Fall Detection System with Accelerometer and Threshold-based Algorithm

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ABSTRACT

Most presently available fall detection systems that are marketed for commercial use predominantly consist of wearable technologies. These technologies often involve a device positioned on the wrist, which may lead to the occurrence of false positive alerts due to the movements of the wrist. This paper proposed a fall detection system that aims to improve both reliability and cost-effectiveness. The system is designed to promptly inform surrounding individuals of their need for assistance in emergency situations. The fall detection system we propose consists of an accelerometer and a gyroscope, which collectively calculate acceleration, orientation, and various other motion characteristics. The resulting system demonstrated a sensitivity of 90%, a specificity of 85%, and an accuracy of 87.5%.

KEYWORDS

Fall, detection, prediction, reliability, Internet of Things.

Introduction

As the birth rate declines and life expectancy increases, global ageing has become problematic. The World Health Organisation (WHO) reported that the number of people who are above the age of 50 is expected to double by 2050 or over, increasing to around 20 billion by 2050 from 900 million in 2015, which accounts for 22% of the world population (Brunier & Lindmeier, 2015). With the increasing number of elderly people, the demand for health care services increased. To meet the increasing numbers of elderly people, the World Health Organisation (WHO) states that "28 to 35% of elderly people aged 65 and above" will experience any type of fall each year. Following this, increase to "32 to 42%" for elderly people who are aged above 70 (WHO, 2007).

The elderly who lives independently are at risk of a fall, which can cause psychological, physiological, and physical damage that leads to injuries or death if the patient cannot receive immediate medical assistance. To reduce the time spent seeking medical attention after a fall, a fall detection system is required to fill this void. Alongside this, the fall detection system should be reliable and be able to contact staff to assist the elderly person who has fallen. Following from this, the fall detection system should be user-friendly and not interfere with other daily activities such as walking, squatting, or other daily activities.

Embedded systems are microprocessor computer hardware that can be programmed with software that is designed to perform a specific function or task. For example, a calculator and a desktop computer can both calculate functions such as basic addition functions; however, due to the size comparison between both systems, the power requirements for these two are significantly different, as a modern desktop requires 240+ volts to power it while a calculator requires a button cell battery. Overall manufacturing enables mass production of embedded systems such as calculators. Embedded systems are made up of two key components: hardware and software. The software side is used to programme the embedded systems, and that runs Real-Time Operating Systems (RTOS), which supervise the software and provide a mechanism that allows the processors to run instructions and schedules. An example of Real-Time Operating Systems is the Central Processing Unit (CPU) on a Raspberry Pi and Arduinos; however, not only these two applications but, more importantly, Embedded Systems are continuing to be developed in the Internet of Things sector and the Artificial Intelligence field.

The Internet of Things has made a rapid push in the development of IoT devices within the medical and health care industries, such as blood oxygen monitoring systems, heart rate monitoring, and many other components that can be used in the medical and health care industries. An example that could improve is the fall detection system that uses IoT devices to detect a fall at a reasonable cost to produce and maintain. Fall detection systems are important due to the probability of a fall occurring in an elderly patient. They are also important due to the post-impact phase, which can cause severe injuries or, in the worst-case scenario, death. With the increase in life expectancy and the decrease or lack of elderly care staff able to monitor, it has become a challenge to look after the elderly, especially those who are living alone. If a person falls and possibly becomes unconscious, this could lead to death. With the rise of the Internet of Things, researchers have developed fall detection systems that could increase the quality of elderly care, which could be monitored by care staff and reduce the negative consequences of a post-impact fall, according to the World Health Organisation (WHO). The WHO has provided statistics on falls across the globe, which, according to the WHO, are the second most common incident that elderly people may face, which could lead to death.

Detecting a fall can be monitored by two methods of approach: physical signals and physiological signals, both of which can detect a fall that has occurred. An example of the physical category is using an accelerometer, which is used to detect any change in acceleration caused by falling, which is categorised as body motion. An example of a physiological approach is a blood pressure sensor, which is used to detect pressure changes due to temporary spikes in blood pressure due to stress hormones released into the bloodstream due to adrenaline.

Physical signals are the most common method to detect falls due to acceleration from the initial impact when a person is falling, and then the impact itself can be monitored and measured to determine if a fall occurred. With this, embedded systems can create a fall detection system using physical signal sensors such as an accelerometer to replace mobile phones or smartwatches due to the cost of a smartwatch with a smartphone due to micro-controllers and sensors becoming cost-efficient to mass-produce components. This literature review will review the current literature surrounding wearable fall detection systems and use a physical approach for the development of fall detection systems.

Related Work

According to Mozaffari et al. (2019), there are three types of methods to detect physical signals: Vision, ambient, and wearable. For example, vision detection uses a video stream that relies on closed-circuit television (CCTV) or a Raspberry Pi camera that uses visual machine learning techniques to detect a fall. An ambient method based on environmental changes, for example, sound and or vibration, which detects sound caused by falling, and voice detection if the patient requires asking for help verbally. Finally, Wearable devices that use small microprocessors to detect a fall, such as electrocardiograms (ECGs), detect pressure changes in the blood and are classified as wearable devices; however, the most reliable form of detecting a fall is through wearable devices. Methods.

Wearable technology has recently become popular, this includes wearable Internet of Things glasses, bracelets, and other devices that can be useful functionalities and as well possibly collect data from users' examples, how many steps, heart rate monitoring, GPS location, etc. Not only from user data, but also from environmental such as sound, light intensity, and altitude. The advantage of wearable devices for that wearable device stay natural on the human body, for example, wearable devices have a GPS controller for patients who may have Alzheimer's which could be attached to hidden accessories such as a watch or a bracelet.

An example of a wearable device would be a GPS controller for patients who suffer from Alzheimer's which can be attached to hidden accessories however ethical, and morals consider otherwise. Another example of wearable device sensors by (Hsieh, Chun-Che, Wu, & Tai-Wen, 2014) , used two wearable devices that both attached Tri-axis sensors which are used to detect motion in X, Y, and Z coordinates, which the tri-axis can collect data from the accelerometer, gyroscope, and magnetometer which can be calculated if the patent may or had fallen.

Sensors for Fall Detection

There are different types of sensors for wearable devices, there are two categories for wearable devices: Body Motion and Physiological Signs (Mozaffari, Rezazadeh, Farahbakhsh, Yazdani, & Sandrasegaran, 2019). Body motion sensors can be used to detect movements from the body, while physiological can detect brain reactions such as blood pressure increase due to the heart rate increase. Both categories detect the fall, however, the Body Motion detects the body motion such as the acceleration when a person falls, here are the sensors for body motion:

Accelerometer	Gyroscope	Magnetometer
EMG	Pedometer	GPS
Inclinometer	Altimeter	Ultrasonic / RFID Tags

Table 1: Body Motion Sensors

All these sensors listed above are classified as Body Motion which can be used to detect motion such as movement. Physiological Signs are classified when the brain reacts to something example once a fall occurred your blood pressure increases due to a heart rate increase, which sensors can detect any change in blood pressure from ECG (Electrocardiogram) which detect heartbeat changes and Blood Pressure Sensors to detect blood pressure changes which both are classed as Physiological. List of physiological sensors that can be used in wearable devices to detect a fall:

Temperature Sensor	Humidity Sensor	ECG
Blood Pressure Sensor	Blood Oxygen Sensor	EEG

Table 2: Physiological Sensors

1.1 Review on Tri-Axis Based Fall Detection

(Wu, Zhao, Zhao, & Zhong, 2015) developed a wearable device that uses an ADXL345 accelerometer which is measured at 13 bits ± 16g with a maximum precision of 4mg MCU. In the experiment, there were different activities that participants conduct such as walking, jumping, squatting, sitting a resting throughout the testing phase for daily activities, and repeated 20 times on each participant. During one of the experiments, it shows that ADXL345 did "*not rotate 90 degrees when the peak values were quite high, so the fall alarm has not been triggered"* (Wu, Zhao, Zhao, & Zhong, 2015). This suggests the algorithm is reliable to detect the difference between falls and activities of daily living. In conclusion, the work provides the sensitivity and specificity of the purposed device and reported that the algorithm reported 97.1% and the specificity at 98.3%, and in the testing phase, it was reported that sensitivity was at 91.6% and specificity at 88.7%.

(Rihana & Mondalak, 2016) developed a device that used ADXL345 with identical components as to Wu, F. et al., (2015), however, the experiment consists of 100 simulated activities which are split into half, 50 falls and 50 non-falls which concluded with sensitivity is 90%, specificity 85% and accuracy 87%.

(Kumar, Janardhan, Prakash, & Kumar, 2018) created a device that use EPS8266 and MPU 60 50 (Accelerometer), concluded that it produced 99% accuracy, however, data analysis suggests that backward falls are difficult to detect, and overall accuracy for backward fall were 66%, while forward falls at 80% accuracy. On another note, added a reset button which is used to reset if a false positive was flagged by the device (Kumar, Janardhan, Prakash, & Kumar, 2018).

(Guo, 2015) used accelerometer and gyroscope sensors for fall detection, which is used to capture 8 different types of simulated falls and 6 different types of activity of daily living activities. The threshold algorithm uses a device that determines if the user had fallen during a fall event. approached used wearable system which uses XYZlife Bi-Clothing which allows fitting a wearable device with a built-in MPU-6500. The fall detecting device is in front of the right chest (Guo, 2015).

(Guo, 2015) developed a wearable clothing fall detection system that uses MPU 6500 built-in on the top left side of the breast, with a threshold base algorithm that has three conditions that must be met: FT1 (lower acceleration threshold), FT2 (upper acceleration threshold, and finally FT3 lower angular acceleration threshold which all three conditions must be met) which can be visualized in figure 2. During the experiment, simulated different simulated falls such as backward fall, forward fall, and knee flexion, and the activities of daily living example sitting down, standing up on a chair, laying down, and getting up from a bed. In conclusion, limited participants, and the age range were 30 to 39 years old require optimization, however, the device can perform and detect a fall and ADLs with the specificity of 100% under test conditions.

1.2 Fall Detection Algorithm

Algorithms can be used to determine if a fall had occurred, for example detecting the change of the velocity. By defining a set of rules to determine if a fall had occurred the micro-controllers could decide if a fall had occurred using calculations to detect if a fall had occurred. Alongside converting raw data to meaningful data from the sensors. An example of algorithms, using Hidden-Markov-Model (HMM) which is used for machine learning can be used to decide if a fall had occurred or not, another algorithm is threshold-based which can use a 3-Dimensional vector using X, Y, and Z-axis with this method of detecting a fall requires body acceleration which can be achieved in this formula that detects the magnitude of the acceleration of three values ax, ay and az values.

Equation 1: Equation of 3-Dimension Vector (Strang & Herman, 2016):

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

Machine Learning (ML) can improve the overall performance of the fall detection system, example of an ML model is the Hidden-Markov-Model (HMM), Tong, et al., (2013) used HMM, and concluded it was a reliable system that can predict a fall within 200 to 400ms (millisecond) range. Overall concluded with 100% sensitivity and specificity while during the testing phase, received 81% for accuracy and sensitivity.

(Guo, 2015) used a threshold-based without ML techniques, it requires a set of rules such as FT1 will trigger if lower acceleration was detected, FT2 upper acceleration will trigger, and FT3, if lower angular acceleration detected will flag up. If one of three conditions were met, then it will trigger the fall detection system. Thus, concluded 100% specificity, however, the threshold-based is not accurate compared to ML but can produce reliable results.

(Waheed, 2017) conducted research that use Camera Technology that used Motion History Images that provides information on the movement of the human body. The technique used Fore-ground splitting, which creates the background into black and the outline of a human to be white which creates an Adaptive Gaussian Mixture model to the value of the intensity matching varying backgrounds. False-positive was detected during the experiment, however, in my opinion, there should be a device that confirms that the human has fallen such as motion sensors to confirm whether the person is moving or not, motion sensors are cheap and easier to implement confirmation. During the testing, it did detect motions that are greater than the threshold values, however, it detected the 'fall' however it was a false positive detection.

1.3 Review of Sensor Placement

There are many different positions that a fall detection device can be placed and the position can affect the performance example wrist placement experiment, "*the arm, wrist, hip and leg are not the suitable positions for the accelerometer, based devices due to their high movement frequency and complexity, although they may be the more comfortable place to wear*" (Tong, Quanjun, Yunjian, & Ming, 2013). However (Özdemir, 2016) performed a different machine learning algorithm, which study has achieved accuracy above 95% example between the crown and nape of the head had produced a result of 96.61%, chest at 96.50%, the waist at 98.42%, wrist at 94.92%, thighs 97.89% and final the ankles at 97.00%, however from Özdemir's method of setting up the sensors use specialized steps that housing the sensors as shown by (Özdemir, 2016) work in Figure 1.

Figure 1: Sensor Placement Locations (Özdemir, 2016, p. 7)

Overall it suggests that the chest is the most suitable to mount the detecting device on the chest, and the wrist can perform the worse out of the sensor placement.However, a concern that needs to be raised is that the datasets collected are dominantly male, which made the dataset unbalanced, however, the dataset collected 36 types of movements which includes 16 ALDs and 20 falls, with 378 sensors that were investigated.

