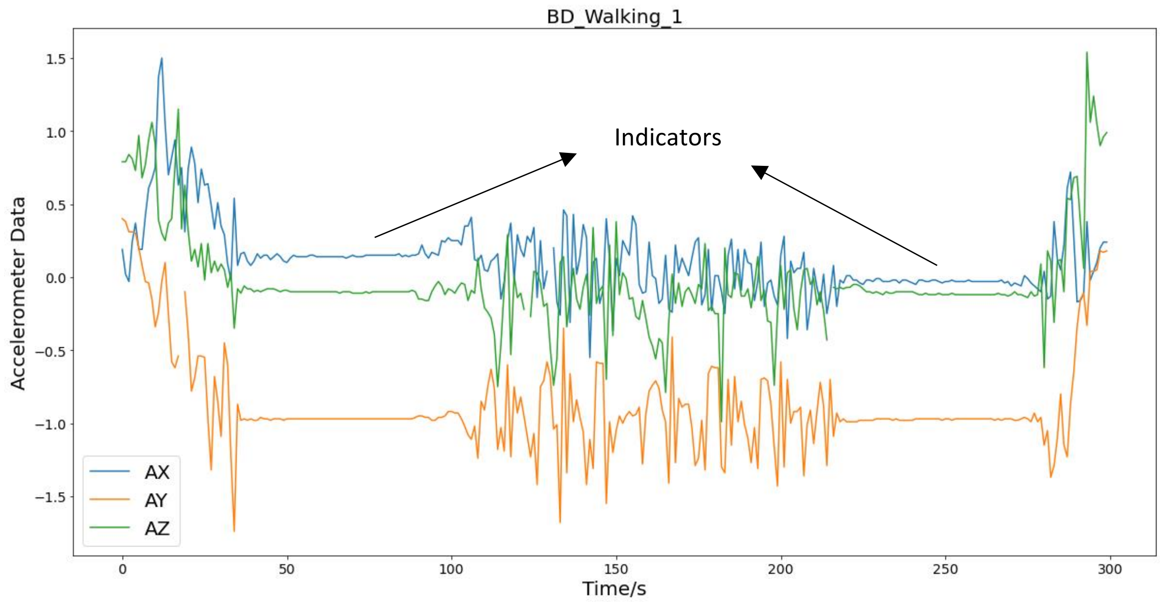

Figure 14

There were some gaps in the data, examples circled in Figure 15. This did not greatly affect detections made by the threshold but did significantly reduce the performance of the learning algorithm, which detected one motion for all test data and resulted in an accuracy rate of 20%. Gaps were likely a result of the phone's sensors not being real time, so if the CPU received a task with higher priority, it would postpone collecting the data until it finished its current task, leaving blank spaces where the data continued to change. Specialized sensors such as IMUs do not suffer from this problem since they collect data in real-time, so new data is regularly recorded every few milliseconds. Gaps were linearly interpolated to remove them – two adjacent datapoints were connected using a straight line. Although this may not have been the most precise method, it was the quickest and easiest to implement and did not greatly affect the result as gaps were quite rare. Most datasets had no gaps with few having one or two. Alternatively, a better method would be to optimize the application to allow sensors to consistently record data regardless of CPU activity.

