Determination of ideal sensor placement for activity recognition using Inertial Measurement Units: A pilot study with a single participant

By

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EXECUTIVE SUMMARY

The effectiveness of activity recognition systems is highly dependent on the placement of sensors used. This project determines the optimal sensor placement for activity recognition using the Axivity AX6 Inertial Measurement Unit (IMU). The study evaluates how activity recognition accuracy varies with different sensor placements and the number of sensors used. The research aims to identify the most effective sensor placement for activity detection while performing the following four activities: sitting, reaching and grabbing, walking, and brisk walking. Brisk walking is distinguished from walking by its faster pace and higher intensity.

Accelerometer data was collected from 10 different sensor positions (right wrist, left wrist, right knee, left knee, right ankle, left ankle, neck, chest, waist, and low back) using the Axivity AX6 IMU sensor, including the neck position that is novel to the research. Combinations of sensor placements were investigated in this project. The Axivity AX6 sensors were configured by connecting to the Axivity's OMGUI software, which acts as an interface between the sensor and the computer system for data collection and retrieval. The data was collected from a healthy adult who performed the four activities five times each, over the course of five consecutive days. The collected activity data was visualized and analysed using MATLAB. Data from the four different activities was read from Excel files, concatenated, and combined into a single dataset. The data was aligned and trimmed, ensuring that the length of data from different excel files matched before concatenation. Feature extraction was performed using both time-domain (mean, standard deviation, maximum, minimum, root mean square, skewness, and kurtosis) and frequency-domain (FFT, energy, correlation) features. A multiclass Support Vector Machine (SVM) using Error-Correcting Output Codes (ECOC) was employed to classify the four different activities. The classification accuracy, which indicates the ability to distinguish between the activities, was used to identify the most effective sensor placement from the various positions considered. The model's performance was evaluated using a confusion matrix, and key metrics such as accuracy, recall, and precision for each activity.

Results showed that the right wrist achieved the highest classification accuracy of 96% among single sensor positions. Combination of right wrist and low back achieved the highest accuracy of 98.3% among the combined placements of 2 sensors and the classification accuracy improved overall across all positions. With combinations of three sensor positions, there was not much difference in accuracies and therefore considering the wearability comfort, less number of sensors are preferred. Precision and recall rates provided additional insights into the classifier's performance.

This research contributes valuable insights to the field of activity recognition, particularly in healthcare, sports, and rehabilitation, where accurate activity monitoring is crucial. Future work could expand to include more diverse activities and replicating the study with a clinical population, to further validate the findings and enhance the applicability of the results.

DECLARATION

I certify that this thesis:

1. does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university
2. and the research within will not be submitted for any other future degree or diploma without the permission of Flinders University; and
3. to the best of my knowledge and belief, does not contain any material previously published or written by another person except where due reference is made in the text.

Signature of student A.D.Keerthana..

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Date 08/08/2024..

I certify that I have read this thesis. In my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Engineering (Biomedical). Furthermore, I confirm that I have provided feedback on this thesis and the student has implemented it fully.

Signature of Principal Supervisor D. Hobbs..
Print name of Principal Supervisor Dr. David Hobbs........................
Date 08/08/2024 ....

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to my supervisors, Dr. David Hobbs and Mr. Thomas Beltrame, for their unwavering support, insightful guidance, and timely assistance throughout the duration of my project. Their invaluable expertise and dedication were the pillars of this work, and without their contributions, this project would not have been possible.

I’m also deeply thankful to Dr. Kenneth Pope, for helping me explore project ideas and connected me with Dr. David Hobbs, given my interest in wearable technology.

My sincere appreciation extends to Dr. Russel Brinkworth for providing me with crucial knowledge relevant to this project.

Lastly, I would like to thank my family and friends for their constant care, encouragement, and support. Their presence has been a source of strength throughout this journey.

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INTRODUCTION

Project Background

In recent years, there has been a growing interest in using wearable sensors, such as Inertial Measurement Units (IMUs), comprising of accelerometers and gyroscopes, for activity recognition in various fields such as healthcare, sports, and rehabilitation (Smith et al, 2015). These sensors offera non-intrusive way to monitor human movements and activities, providing valuable insights for health monitoring, sports performance analysis, gesture recognition in interactive systems, and in the field of rehabilitation and physical therapy (Giggins et al, 2013). In the field of rehabilitation, activity recognition using wearable sensors can provide clinicians with objective data to assess patient progress, customize treatment plans, and track recovery over time (Giggins et al, 2013).