In conclusion of this literature review, firstly address what fall detection system will be developed for this research. This research will use a Tri-Axis based which falls into the wearable category due to the cost-efficient way to set up and implement a fall detection device. To create a cost-efficient and energy-efficient device, it is suitable to develop a threshold-based algorithm instead of Machine Learning due to high-quality data input requirements from a wide range of data sources or from pre-existing databases which includes fall detection which is very unlikely to obtain from organizations alongside power consumption using machine learning and the cost of maintaining Artificial Intelligence, to maintain power-efficient and the cost-efficient device it is suitable to use a threshold-base algorithm.

The tri-axis placement will be placed on the chest, due to less motion compared to the wrist where there is a lot of movement compared to the chest which if it was placed on the wrist, there is a high chance of setting off false positive input from the tri-axis, however, the chest is more suitable to place to gain desirable results. Due to its small capacity, it can be placed on the chest, Özdemir, (2016), published results of the suitable locations for a Tri-Axis with the assistance of Machine Learning and found that the wrist is unsuitable due to the movement of the arms, wrist, and hand movement impact the study. To analyze the results, the results will be displayed on a serial plotter graph.

Results from Tong, et al., (2013) method of approach using MMA72060Q with MMA7260Q produced a sensitivity of 100% and specificity of 100% which raised the question about getting both sensitivity and specificity to 100% on ADL while on the initial test run where the sensitivity and accuracy were dropped to 81% compared to ADL, this was the lowest sensitivity and specificity reported from the literature review that used a threshold-based approach. Rihana & Mondalak, (2016) used the same hardware as Tong, et al., (2013).

In previous papers, we saw that they have used a Tri-Axis accelerometer to use to detect if a fall had occurred, a 3-dimensional vector (threshold-based) algorithm will be used in this experiment due to the lost cost, and energy-efficient of the Tri-Axis accelerometer and the placement of the Tri-Axis will be placed on the wrist where it is easy to access the Tri-Axis and should feel ‘natural’ for the user to wear the device.

Three objectives have been formed:

- Investigate methods of what are fall detection systems and their key components through literature review.
- Produce an embedded system for fall detection.
- Gain data from the fall detection system and analyse it to see if it’s reliable (accuracy is above 85%).

2 Methodology and Experiment

2.1 Fall Detection Algorithm

To determine if a fall had occurred for the threshold-base algorithm, firstly measure the current magnitude of acceleration, if condition one is true then, acceleration is great than the threshold which is 40gs then if true it will check if the orientation has changed within 500 milliseconds, if this is true then the buzzer will trigger until the user press the reset button, if not it will continue till it reset, if any conditions are false then it will loop back to magnitude of acceleration measurement. Overall basic algorithm design is in figure 2.