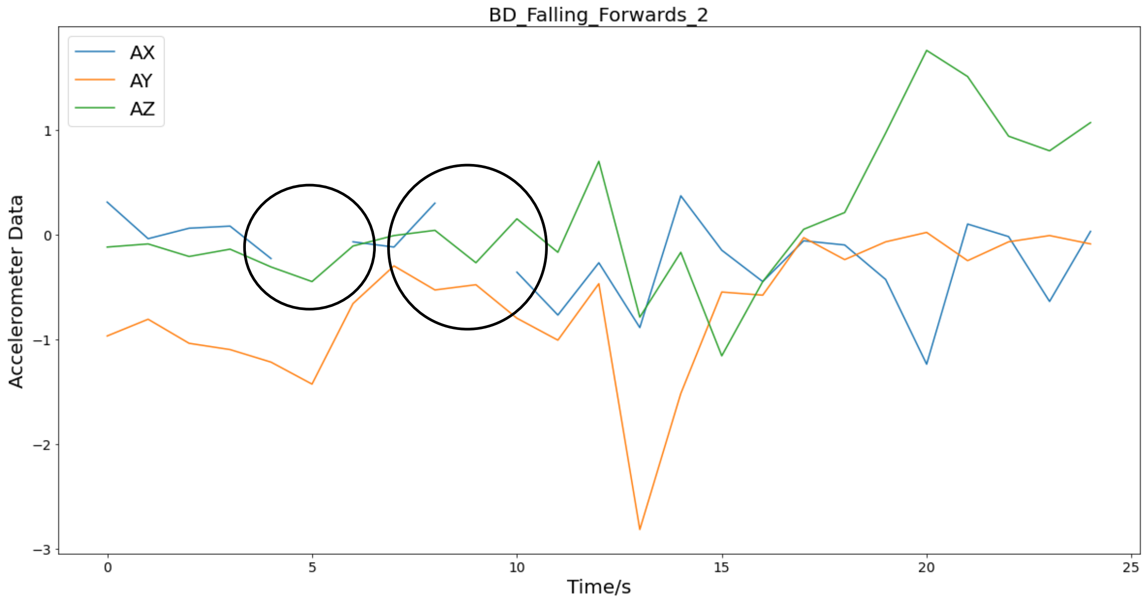

Figure 15

Only the datapoints of when the participants were falling/dropping the phone was captured, to reduce the influence of walking data prior to these motions. As a result, they had much less datapoints than the walking motion. This led to the machine learning algorithm outputting biased detections, in favour of the motion with the most datapoints (walking). Therefore, the number of datapoints of all motions were made to match the motion with the least number of datapoints, which happened to be falling forwards.

4.2 Data pattern

The data pattern of each motion differed visually. For example, Figure 3, which showed accelerometer data of participant TV walking, had a rhythmic pattern, with data constantly fluctuating by 0.5g to 1g, while Figure 4, showed the same participant falling forwards, and had significant spikes in all axes. This was strong evidence that the phone's orientation was dependent on the motion.

Data patterns also differed throughout repeats although visually, much more discrete. This was clearest between Figure 6 and Figure 7; both showed the accelerometer data of participant TV dropping the phone. The axes of both figures spiked by different amounts. How the phone was dropped greatly influenced the data. For instance, if the phone landed on its side, it bounced, which generated multiple spikes that decreased in magnitude over time. However, if the phone landed flat, it did not bounce and only one spike was produced. Similarly, if the phone was dropped with a rotational force, its pattern would be different to if it was dropped with no external force applied. It would be difficult and unrealistic to make repeats exactly identical. Instead, having 'human errors' and inconsistencies in this case would allow algorithms to better generalize over a wider variety of possible motions.

Participants involved also influenced the pattern of data. Participant BD was much larger than Participant TV and wore tighter clothing. Subsequently, although the time frame was very similar, Participant BD's walking data, Figure 2, had peaks closer together than Participant TV's walking data, Figure 3. The effect of the participant's size and choice of clothing had no obvious visual correlation to the difference in falling and dropping data, as the data of those motions varied among repeats. Again, it would be unrealistic to choose participants of a certain size and/or limit their choice of clothing as this would make the data less generalized.

4.3 Threshold Result

Two methods were developed to detect falls, the first was to set thresholds. If the data exceeded the threshold, it was classified as a fall. Thresholds were found using a trial-and-error method, firstly by studying a small sample of datasets before applying the threshold to every dataset and adjusting it accordingly until maximum accuracy was reached. When both accelerometer and gyroscope data was used, this method achieved an accuracy rate of 87%. Participant TV was much smaller than Participant BD meaning although they performed the same sets of motions in the same environment, the shapes of the data were very different. The same threshold was implemented across datasets of both participants and its performance was identical, meaning the accuracy of this method is not dependent on the user's size. Accuracy rate of using accelerometer data only, matched that of using both accelerometer and gyroscope data. This suggested that additional gyroscope data did not contribute to the effectiveness of the data and/or method.