The placement of sensors on the body is one of the critical factors influencing the performance of activity recognition systems. Previous studies have shown that sensor placement plays a critical rolein the performance of activity recognition algorithms. The choice of sensor placement can impact the accuracy, reliability, and overall performance of the activity recognition algorithms (Jones et al,2018). Some studies have suggested that combining multiple sensor placements can improve the overall accuracy of activity recognition systems (Patel et al, 2016). For example, the placement of sensors on the chest and wrist has been found to be ideal for certain activities, while other placements, such as the arm, waist, knee, and ankle, may be more suitable for different activities (Davis et al, 2019). However, the effectiveness of these combined placements, including theadditional number of sensor placements that are novel to the research, and their impact on accuracyand reliability, need to be further investigated.

This project aims to address these gaps by evaluating the effect of sensor placement on the performance of activity recognition systems. By comparing the accuracy and reliability of different sensor placements for a set of common activities, the most suitable sensor placement or combination of placements for accurate and reliable activity recognition can be identified in this project. This project utilises machine learning to identify and classify activities. The collected data is based on accelerometer data alone from the IMU sensors, as gyroscope is sensitive to drift and can cause substantial errors in orientation calculations and overall measurement accuracy (Li S et al, 2019). In this project, as shown in Figure 1, the system identifies if an activity is being performed and classifies the activities. The ideal sensor placement is determined based on the classification accuracy.

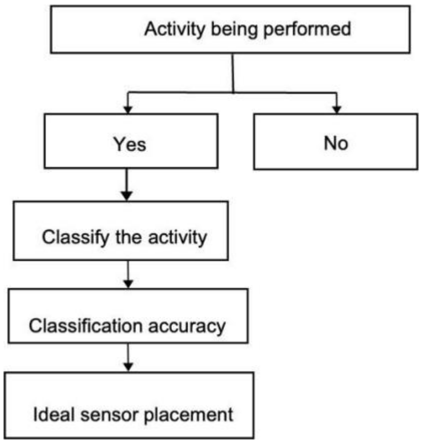

Figure 1 Project Outline

Project Objective

The aim of this project is to identify the ideal sensor placement to track and record body movements while performing certain physical activities.

The objectives of this project include:

- Employing multiple IMUs and evaluating the classification accuracy for four different considered activities.
- Identifying the most accurate and reliable sensor placement for data collection and activity recognition based on the highest obtained classification accuracy.
- Including sensor placement that are novel to the research and to observe their reliability.
- Comparing the performance of single sensor placements with combinations of two and three sensor positions.
- Seeking to achieve maximum classification accuracy while minimising the number of sensors used.

Scope of the Project

The project exclusively utilizes the Axivity AX6 IMU for data collection, excluding the use of other IMUs or accelerometers. A total of 10 sensor positions have been selected for this study. Notably, the neck position is introduced as a new placement location that has not been previously explored in similar studies, providing novel insights compared to more commonly used positions like the wrist or ankle and potentially improve the overall accuracy of activity recognition.

Data collection involves recording three-dimensional accelerometer data across X, Y, and Z axes from each sensor position and interfacing with a computer system through Axivity's OMGUI software tool. Graphs of the accelerometer data are generated to visualize the characteristics of each activity. Feature extraction is performed on the collected accelerometer data using 5-second non-overlapping windows. For each window, time-domain features and frequency-domain features are derived using the Fast Fourier Transform (FFT). An energy feature, representing the sum of the squared magnitudes, is also computed. Correlation coefficients between the X, Y, and Z axes are included as features to capture the relationship between the axes.

Classification of the four activities is achieved using a multiclass SVM classifier implemented with MATLAB's machine learning algorithm. The classification accuracy, determined by analysing the confusion matrix for each activity, serves as a key metric for identifying the most suitable sensor placement for the activities. Precision and recall rates are also considered to evaluate the classifier's performance.

Thesis Outline

The thesis encompasses various key sections essential for a comprehensive study. The Introduction section provides an overview of the project, by outlining its background, objectives, and scope. In the Literature Review section, topics including IMUs, criteria for sensor selection, the significance of determining optimal sensor placement, the role of classifiers in activity recognition and finding the optimal sensor placement, and project limitations are discussed.

The Methodology section elaborates on the step-by-step procedures involved in sensor usage, data collection, and the classification of activities. Following this, the Results and Discussion section critically evaluate and compare the classification outcomes obtained from different sensor placements, ultimately identifying the most suitable sensor positions. Finally, the Conclusion and Future Work sections summarise the project's findings and proposes potential future extensions of this work.