The equation for the 3-Dimension Vector can be translated from Equation 1 to programming language as follow:

```
Float [NAME] = power(power(X-Axis,2) + power(Y-Axis,2) + power(Z Axis, 2));
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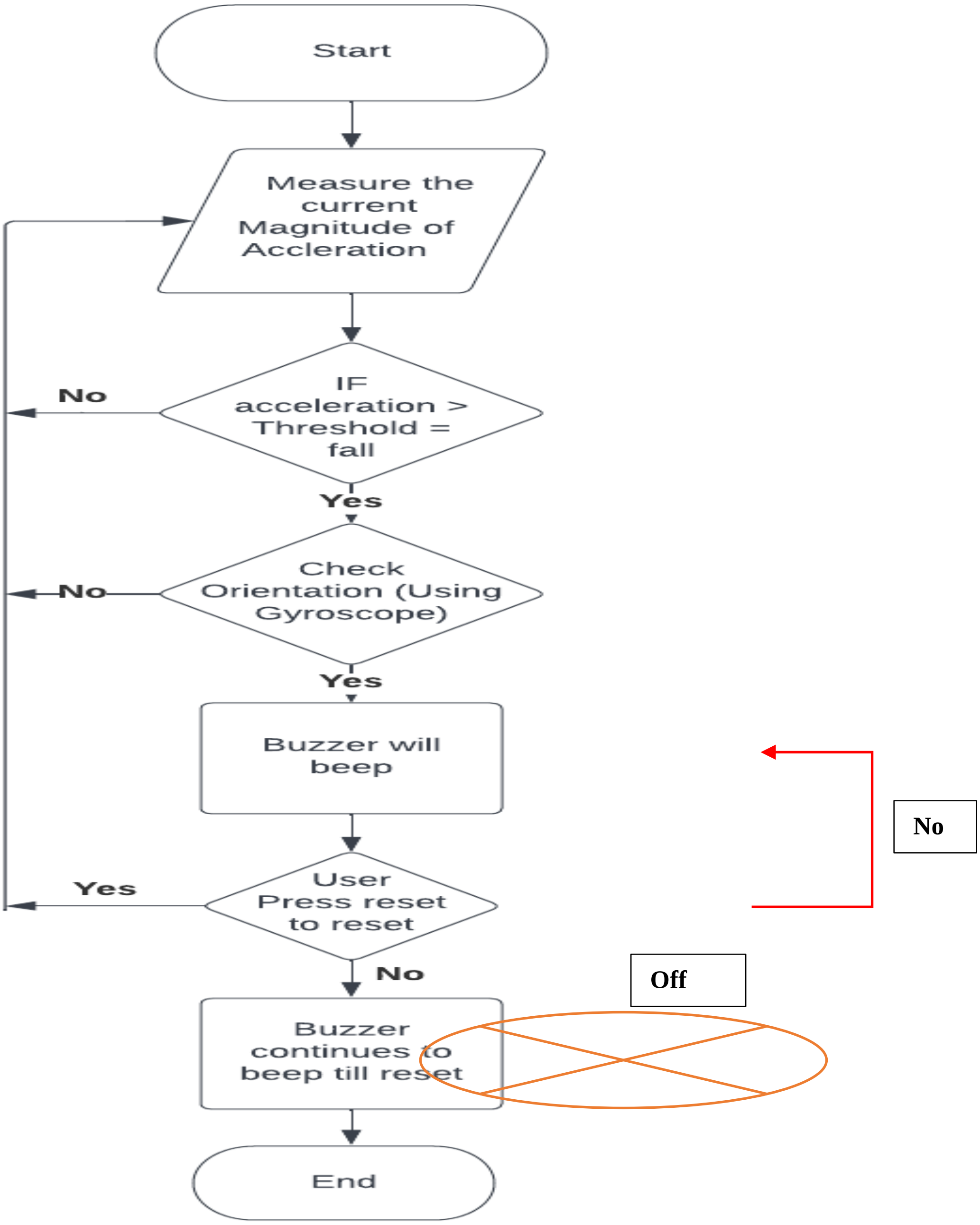

Figure 2: Threshold-Base Algorithm Design

2.2 Hardware

The hardware that used in this work is an MPU6050 IMU, which has an integrated accelerometer and gyroscope onto a single microchip. The gyroscope measures the rotation acceleration which is the rate of the change of the position and this can be visualized in X, Y, and Z axis (or concordance), MPU6050 IMU uses MEMS (Micro-Electro- Mechanical-System) technology, which is composed of micro components ranging from 0.001mm (millimeter) to 0.1mm in size, this is usually combined with a microcontroller (CPU) to create a system using both integrated devices or using systems that combined mechanical and electrical components. Overall, the MPU6050 IMU has six-axis motion tracking which detects six Degrees of Freedom, due to the 6 outputs from 3 accelerometers and 3 gyroscope outputs. Arduino Nano board is the processing unit that processes and calculates the algorithm and collects data from sensors that will be attached, and a buzzer will be attached to the device, to allow to indicate that a fall had been detected by the device and algorithm, a reset button will be placed to reset the algorithm and the device. Figure 3 shows the schematics of the fall detection, and Figure 4 shows the physical components of the fall detection system.

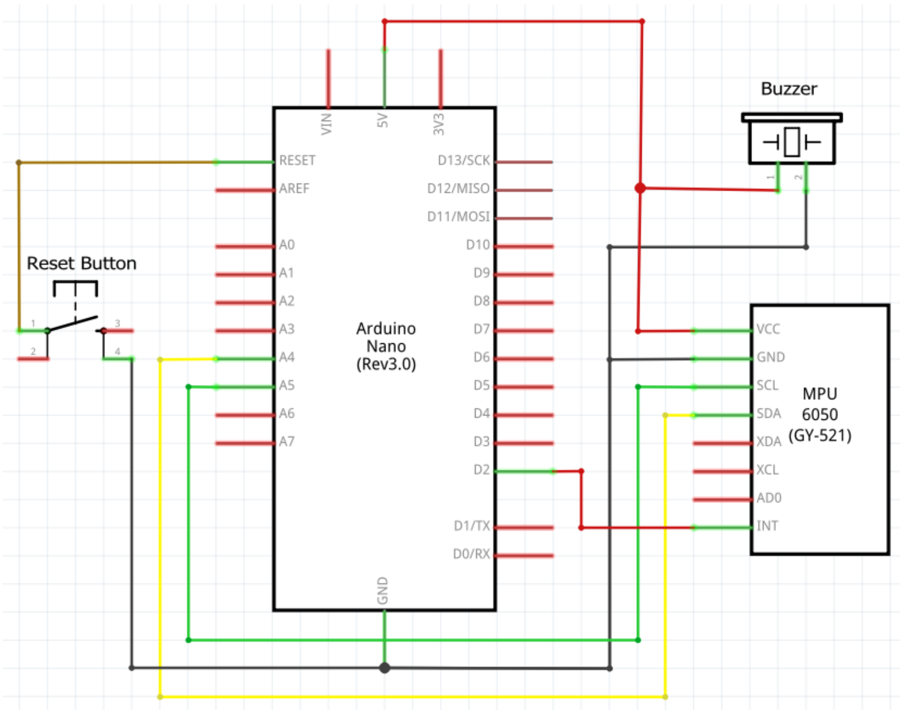

Figure 3: Schematic View

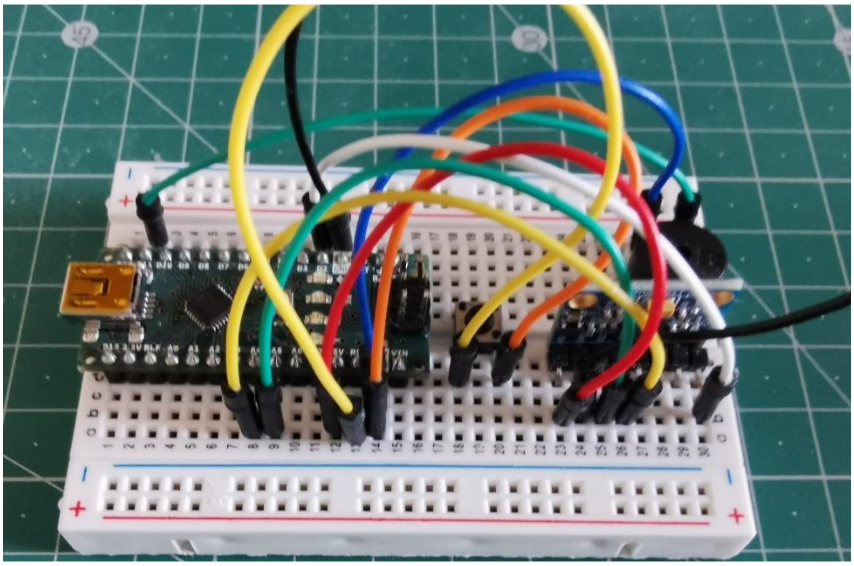

Figure 4: Physical Device

Figure 3 shows the components are connected between Arduino Board and the MPU6050 IMU to create the fall detection systemHowever, this shows similar on how the fall detection device looks due to the limitation of the software to create similar results in Figure 4. Figure 4 shows the physical connection between devices and the final prototype for the fall detection system.

2.3 Software

Arduino IDE was used efficiently to implement the algorithm which can convert the raw data from the MPU 6050 to readable data which generates signals if the accelerometer exceeds the threshold value and allow to view real-time graphics and values which can be viewed on Serial Monitor (Figure 5) and Serial Plotter (Figure 6).

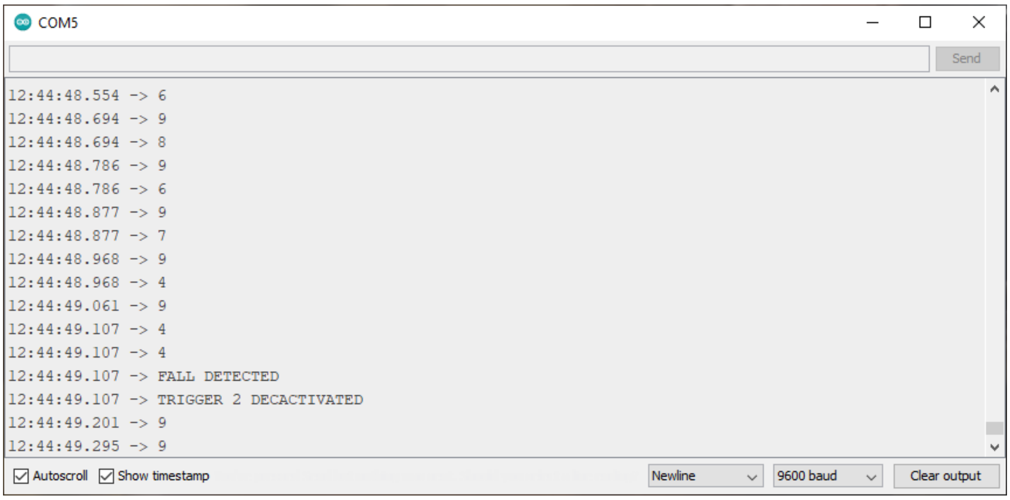

Figure 5: Serial Monitor

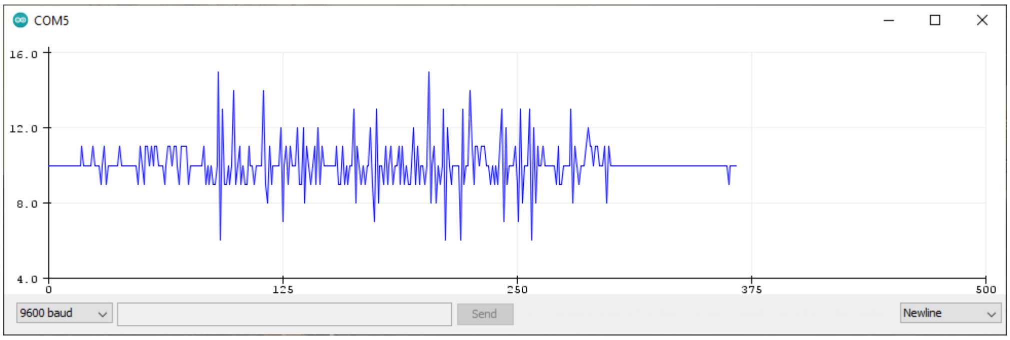

Figure 6: Serial Plotter

Arduino IDE provides an open-source environment and libraries for most components including sensors modules such as MPU6050 IMU and other types of sensors which is available online by communities' developers and or by the manufacturer provides open-source libraries to read the RAW input data from the sensors that it produced such as values for roll, pitch, and yaw. The library that will be imported is the MPU6050 by Electronic Cats Version 0.5.0 from the Library Manage, and the program code is located appendix under Program Code. Due to cloud limitations connecting to the internet to the cloud will not be used.

2.4 Tri-Axis Placement Location

The placement of the tri-axis will be located on the chest, from the literature review suggest that there is less movement on the chest compared to the wrist which according to Tong, et al., (2013) is not suitable for the arms, wrist, hips, and legs are not a suitable position to place the fall detection system due to moment, to make the device feels ‘natural’ to wear, it is suggested to place the fall detection system on the chest, despite there are many different areas that fall detection can be placed on the body.