The static thresholds method was unable to differentiate between different types of falls. Manually applying different thresholds for each motion was not a viable method since it would have been too time consuming and impractical – it was unlikely to scale well as the amount of data increased. This agrees with Ren and Shi's study [14], that static thresholds were inflexible. As results by Ge and Xu's study suggested [13], adaptive thresholds would be more suited to fall detection.

4.4 Machine Learning Result

The second method of fall detection was using a Convolutional Neural Network (CNN). The machine learning algorithm would classify input data into groups based on its shapes and characteristics. As data size grows, thresholds would likely be less effective as it would have to be implemented over a larger variety of patterns. The opposite is true for a machine learning algorithm, more data means more training allowing it to spot indicators of a fall more accurately. Furthermore, using machine learning would save time as thresholds need to be found and set manually. Using accelerometer data only, the CNN was able to correctly differentiate between fall and not fall with 86% accuracy, similar to setting thresholds. The CNN was also able to differentiate between the types of falls, with 77% accuracy. This suggests that the machine learning algorithm was more flexible than the static threshold. Potentially, it may be able to adapt to a phone being located elsewhere, for example, being held in the user's hand rather than placed in their pocket.

When using data from both sensors, the CNN's accuracy of differentiating between fall and not fall stayed at 86% but when asked to differentiate between the types of falls, accuracy fell to approximately 61%. This further supports the idea that gyroscope data does not help improve accuracy. However, this idea conflicts with the research found by Huynh et al [12], who argued that gyroscope data contributed greatly to fall detection, especially its sensitivity. The difference could be due to Huynh's study having had significantly more data, with the involvement of 27 participants in comparison to 2 for this study. Therefore, their machine learning algorithm had much more training and testing. Moreover, their algorithm was optimized for using both accelerometer and gyroscope readings while the algorithm for this study was developed for accelerometer only. With low amounts of data, the inclusion of gyroscope readings may have made it too complex for this study's algorithm, so the gyroscope data was not fully utilized.

4.5 Limitations

The following limitations can be found in this study.

Currently, the sampling rate of the application is 14Hz which could be increased to give more samples for each motion, especially motions with a short time frame such as falling and dropping the phone.

Increasing the sampling rate would also mean the collected data's pattern is a closer match to the actual pattern of movement. There would be less values missing, some of which may be important, for example, the maximum value of a spike, which was crucial when thresholds were used. Gaps in the data were linearly interpolated, potentially making it unrealistic as it may not have been the value at that sample point.

The amount of data collected and analysed in this study was quite low in terms of variety and volume. High intensity motions such as jogging, running, and jumping could have been included to see whether the methods used in this study would be able to differentiate between them and the current motions – walking, falling forwards, backwards, to the side and dropping the phone. The number of participants for this study was two, which could be increased to give a larger volume of more inclusive data. Participants of this study had different builds but were both male and lived in Leeds, which cannot be used as a generalization of the UK population. The inclusion of more data and a more optimized machine learning algorithm would mean falls would be detected with better accuracy.

This study agrees with prior research on realistic fall data being hard to obtain. For example, participants fell onto gymnastic mats to minimize the impact. This may have had an effect on the pattern of data, as gymnastic mats provide a different interaction to grass and/or hard ground. Similarly, when people drop their phone, they usually pick it up instantly so the pattern of data for dropping the phone would be different to the one found. This idea was neglected in this study.

5 Conclusion and Further Research

Fall detection is an essential area of research in elderly care and global health and is becoming more important as the population ages. This study aimed to see whether the built-in accelerometer and gyroscope sensors of a mobile phone was suitable for fall detection. Setting thresholds was the first method implemented and achieved an accuracy rate of 87%. A machine learning algorithm was the second method of fall detection and achieved an accuracy rate of 86% but was also able to consistently detect the type of fall. These results were found from 2 participants performing 5 motions, repeating each one 3 times resulting using 30 different datasets.