LITERATURE REVIEW

Introduction

Monitoring physical activity is crucial for understanding and improving health outcomes. It plays an important role in the field of health, sports and fitness, and rehabilitation and physical therapy. It provides valuable insights into patients' daily activities, exercise capacity, and adherence to prescribed exercises from a healthcare provider. Physical activity monitoring helps to identify changes in physical activity levels over time, which may indicate overall improvements in activity performance that assists in the field of rehabilitation and play a significant role in improving health outcomes in the population (Klompstra et al., 2021).

The placement of sensors on the human body can assist in recording movement changes in body position while performing physical activities. The sensor placement varies according to the type of activity performed. It is believed that the best location is not always where the symptoms occur, as a head-worn sensor was proved to be the optimal location for gait-feature detection rather than placement on the legs in one study performed using healthy adult (Atallah et al., 2011). Thus, 10 sensor positions were selected in this project to assess the importance of each location for the activities being performed. The use of additional sensors can improve the accuracy of recognising physical activities, and therefore combinations of two and three sensors were included. However, considering users' wearability and comfort, it seems that a single accelerometer is sufficient for estimating energy expenditure and recognising activity categories in older adults (Davoudi *et al.*, 2021). Thus, identifying the number of sensors and their ideal placement is important in terms of accurately recognising daily life activities.

Inertial Measurement Units

In recent years, IMUs have become increasingly popular for measuring the motion and orientation of objects in a variety of applications, including robotics, virtual reality, and human motion analysis (Fang *et al.*, 2023).

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Figure 2 An Inertial Measurement Unit

IMU sensors are small, lightweight devices that typically consists of three types of sensors: accelerometers, gyroscopes, and magnetometers (Filippeschi et al., 2017). These sensors can provide information on linear acceleration, angular velocity, an object's orientation, and magnetic field strength, which can be used to derive three-dimensional (3D) motion information. IMU sensors are used for motion tracking and hence, they are implemented on wearable devices (Song et al., 2021).

In this project, the data were obtained from accelerometer measurements using IMU sensors. The gyroscope was excluded due to its sensitivity to drift, which can lead to significant errors in orientation calculations and overall measurement accuracy (Li et al., 2019). Also, considering the future expansion of this project, focusing solely on accelerometer data will be appropriate when incorporating different accelerometers.

Sensor Selection: The Axivity AX6

Commonly used accelerometers such as the ActiGraph GT3X+ and Axivity AX3 were validated to detect physical activity intensity and body postures, and it was found that Axivity performed better in detecting postures and physical activity intensity and had higher balanced accuracy (Hedayatrad, Stewart and Duncan, 2020). In a study that compared the Axivity and Actigraph sensors, it was found that Axivity was more practical to wear than Actigraph (De Craemer et al., 2022). The GENEActiv, Axivity AX6 and many other wearable light and motion dataloggers were compared with respect to appearance, dimensions, weight, mounting, battery, sensors, features, communication interface, and software in sleep/wake research. It was determined that the Axivity and GENEActiv sensors are known to have good battery life (Danilenko et al., 2022). The Axivity AX6 was selected for this project to record the daily life activities, which is a data logger and an effective IMU sensor for human activity monitoring due to its high accuracy, battery life, and affordability (Gafoor F et al, 2024).

Determination of ideal sensor placement by using classifiers

Classifiers such as decision tree, random forest, and support vector machine have been employed in previous studies to determine ideal sensor placement. The classifier assigns data labels for each activity and predicts if the given accelerometer data falls under the designated activity (Atallah *et al.*, 2011). Previous studies compared different body sites such as the ear, chest, arm, wrist, waist, knee, and ankle, and it was observed that a waist sensor provided higher accuracy for low-level activities (eating, drinking, getting dressed), chest and wrist sensors for medium-level activities (walking, vacuuming, wiping table), ear-worn sensors for high-level activities (running, cycling), and waist, chest, and knee sensors for transitional activities (sitting from standing, lying down from standing) (Atallah *et al.*, 2011).

In a study with Axivity AX3 sensors, combinations of thigh-back, thigh-wrist, and back-wrist sensor positions were evaluated. The thigh-back position was identified as the most effective in distinguishing between seven activities in adults (95.6% accuracy) and eight activities in children (92% accuracy) using a random forest classifier (Narayanan, Stewart, and Mackay, 2020). The accuracy decreased by 11% when using other sensor placements (Narayanan, Stewart, and Mackay, 2020). Another study comparing thigh and lower back placements reported an accuracy of 99.1% in adults and 97.3% in children using a random forest classifier (Stewart et al., 2018). When only a single thigh or back position was used, the accuracy dropped to 26.4% (Stewart et al., 2018). In another study, when comparing the lower, middle, and upper backbone using Axivity sensors, it was found that the lower back was better for sensor placement, with 92% accuracy using the decision tree classifier (Mehmood Khan, 2013). Thus, the lower back is chosen as one of the 10 sensor positions, rather than the upper and middle parts of the backbone. Similar studies that used decision tree classifiers obtained an accuracy of 84% with sensor positions at the hip, wrist, ankle, arm, and thigh (Ravi *et al.*, 2005) and 93% at the lower back (Bonomi et al., 2009).