2.5 Data Collection

Data from collected from 5 participants’ movement signals from the MPU6050 IMU, which has an embedded system comprised of an accelerometer, gyroscope, and magnetometer embedded into a small chip. The participants will conduct four simulated falls and four activities of daily living. In this experiment, the activitieswere be split into two categories:

- Falls:Forward falls (Fall exp. 1), backward falls (Fall exp. 2), sideway falls (Falling onto the arm) (Fall exp. 3), mixed between backward and sideways falls (Fall exp. 4).
- Activities of Daily Living: Walking (ADL exp. 1), squatting (ADL exp. 2), standing, and sitting on a chair (ADL exp. 3), opening, and closing doors (ADL exp. 4).

Forward Fall (Fall 1), landing chest-first, fall 2 backward falls onto the mattress where the back spine will contact. Sideway falls are where the arms will contact first, and the final fall will be in between backward and sideways fall. Overall, 20 falls and 20 ADL in a total of 40 experiments in total, to confirm if a fall had occurred a buzzer will be triggered to notify if a fall had been detected by the algorithm. Each participant will do two categories and each activity will be done once.

2.6 Participants

Due to ethical issues due to the recruitment of elderly participants and the potential hazards and high possibility of injuries, this experiment will not include elderly participants. However, in this research, 5 participants were involved in this experiment, and the general average characteristics of the participants were:

- Average Age: 21.2 years.
- Average Height (cm) 178.4cm
- Average Weight (kg): 68.4kg.

3 Results, Findings, Analysis, and Discussions

The experiments were conducted using the MPU6050 IMU Accelerometer as the data input from the participants, which is processed by the Arduino board (Arduino Nano) to collect acceleration and orientation while conducting daily life activities and fall detection scenarios. In this experiment, the results have been split into two sections, the first section will review the Activities of Daily Living (ADL) and the second part will review the Fall Events when the participants conduct a fall.

The raw input from the MPU6050 will be converted from raw data to calculate if the amplitude had met one of three conditions that have triggered a fall (if it breaks the threshold at 3g if the amplitude is broken the lower threshold at 40g and if orientation changes remain between 0-10 degrees). The data will be displayed on a time graph that shows Acceleration vs Time, and to detect a fall, we will monitor if the fall has been triggered by the algorithm.

3.1 Activity of Daily Living (ADL)

Activities of Daily Living (ADL) was conducted using MPU 6050 to collect the acceleration and orientation during the experiment phase for Activities of Daily Living.

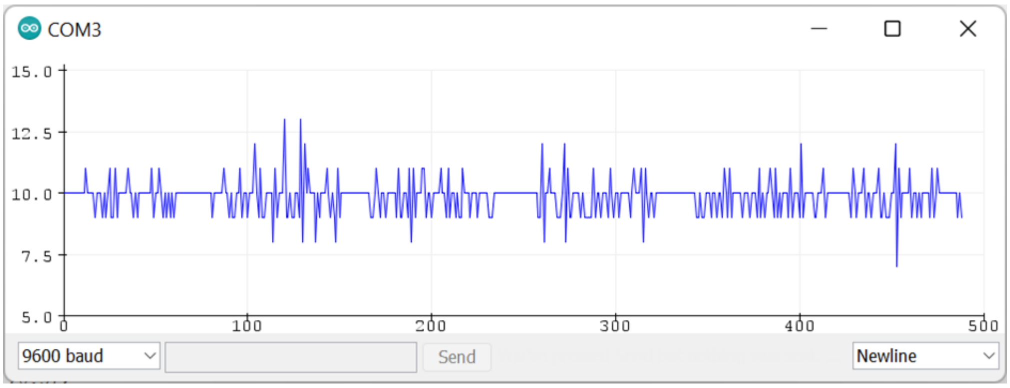

Figure 7: Acceleration Graph for Walking (ADL 1)

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	13.00	7.0
2	13.00	7.0
3	16.00	4.0
4	15.00	5.0
5	14.00	6.0

Table 3: Results Table for Walking (ADL 1)

Table 3 average maximum peak acceleration is 14.2g and the minimum peak acceleration is 7.4g, and the fall detection system did not trigger.

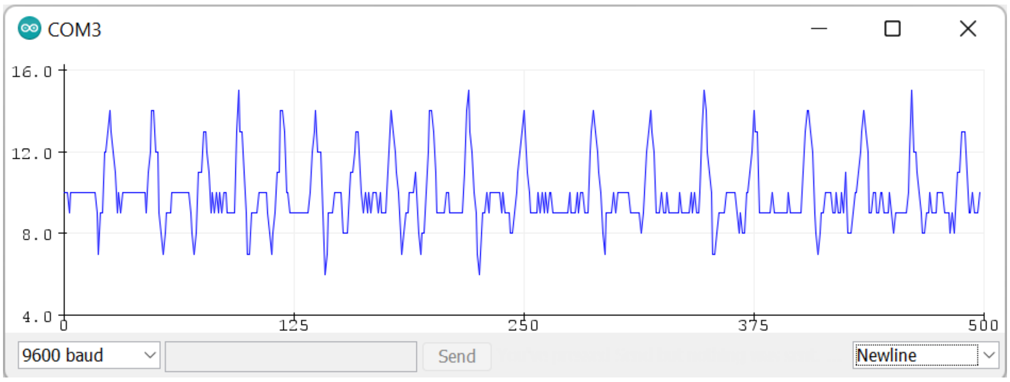

Figure 8: Acceleration Graph for Sitting and Standing (ADL 2)

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	15.00	6.0
2	15.00	7.5
3	45.00	7.5
4	50.00	7.5
5	16.50	4.0

Table 4: Results Table for Sitting and Standing (ADL 2)

Experiments 3 and 4 for ADL 2, had peak acceleration above 40g, and the buzzer had triggered to indicate that a fall had occurred. Table 4 average maximum peak is 28.3g and the minimum peak average is 6.9g.