Similar studies using IMU devices produced detection with accuracy rates exceeding 95%. Typically, those studies had between 20 to 30 participants and a sampling rate of over 20Hz. They had significantly more optimized machine learning algorithms as well as data for training and testing. For future works, this study suggests scaling the experiment to collect more data from a phone and optimizing current learning algorithms to find the maximum detection accuracy that can be produced by data from a phone's motion sensors. The results will better determine whether a phone can be as effective as alternative technologies such as IMUs and context-aware systems.

Considering the limited amount of data, results from this study suggest phones can provide an inexpensive and easily accessible method of fall detection with relative reliability, which can be improved by further research. This will predominantly benefit the elderly, who are most susceptible to falling. An application could be made that constantly monitors sensor data and calls a family member or the health services if it detects a fall. Therefore, with minimal financial investment, the elderly can be confident that there would quickly be support if they were to fall.

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7 Appendix 1 – Experimental Method

7.1 Aim:

The aim is to collect a sufficient amount of gyroscope and accelerometer data, enough to effectively analyse and produce a machine learning algorithm that can detect a fall, based on real-time input from the sensors.

7.2 Resources:

- Phone with Data Collection App
- Participants
- Gymnastics Mat
- Stopwatch

7.3 Process:

The participant(s) will be given a briefing on the safety precautions taking place, what they are meant to do, what data is being collected and how the data will be used before the data collection process begins. The number of participants will range from 1 to 5 and each data collection step will be repeated 3 times by each participant. This is to ensure that a sufficient amount of data is collected and minimizes the impact of anomalies. Any delays mentioned below will be recorded by a stopwatch (this data does not need to be saved).

1. The participant(s) receive a phone with the Data Collection App pre-installed. They then open the app and turn on the sensors, allowing data to be collected. The phone will be placed in their trouser pocket for the duration of the test. There will be a 5 second delay before the phone is put into their pocket and the beginning of the data collection process, to mark the start of each process.
2. Motion 1 will be 'normal walking'. (After the 5 second wait), the participant will walk 3 meters forward as naturally and comfortably as they can. They will stop, turn around and return to the original starting point. They will then wait another 5 seconds, this time to mark the end of the process. Finally, the participant will take the phone out of their pocket and turn off the sensors. This will also save the data at the same time.
3. Motion 2 will be 'falling forwards'. Similar to before, the participant will walk 3 meters forwards, this time, they will stop and instantaneously fall over in the direction of travel. A soft object may be placed on the ground to simulate them tripping over more accurately. They will rest on the ground motionless for 5 seconds to mark the end of the process. Then, they will stand up, and turn off the sensors, saving the data.
4. Motion 3 will be 'falling backwards'. Once again, the participant will walk 3 meters forward, stop, but instead of falling forwards, they will fall backwards. They will stay there for 5 seconds before standing back up and disabling access to the sensors, also saving the data.
5. Motion 4 will be 'falling to the side'. The participant will walk 3 meters, stop, and fall to the left or right. It is recommended that they fall onto their dominant side, as this will make it easier to 'breakfall', however, this choice is up to them. Once they have fallen, the participant will lay there for 5 seconds before standing up and turning off the sensors, saving the data.
6. Motion 5 will be 'dropping the phone'. This is the last data collection process. The participant will walk 3 meters, stop, take the phone out of their pocket, and raise it up so that their elbows are at 90 degrees, forearm parallel to the ground. Once they have reached

this position, they will instantly drop the phone and let it stay on the ground for 5 seconds, before picking it up and doing the usual ending procedure.

7. Datasets will be saved in the following form:

   CandidateInitials_MotionNumber_RepeatNumber.

7.4 Reliability and Validity:

To make the primary research valid, the data collection will be following the basic scientific method.

Control variables are constants, variables that are unchanged throughout the process. In this experiment, the control variables include the sensors used to collect the data, the distance the participant(s) walk, the way they walk, the position of the phone and the surface at which they fall onto. This ensures that the dependent variable is only changed by the independent variable and no other factor. In other words, the data collected is only changed by the motion of the participant(s), and how they fall.

Repeating the experiment will make the data more reliable, remove anomalies and produce more data points for the machine learning algorithm.