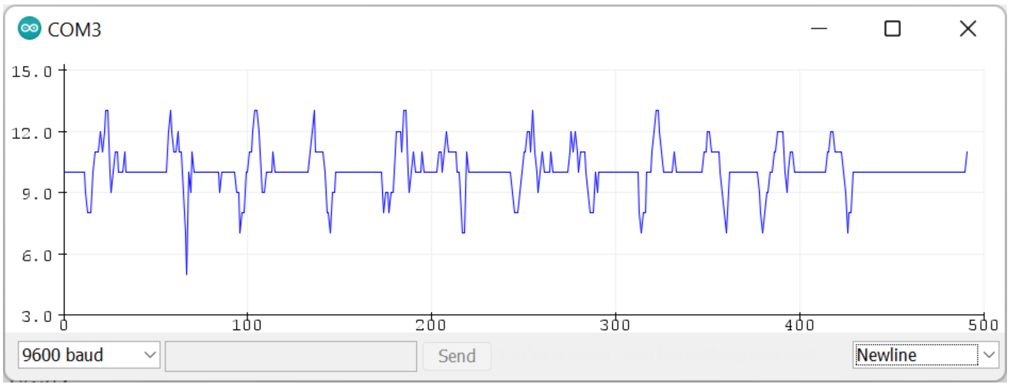

Figure 9: Acceleration Graph for Squatting and Standing (ADL 3)

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	13.50	5.5
2	15.00	5.0
3	20.00	5.0
4	45.00	5.0
5	20.00	4.0

Table 5: Results Table for Sitting and Standing (ADL 3)

Table 5 shows the maximum peak value of 45.00g which triggered the buzzer to activate due to the algorithm detecting a fall from experiment 4. The maximum peak average is 22.7g and the minimum peak average is 4.9g.

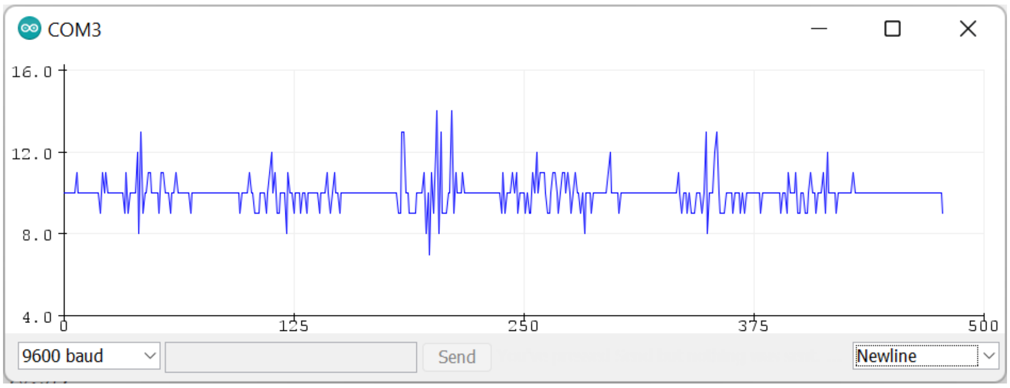

Figure 10: Acceleration Graph for Opening, closing, and walking through doors (ADL 4).

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	14.00	57.5
2	13.00	6.0
3	15.00	8.0
4	14.50	8.5
5	17.00	8.0

Table 6: Results Table for Opening, closing, and walking though doors (ADL 4)

Table 6 produced no false negatives produced as expected, the maximum average peak was 14.7g, and the minimum peak average was 7.6g. The fall detection system did not falsely detect a fall during this experiment.

Participants	ADL Exp. 1	ADL Exp. 2	ADL Exp. 3	ADL Exp. 4
1	0	0	0	0
2	0	0	0	0
3	0	1	0	0
4	0	1	1	0
5	0	0	0	0

Table 7: Binary Table for ADL Experiments.

Overall, there were three false negatives that three activities of daily living were triggered by the algorithm, mainly due to the maximum acceleration being above 40g therefore they were triggered, however, seventeen were not triggered by the algorithm. All the graphs from the experiments are in the appendix section under Test graph data and a binary table in table 7.

3.2 Fall Detection Event

For every category fall, the participants will be asked once, however, they will not repeat the same category, alongside there were 2 false negatives that did not detect by the algorithm, as you can see in Figures 11 and 12, where both did not trigger fall detection due to acceleration did not calculate or some other fault, however, overall, 18 out of 20 falls were detected.

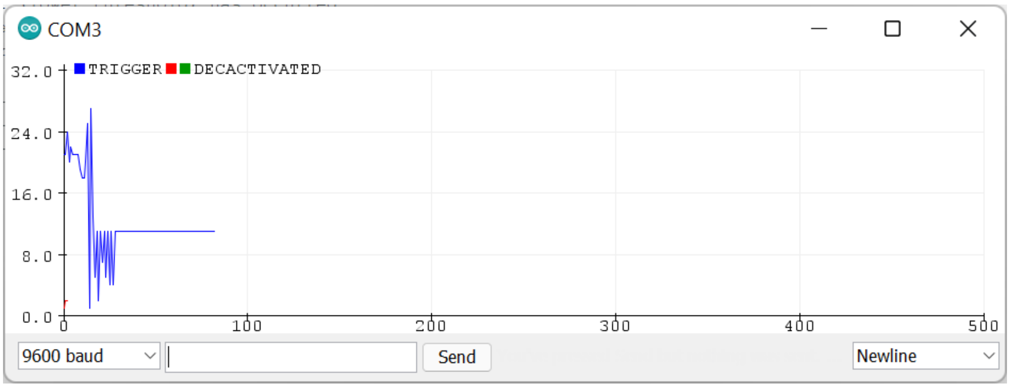

Figure 11: Fall 1 False Negative Detected.

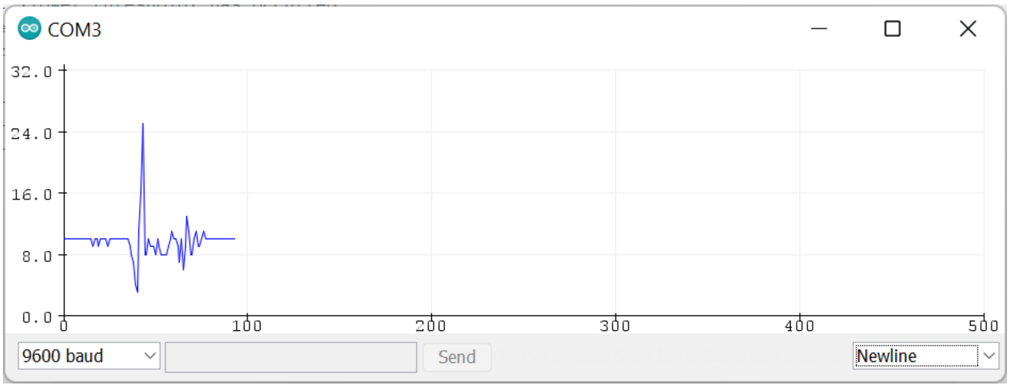

Figure 12: Fall 2 False Positive Detected.

Participants	Fall Exp. 1	Fall Exp. 2	Fall Exp. 3	Fall Exp. 4
1	1	1	1	1
2	0	1	1	1
3	1	0	1	1
4	1	1	1	1
5	1	1	1	1

Table 8: Binary Table for Fall Detection Event.

The binary table (Table 8) shows all the fall experiments, presented in a binary form to show two conditions, 0 (zero) shows that the fall detection did not detect, and 1 (one) shows that the algorithm triggered and detected a fall. Overall, 90% of this data was successfully detected by the algorithm. Sample time graph data in Figure 13 and more detail in the appendix.

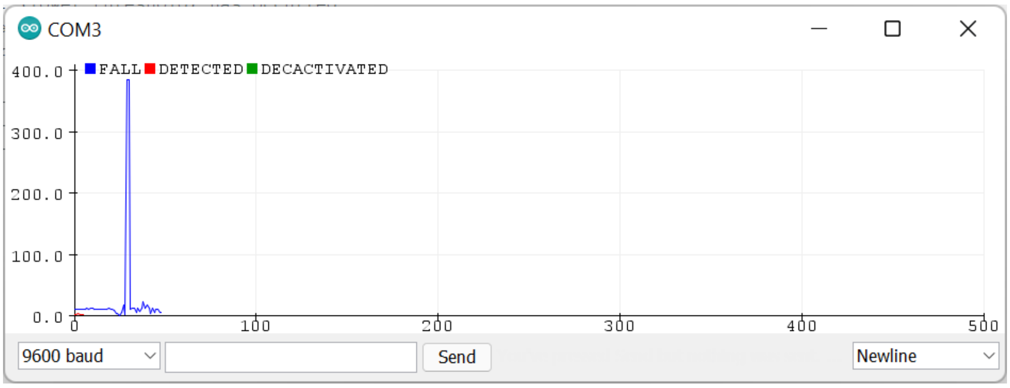

Figure 13: Acceleration Graph for forwarding Fall (Fall 1).

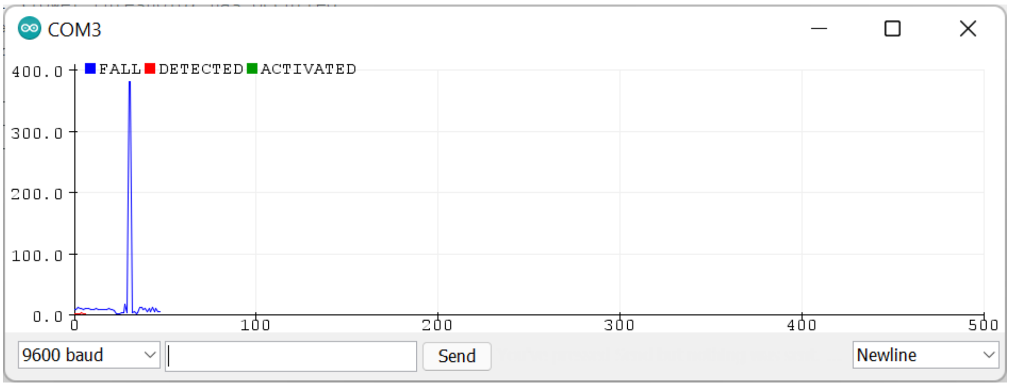

Figure 14: Acceleration Graph for Backward Fall (Fall 2).

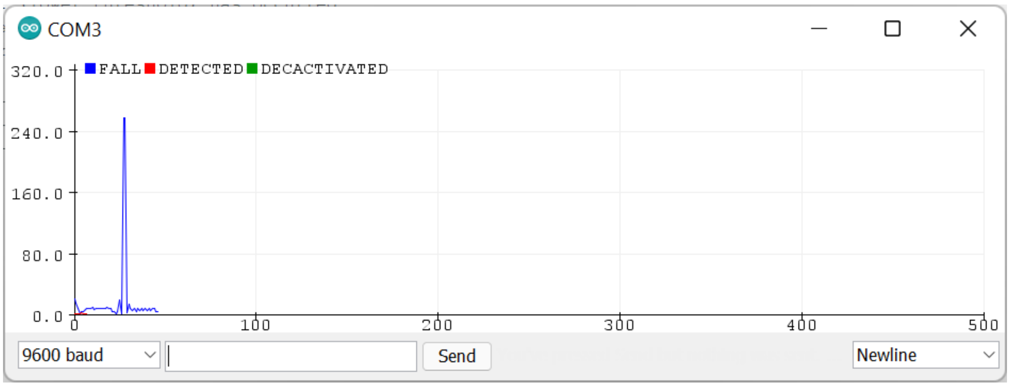

Figure 15: Acceleration Graph for Sideways Fall (Fall 3)

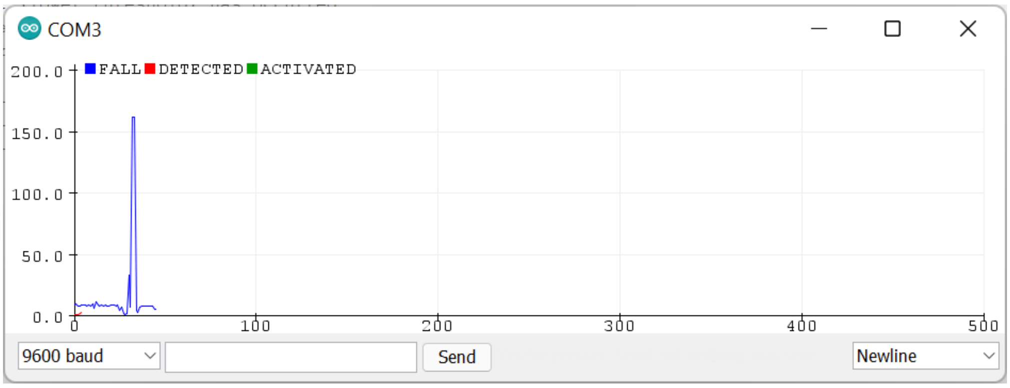

Figure 16: Acceleration Graph for Mixed between backward and Sideway Falls (Fall 4)

3.3 Binary Table Overall Experiment

Table 9 shows all experiments carried out and presented in a binary way to show two conditions, 0 (Zero) alarm did not trigger, or a 1 (one) alarm was triggered, overall, 18 out of 20 correctly triggered when a fall was detected. While 17 out of 20 did not detect a fall during Activity of Daily Living (ADL). However, 3 out of 20 from ADL triggered.

Participants ID	Fall Exp. 1	Fall Exp. 2	Fall Exp. 3	Fall Exp. 4	ADL Exp. 1	ADL Exp. 2	ADL Exp. 3	ADL Exp
1	1	1	1	1	0	0	0	0
2	0	1	1	1	0	0	0	0
3	1	0	1	1	0	1	0	0
4	1	1	1	1	0	1	1	0
5	1	1	1	1	0	0	0	0

Table 9: Binary Table for Findings.

3.4 Data Analysis

As with any other experiment, this fall detection system is reliable, it has four test outcomes to determine if the system is reliable, and a confusion matrix is used to predict results on classification problems in which the amount of positive (correct) and negative (incorrect) predictions are summarized into four possible outcomes from this reliability test:

- True Positive (TP): Correctly detected a fall correctly.
- False Positive (FP): Incorrectly detected a fall that did not happen.
- True Negative (TN): Correctly detected that a fall did not happen.
- False Negative (FN): Incorrectly detects a fall when it did not occur.

		Daily Activity (Actual)	
		Fall (True Positive)	ADL (True Negative)
Fall Detection (Predicted)	Fall (Predicted Positive)	18 (True Postive	3 (False Positive)
	ADL (Predicted Negative)	2 (False Negative)	17 (True Negative)

Figure 17: Confusion Matrix Fall Detection vs ADL.

From Figure 17 the rows (Fall Detection Predicted) correspond to the predicted outcome, and the columns (Activity of Daily Living) correspond to the known truth. There are only two categories, Fall and Activity of Daily Living, in which that True Positive mean that the participants that had fallen, was correctly detected by the fall detection system, and 18 out of 20 correctly triggered a response.

The True Negative are activities of daily living that did not detect falls, 17 out of 20 were activities of daily living. Therefore out of 17, only 3 had been flagged as false positives. The False negatives are when detection did not occur in a fall which only 2 out of 18 experiments, only two had been flagged as false negatives. And finally, the false positives, these are where a fall had been detected during the activity of daily living in which only 3 had detected as a fall during an activity of daily living.

Calculating two metrics, sensitivity and specificity, sensitivity gives us the value of the fall that was correctly detected which is calculated by True Positives divided by True Positives and False Negatives. Specificity tells us the value of Activity of Daily Living was incorrectly triggered. Specificity, this is calculated by True Negatives divided by True Negatives and False Positives; both can be defined below.

- Sensitivity: If it has the capability needs to be detected.

Equation 2: Sensitivity calculation:

$$Sensitivity = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \quad (2)$$

- Specificity: If it is capable to detect only a fall.

Equation 3: Specificity calculation:

$$Specificity = \frac{True\ Negatives}{(True\ Negatives + False\ Positives)} \quad (3)$$

Equation 4: Accuracy calculation:

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Postive + False\ Negative + False\ Postive + True\ Negative)} \quad (4)$$

$$Sensitivity = \left(\frac{18}{18+2}\right) * 100\% \quad (2)$$

$$Sensitivity = 90\%$$

$$Specificity = \left(\frac{17}{17+3}\right) * 100\% \quad (3)$$

$$Speciicity = 85\%$$

$$Accuracy = \frac{(18+17)}{(18+17+2+3)} * 100 \quad (4)$$

$$Accuracy = 87.5\%$$

Sensitivity is 90% of falls were identified by the fall detection system, specificity gave 85% of the activity of daily living was not flagged up as a fall. This means that 90% of the time, the fall detection system will correctly detect Falls, while 85% of the time, the activity of daily living will not trigger the fall detection system. Overall, this experiment achieved above 80% for sensitivity and specificity, and the accuracy was 87.5% which had been achieved is reliable to use, another achievement is to produce the fall detection system. The data table/findings is in the appendix , finding the sensitivity is more important because it represents fall detection. However, the specificity can be lowered due to a button to reset the alarm.