7.5 Safety and Ethics:

To ensure the safety of the participant(s), the following procedures will be taking place:

1. The participant(s) must be able to withstand repeated falls, therefore, anyone participating in this experiment will require a background in Judo and have completed the basic gradings that cover ‘Ukemi’, or Judo falling techniques. These include forward breakfalls, side breakfalls, and backward breakfalls. These techniques will be used in the falling process to make sure the participant(s) are unharmed. Moreover, they will have had lots of experience doing this as it’s the most basic element of this martial art.
2. The participant(s) will be falling onto gymnastic mats, to minimize the impact of each fall, and the possibility of them hurting themselves.
3. During the collection process where participant(s) fall to the side, the phone will be placed in the opposite pocket to the direction of the fall. This is so they do not land on it and hurt themselves or break the phone. For example, if the participant chooses to fall to the right, they will put the phone in their left pocket, and vice versa. During falls backwards and forwards, the participants can put the phone in pockets on either side, but this must be consistent throughout the repeats.
4. The participant(s) can take a break of any amount of time in between each data collection process and may stop whenever they wish. The data of any participant who chooses to stop before completing the experiment will not be used.
5. The identity of the participants will remain anonymous. To ensure this is the case, the name of the dataset that they record during the experiment will only include their candidate number and/or their initials.
6. The usage of their data and the involvement of the participant(s) will only proceed if they have given consent and met the conditions mentioned above.

8 Appendix 2 – Consent Form

Experiment Consent Form

You have been invited to partake in an experiment. The purpose of this experiment is to record the motion of a phone when someone has fallen over. Your participation in this experiment is completely optional, and you may choose to withdraw at any point.

Beginning the experiment, you will be given a mobile phone running a data collection application. You will then be required to turn on and off the app accordingly (more detail in the experimental method), while conducting the following range of motions: normal walking, falling forwards, falling sideways, falling backwards, and dropping the phone.

For your safety, you are required to be of age 16 or above and need to have had at least 6 months experience of Judo to participate. This experiment will be conducted on gymnastics mat to minimize the impact of the falls. You can request to take a 2-minute rest between each data collection process. The experiment will likely take no longer than 10 minutes, excluding any breaks.

The data collected will be from the sensors of the phone, and mainly numerical. It will be analysed and used to detect when a fall may have occurred. Your participation in this experiment will be kept completely confidential, along with any other relevant information. To do this, only your initials will be used to identify your corresponding dataset, no data will be shared, and will be deleted once the analysis is complete. As mentioned before, you are able to withdraw from the experiment if you wish, if this is the case, any data that had been collected will be deleted, as it is incomplete and unsuitable for analysis. If for any reason you wish to withdraw your data after you have completed the experiment, you may do so, and the data will be deleted.

If you agree to participate in the experiment, please fill in the form below:

---

* Required

1. Your initials *

Enter the first letter of your first name followed by the first letter of your surname.

2. Age *

3. Gender *

Mark only one oval.

- Male
- Female
- Prefer not to say
- Other:

4. Home *

The city that you are currently living in

5. Confirmation *

Check all that apply.

- I have read the information sheet above and consent to the usage of my data.
- I understand the risks associated with this experiment and the safety precautions being taken.

6. Date of completion *

Please answer in the following format: DD/MM/YYYY

7. Signature of Confirmation *

9 Appendix 3 – Debrief

Thank you for participating in this experiment.

The purpose was to collect readings of the built-in accelerometer and gyroscope sensors from the phone you were given. The data you collect will be analysed to see whether or not it is accurate enough for fall detection. The results of this study will primarily help the elderly who are most susceptible to falling. I am wanting to see if a phone can be a reliable, inexpensive, and easily accessible implementation of fall detection.

The task given to you was/will be the task given to other participants in this experiment.

The data you collected from this experiment and provided in the consent form will be kept anonymous and confidential. It will only be identified using your initials and will not be shared or distributed. If for any reason you wish to withdraw your data, you can do so within a month of the experiment. Your data will be immediately deleted in response.

If you would like to contact me, please email: phuong.vo@elawnswood.co.uk.

Once again, thank you for taking part.