4 Conclusion and Future Work

Due to ethical issues, we cannot replicate the real world where elders would use this. However, this can replicate for users who are working in industries that have a significant risk of falling such as the construction or food supply industry or a place where individuals would have a high likelihood to be at risk to fall. Compare other related studies such as Wu, F. et al., (2015), produced a sensitivity of 97.1% and specificity of 98.3%, while Rihana, S. & Mondalak, J. (2016) research produced 90% sensitivity and 85% specificity. However, there are flaws and limitations to this research, the primary flaw is due to the data quantity, there is not enough data compared to Rihana, S. & Mondalak, J. (2016) who conducted 50 simulated falls.

Improvements that this research could improve is exploring Machine Learning (ML) algorithm to learn patterns based on previous data and feature extraction However, the problem of ML is the power consumption and more importantly data quality and quantity requirements for ML, which is difficult to obtain data However recently data from SisFall could be used for ML fall detection system, however, there is a lack of data availability in a realistic environment. Due to the benefits of ML in Fall Detection systems, it can produce a reliable detection algorithm that could see both sensitivity and specificity above 90%, however for future studies, using ML algorithm to analyse the results, and predict if the users had fallen or in the activity of daily living phase.

From hardware improvements and changes, swap out Arduino Nano for ESP8266 board, which can access the internet and manufacture ESP8266 are cost-efficient to produce compared to Arduino boards in general. For future work, components consider adding a GPS location module, and a panic button to develop a full fall detection system that includes more functions to help people who could connect to the internet and the cloud. Despite, this fall detection device had produced 90% sensitivity, 85% specificity, and an accuracy of 87.5%, it requires more participants and data to obtain higher and or in-depth data from the fall detection system.

This work aims to improve the reliability of using wearable fall detection system for elderly people who may be living alone which can cause a hazard if the elderly patient had fallen and unconscious which delays the response for medical care to the fallen patient. Not only for the elderly but the possibility for people who work in the construction industry and or people who work where falls can occur when carrying heavy items. There are three different methods for a fall detection system, a visual-based method which relies on camera technology, another method ambient where the environment detects a fallen example sound/ vibration, and the final method the Wearable device which uses small microprocessors to detect fallen example Blood Pressure Sensor which all methods have its advantages and disadvantages.

This research has concluded that the sensitivity and specificity had reached 90% sensitivity and 85% specificity this shows that fall detection is reliable, however, there are better alternatives such as the 3-dimension Vector as shown in Figure 4 to machine learning model to predict and detect a fall, however at a cost of budgeting, portability, most importantly it requires a lot of data example the Hidden-Markov-Model (HMM) to produce machine learning fall detection system. However, due to the sensitivity and specificity was above 90%, it requires more test and data to produce a reliable result for Machine Learning. Overall, this research achieved four objectives, first, to produce a fall detection system, the second objective was to collect data and the final objective is to produce sensitivity, specificity, and accuracy above 85%, in this research has achieved all three goals, which had been achieved.

Overall, this is a foundation for developing a fall detection system which had achieved three objectives. For future studies different approaches methods examples components, algorithms, and the possibility of the fall detection device talking to the internet and to the cloud to help people in need of a fall detection system.

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5 Appendix A – Research Data Graph

5.1 Activity of Daily Living, 1 Walking Graph (ADL 1)

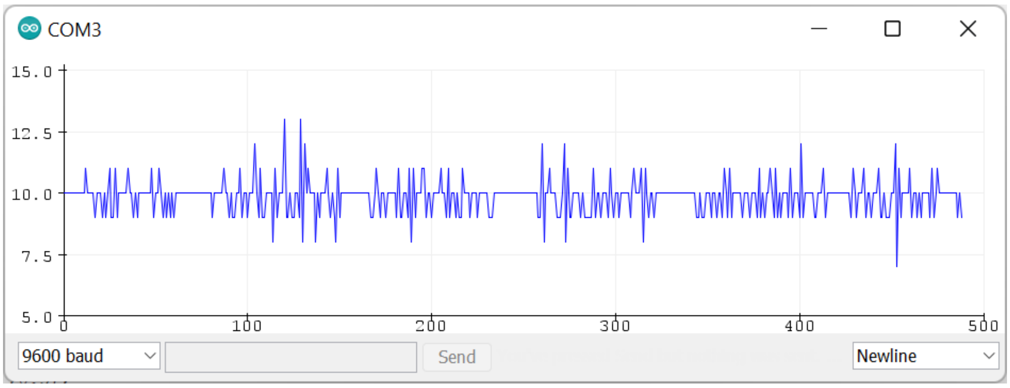


Figure 18: Participant 1

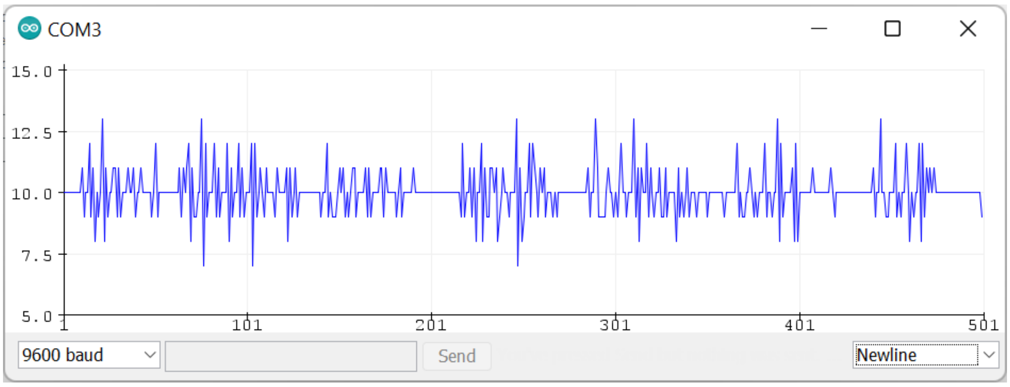


Figure 19: Participant 2

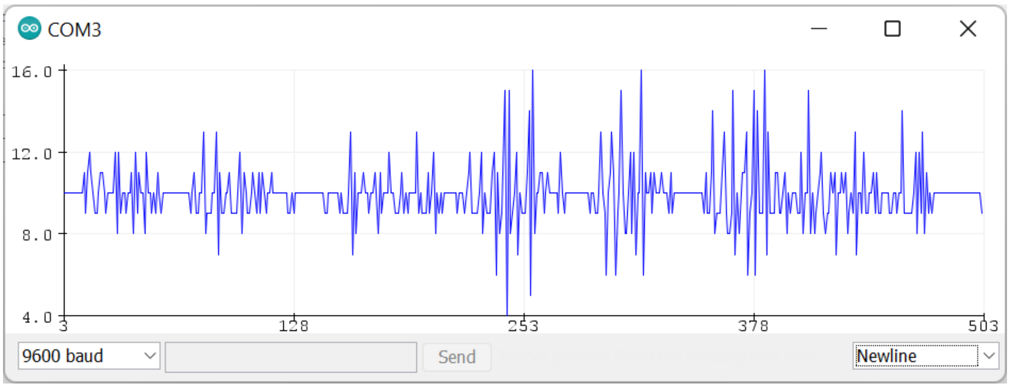


Figure 20: Participant 3

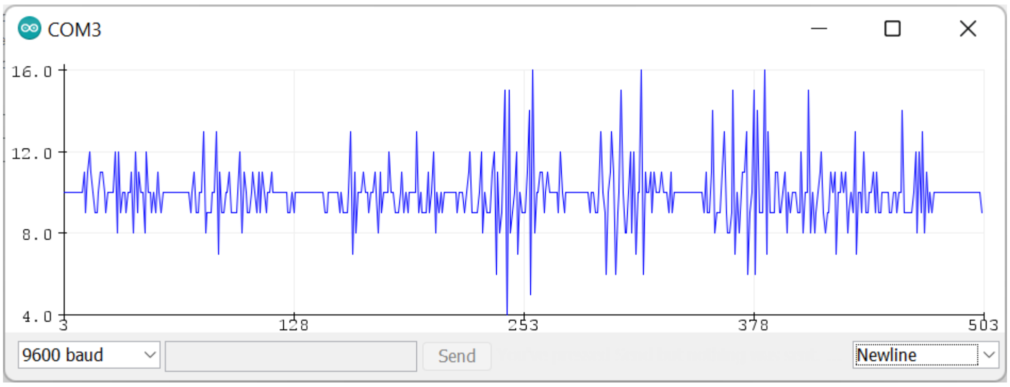


Figure 21: Participant 4

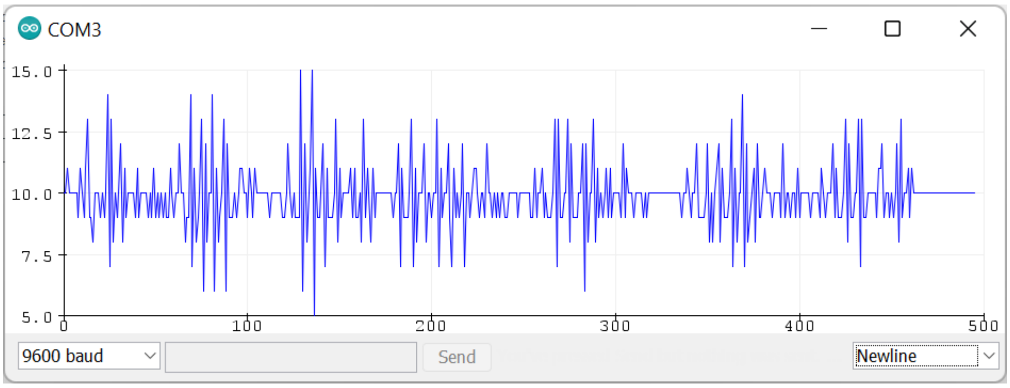


Figure 22: Participant 5

5.2 ADL 2 Sitting and Standing

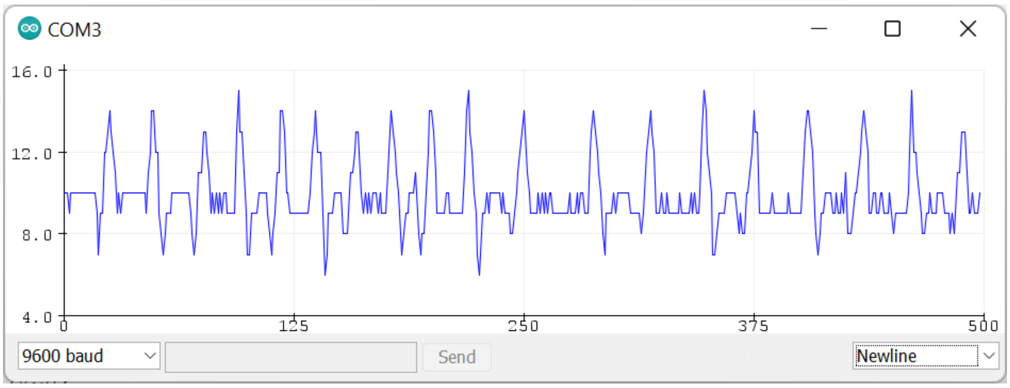


Figure 23: Participant 1

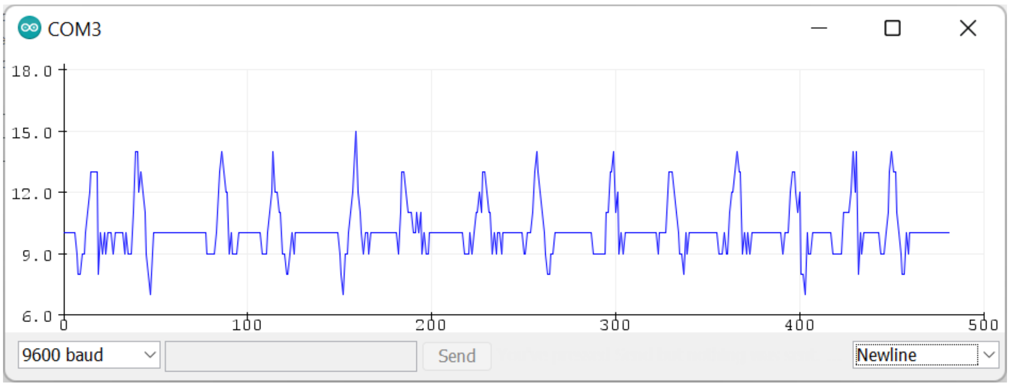


Figure 24: Participant 2

Figure 25: Participant 3

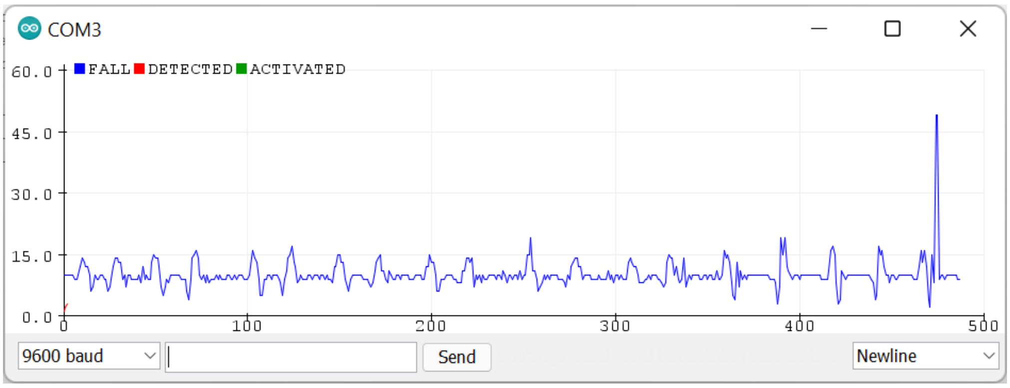


Figure 26: Participant 4

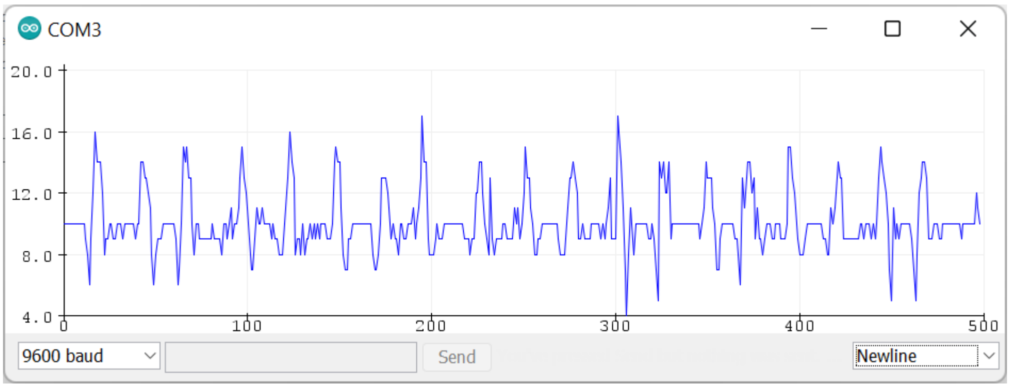


Figure 27: Participant 5

5.3 ADL 3 Squatting and Standing

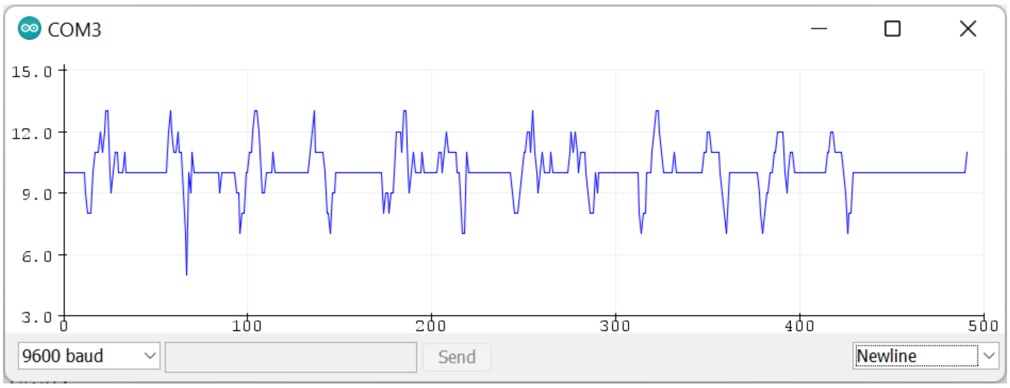


Figure 28: Participant 1

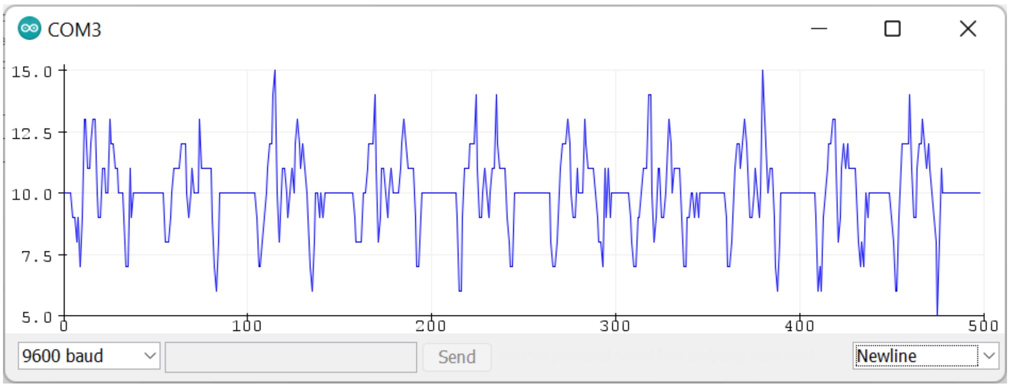


Figure 29: Participant 2

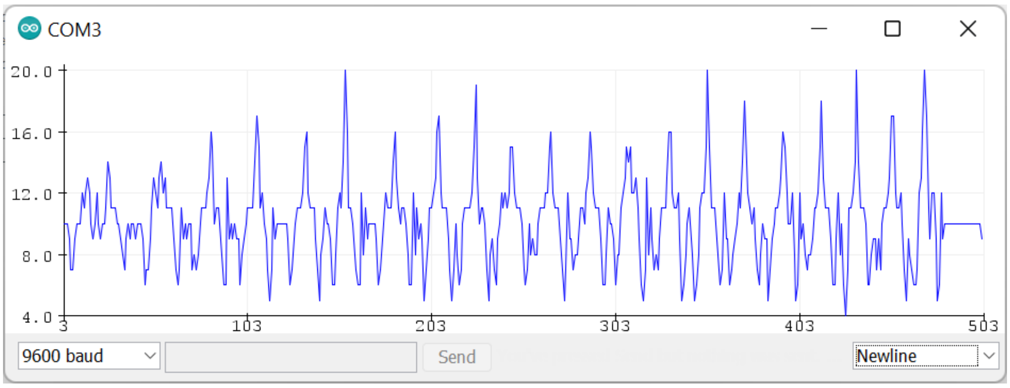


Figure 30: Participant 3

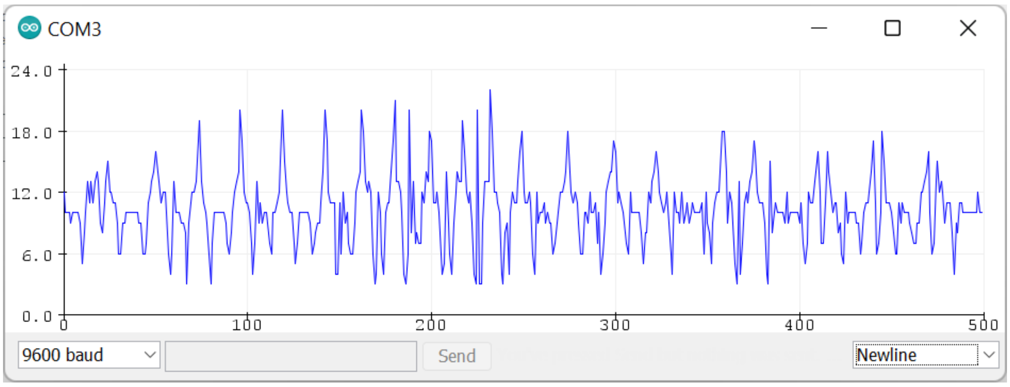


Figure 31: Participant 4

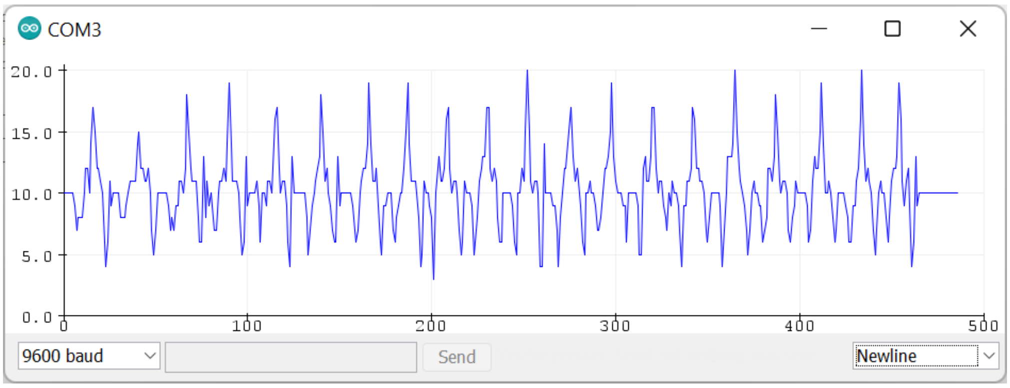


Figure 32: Participant 5

5.4 Opening, closing door, and walking through door.

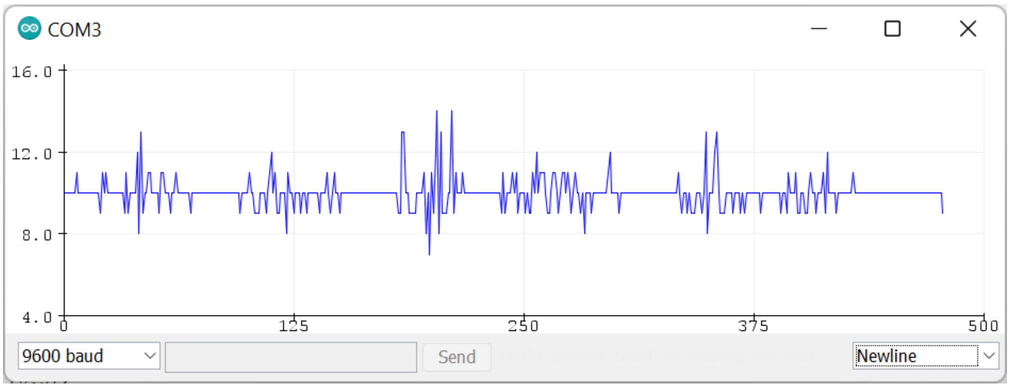


Figure 33: Participant 1

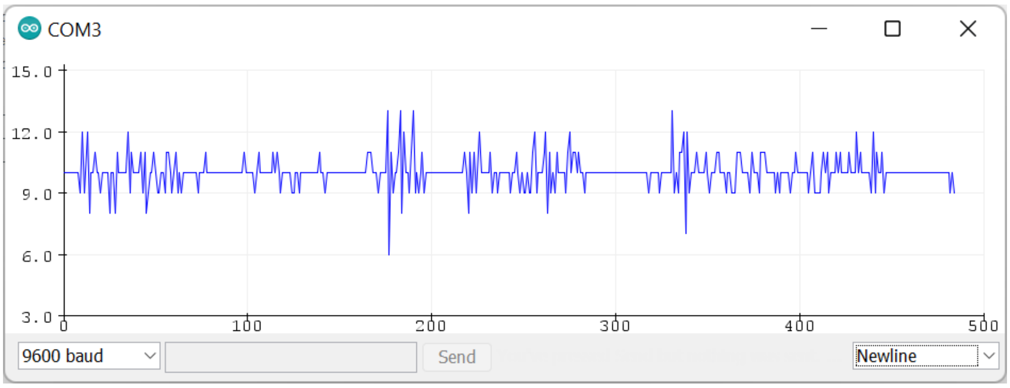


Figure 34: Participant 2

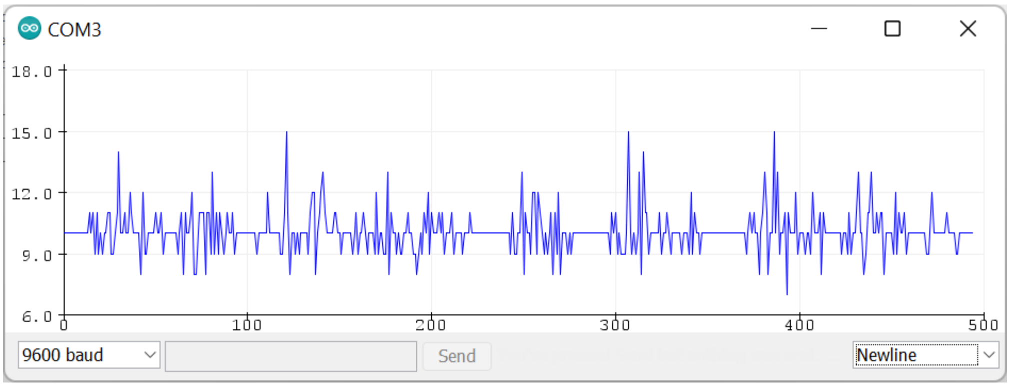


Figure 35: Participant 3

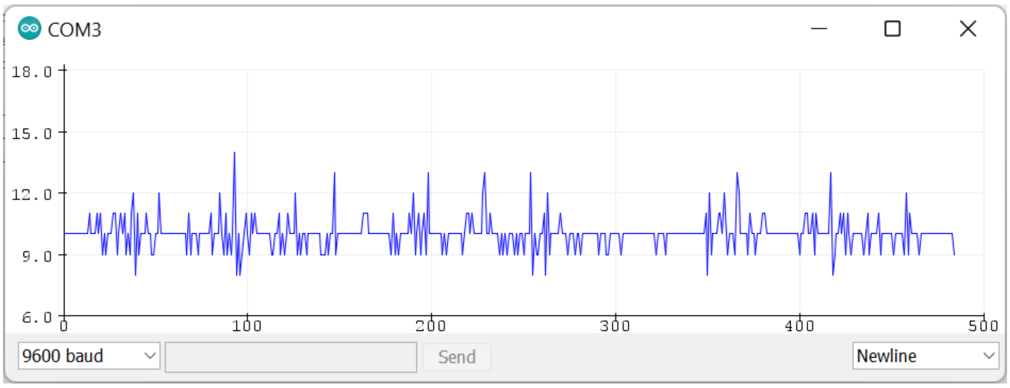


Figure 36: Participant 4

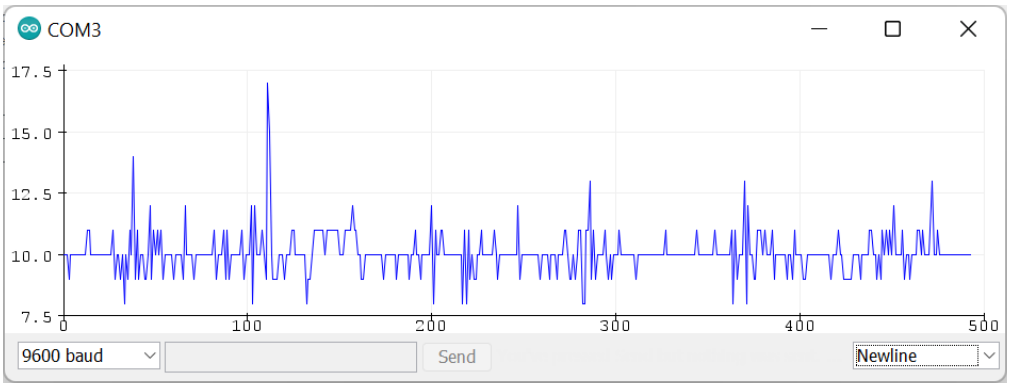


Figure 37: Participant 5

5.5 Fall Detection Event, Forward Fall (Fall 1)

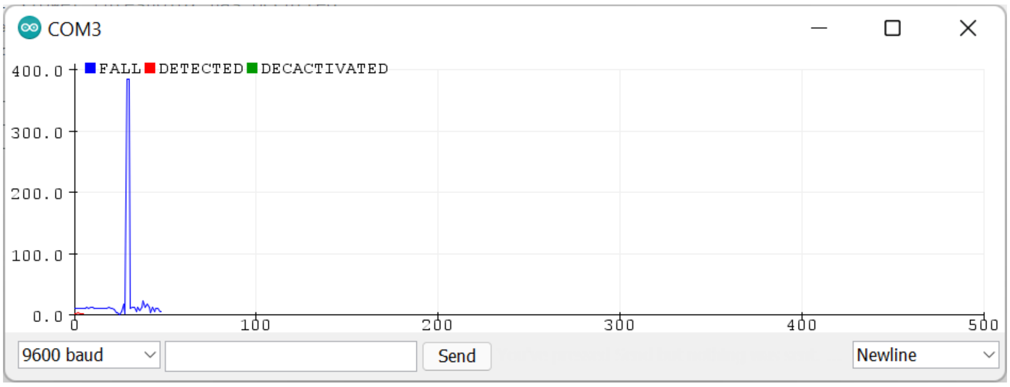


Figure 38: Participant 1

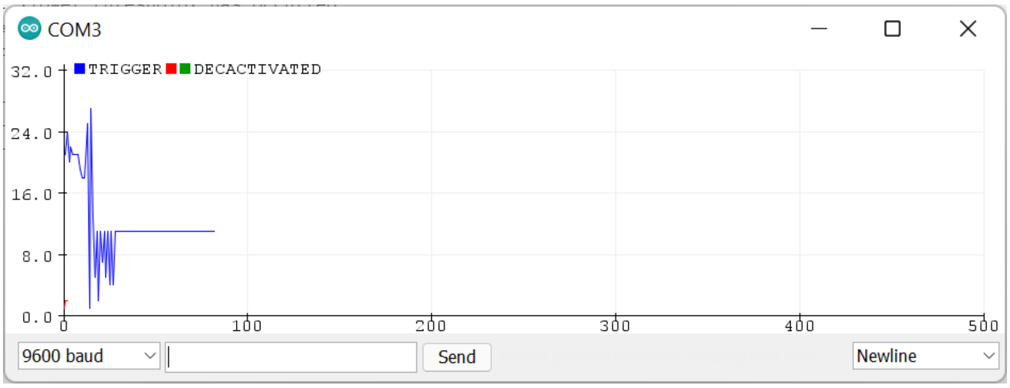


Figure 39: Participant 2

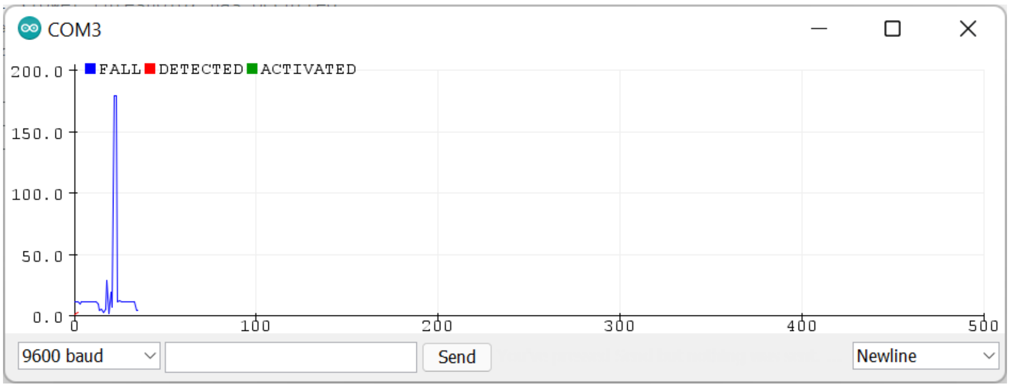


Figure 40: Participant 3

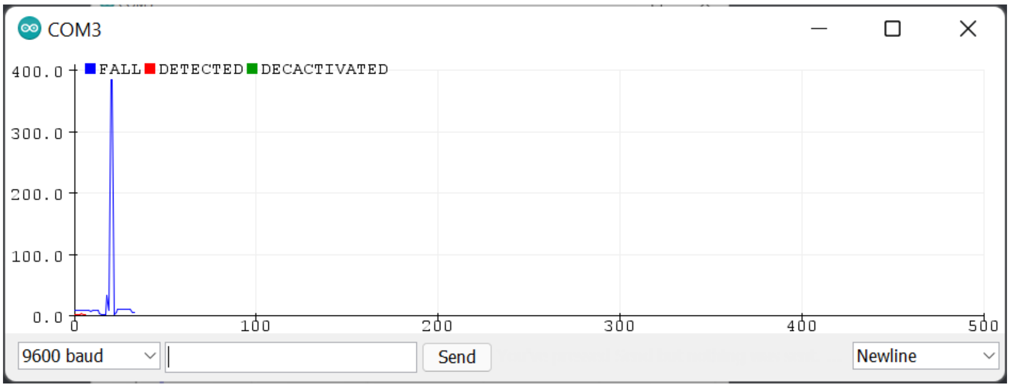


Figure 41: Participant 4

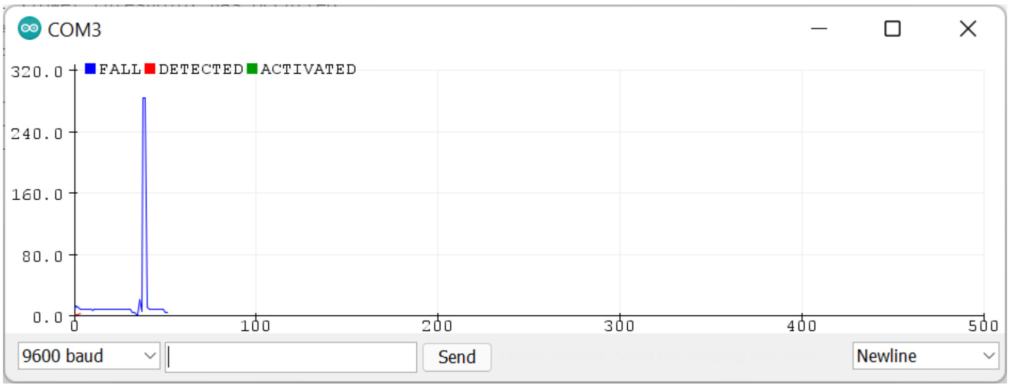


Figure 42: Participant 5

5.6 Backward Fall (Fall 2)

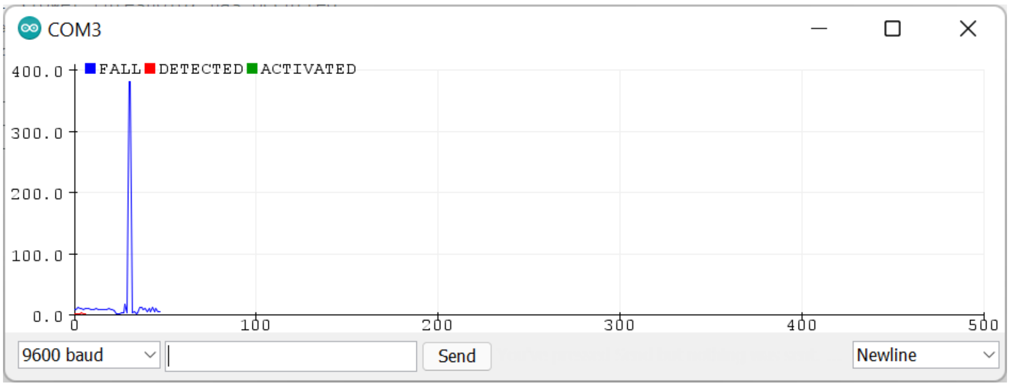


Figure 43: Participant 1

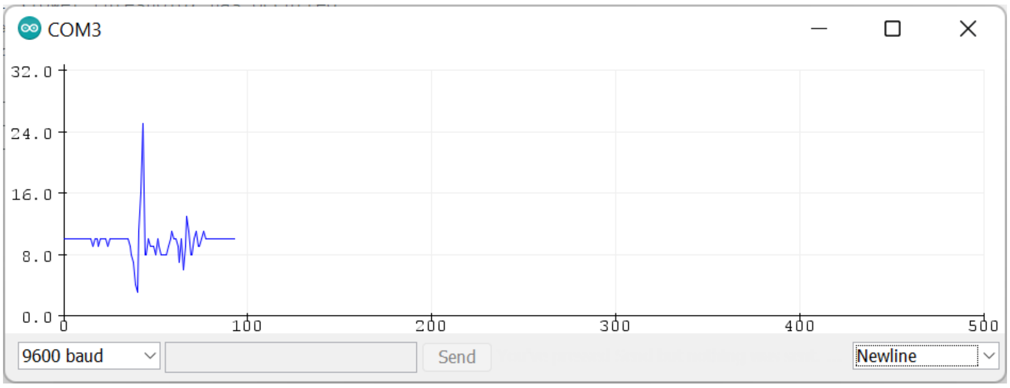


Figure 44: Participant 2

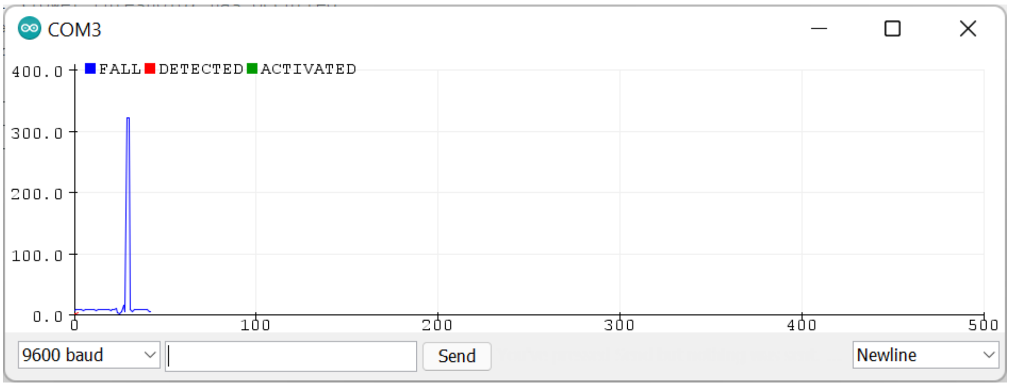
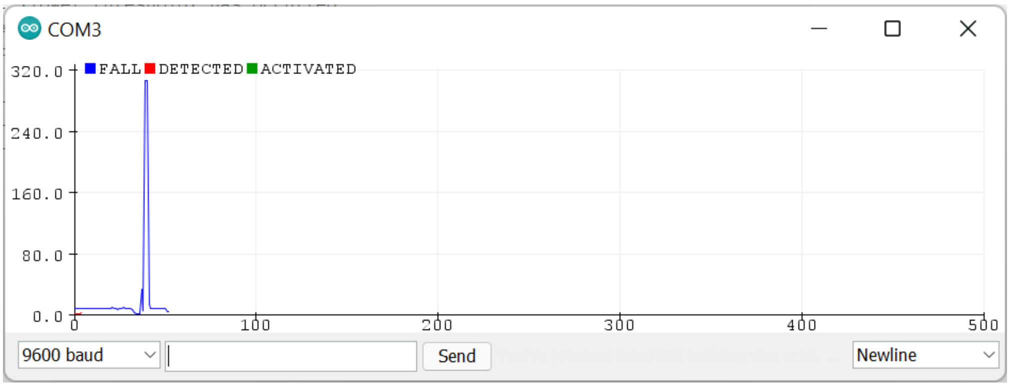


Figure 45: Participant 3



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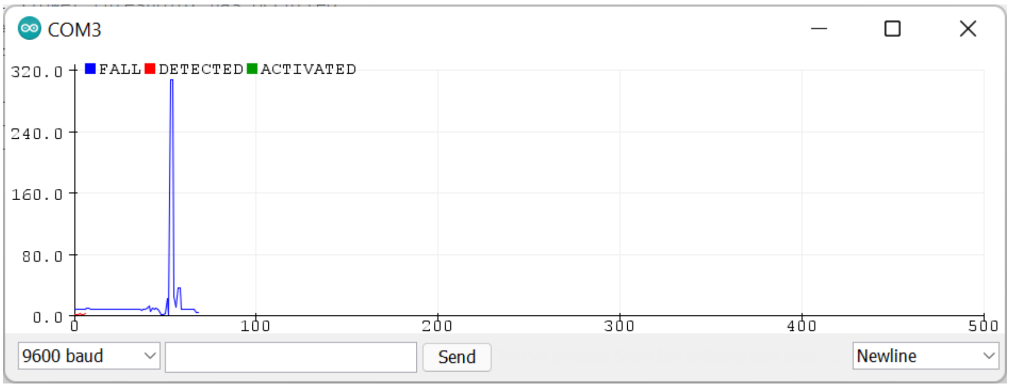


Figure 47: Participant 5

5.7 Sideways Fall (Fall 3)

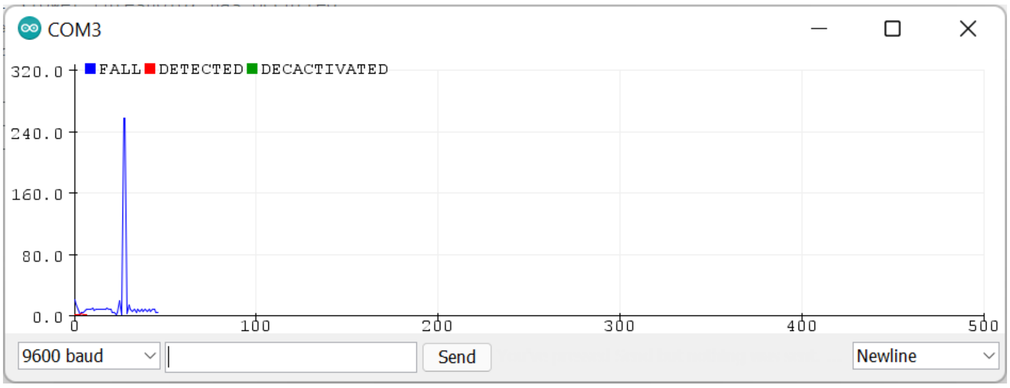


Figure 48: Participant 1

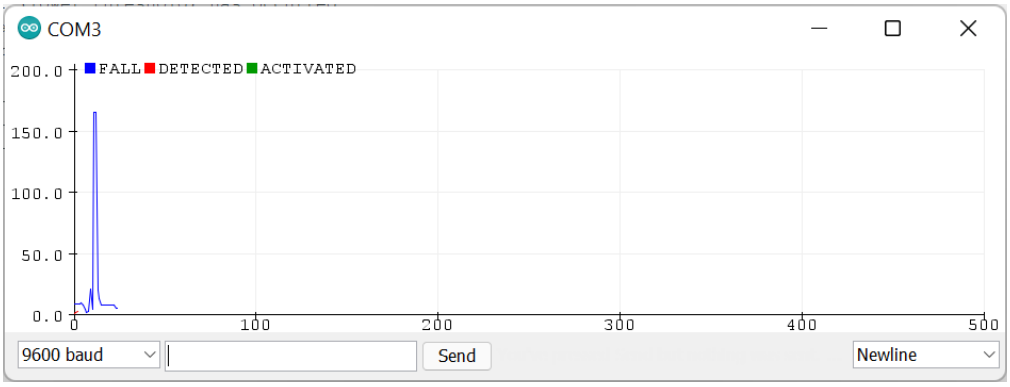
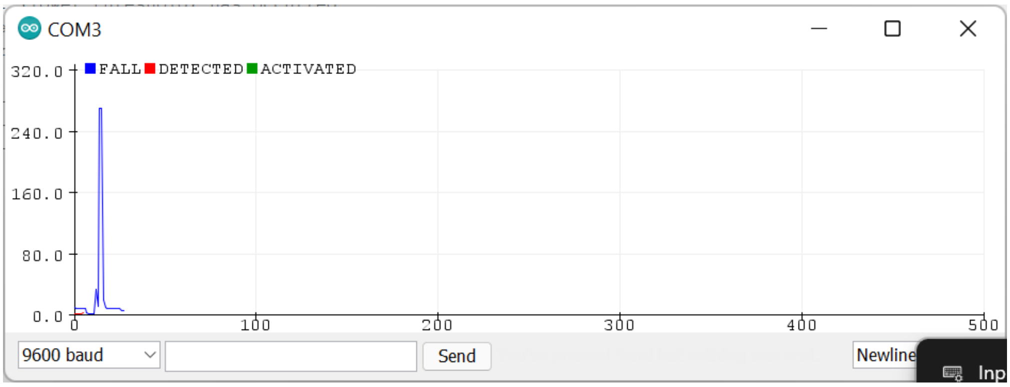


Figure 49: Participant 2



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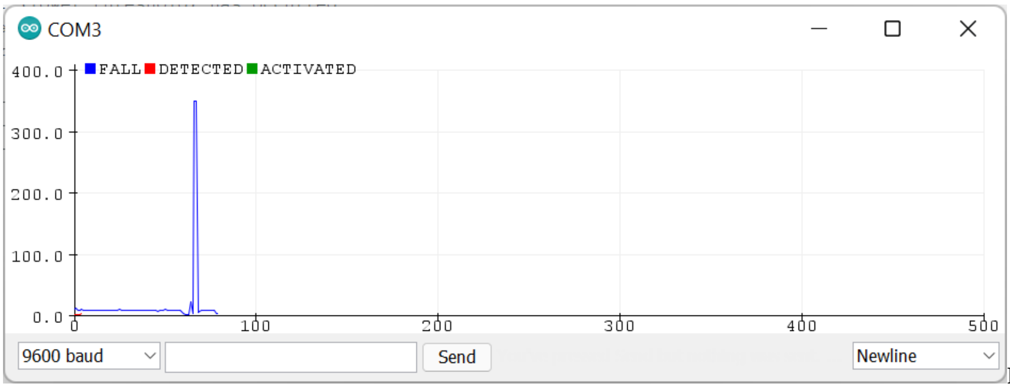

Figure 51: Participant 4

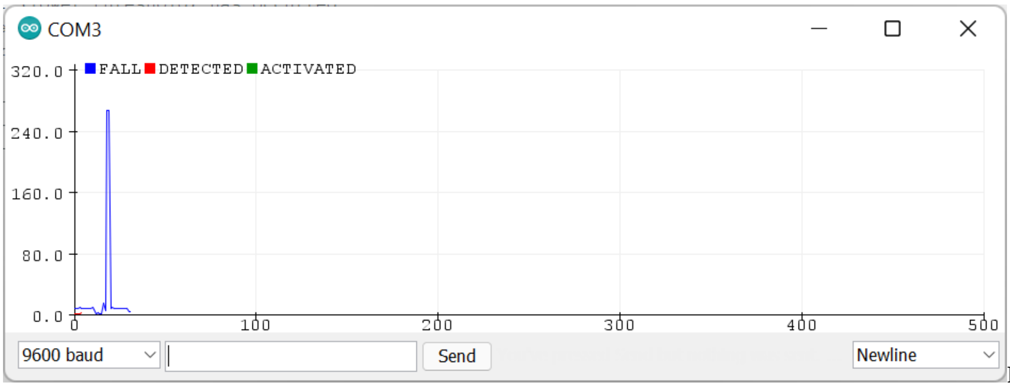

Figure 52: Participant 5

5.8 Mixed of Backward and Sideways Fall (Fall 4)

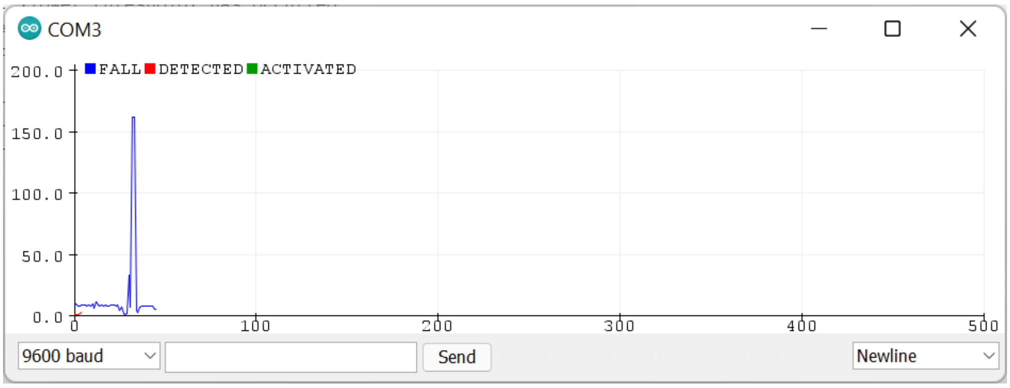

Figure 53: Participant 1

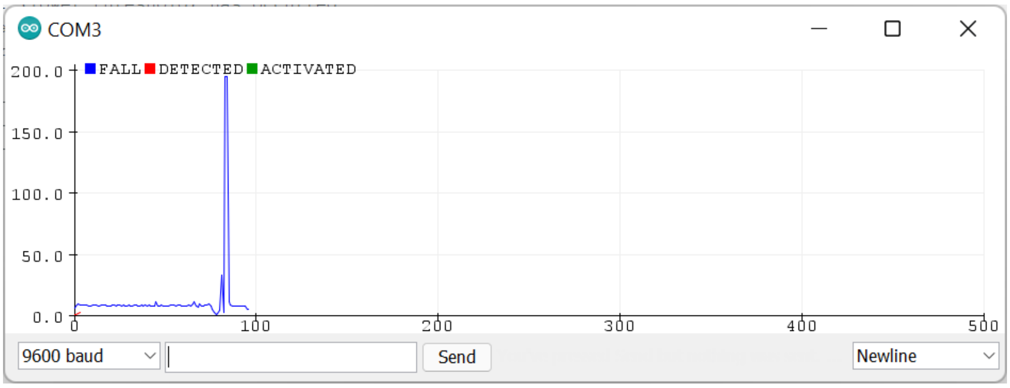

Figure 54: Participant 2

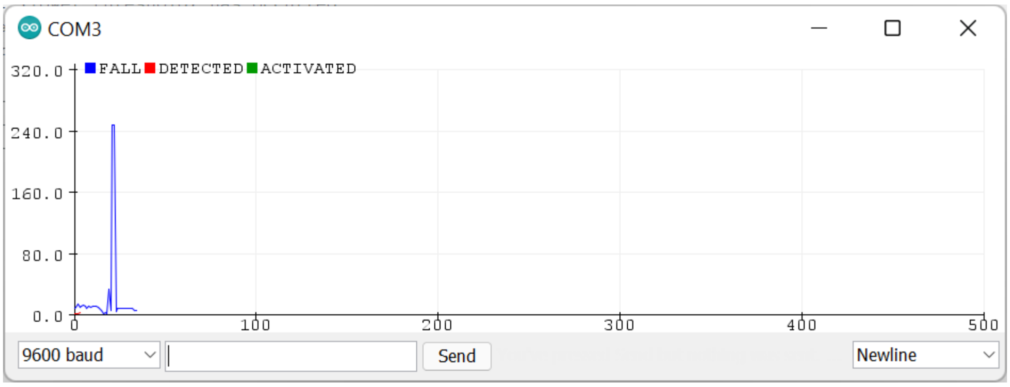

Figure 55: Participant 3

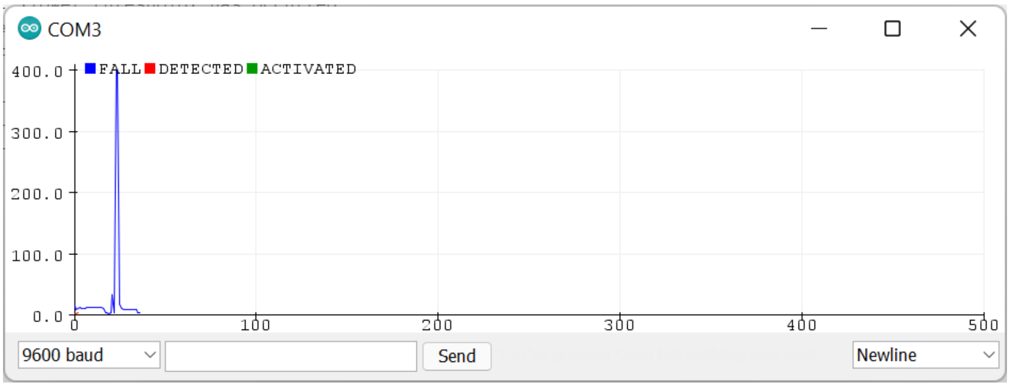

Figure 56: Participant 4

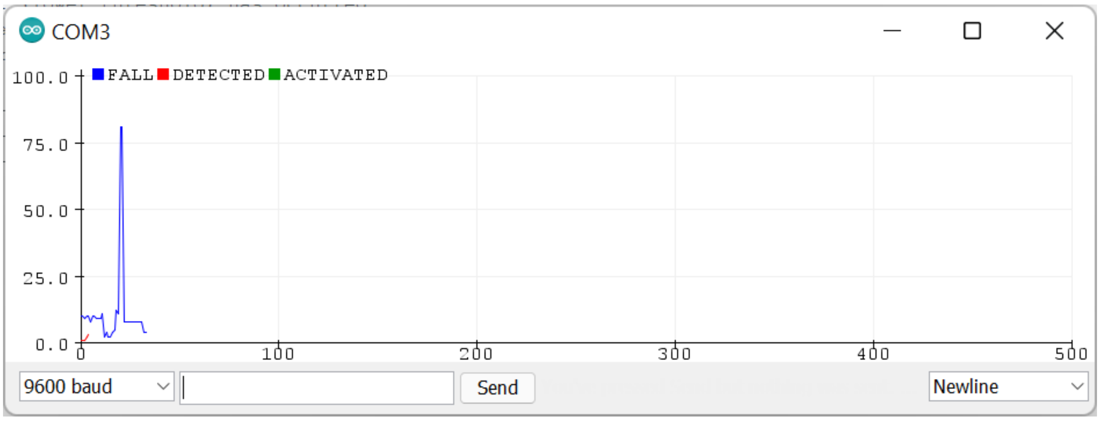

Figure 57: Participant 5