Reference	Sensor positions	Activities	Classifier	Accuracy and Finding
Dehzangi et al, 2018	Wrist	Sitting, Walking, Sleeping, Standing	Bag ensemble classifier	96.30%
Ali Mehmood Khan, 2013	Lower, middle, upper backbone	Sitting, Lying, Standing, Walking, Cycling	Decision tree classifier	92% (lower back best position)
Tom Stewart et.al, 2018	Thigh, lower back	Sitting, Lying, Standing, Walking, Running, Jumping	Random forest	99.1% accuracy in adults, 97.3% in children, accuracy declined upto 26.4% when single thigh or back used
Anantha Narayanan et al, 2020	Combinations of thigh-back, thigh-wrist, back-wrist	Sitting, Lying, Standing, Walking, Running, Cycling	Random forest	thigh-back position found best distingushing 7 activities in adults with accuracy 95.6% and 8 in children with accuracy 92%. Accuracy dropped by 11% at other placement positions
Fleury A et al, 2010	Smart home sensors	Sleeping, dressing/undressing, preparing and having breakfast	SVM	86% was the highest accuracy obtained
Bonomi et al, 2009	Lower back	Sitting, Lying, Walking, Cycling, Running, Working on computer	Decision tree classifier	93%
Bao L et al, 2004	Wrist, arm, knee, ankle	20 activities including sitting and walking	Decision tree classifier	84% accuracy
Atallah et al, 2011	Ear, Chest, Arm, Wrist, Waist, Knee, Ankle	Very low (ying), low (eating, reading), medium (walking), high level (running), and transitional activities (sitting from standing)	KNN, Bayesian classifier	Wrist, Ear - very low level, Waist - low level, Chest, Wrist - medium level, Ear, Arm, Knee - high level, Waist, Chest, Ear, Knee - transitional activity

Figure 3 Previous studies with sensor positions across the body, activities, classifier used and findings.

Choice of Activities

A variety of activities have been commonly selected to assess the effectiveness of sensor placements in studies on human activity recognition. Activities such as sitting and walking are frequently chosen, as shown in Figure 3, due to their distinct physical characteristics and varying intensity levels, which offer a comprehensive evaluation of sensor performance across different conditions. Studies emphasize that incorporating both low-intensity activities such as sitting and high-intensity activities like brisk walking and running is essential for achieving accurate and reliable activity recognition (Atallah et al., 2011; Chen et al., 2012). Thus, including activities like sitting, walking, brisk walking, and reaching/grabbing effectively covers both sedentary and dynamic activity states, which is crucial for determining optimal sensor placement.

Sensor Positions and Combinations

Comparing previous studies as shown in Figure 3, a lower number of sensors have been considered and did not incorporate the neck position. In this project, in addition to the existing research, a greater range of sensor placement positions have been considered (10 sensor positions) including the cervical part of the spine (neck), that is novel to the research. Additionally, comparing the efficiency of combinations of the considered sensor placement positions (two and three sensor positions) have also been included in this project to assess performance with an increased number of sensors. The potential combinations were selected by combining the positions that achieved the highest classification accuracy. The highest accuracy was achieved with the tested combinations, so additional combinations involving more than three sensors were not performed as the goal of this project is to determine the optimal sensor placement using the minimal number of sensors possible, considering economic factors and wearability comfort.

Optimal Sampling Rate Selection

The sampling rate is selected based on the activity performed and battery life of the sensor, thereby reducing unwanted storage (Bent et al, 2020). There is an operating area beyond which no additional information would be gained and thus would rather only waste energy and memory (Khan *et al.*, 2016). A sampling frequency of 20Hz is sufficient for standard and less complex human activities like walking, running, or cycling (Lukowicz et al., 2004). Voluntary human movements do not typically exceed 10 Hz and thus, according to Shannon−Nyquist theorem, data needs to be sampled with at least twice the highest frequency, which is ≥ 20 Hz (Marques et al., 2022).

METHODOLOGY

Axivity AX6 Sensor

The Axivity AX6 sensor was used in this project, as shown in Figure 4, for collecting accelerometer data by recording the performed physical activities across different body positions. The technical specification of the sensor is provided in Table 1.

Table 1 Axivity AX6 Sensor Specifications

Dimensions	23 x 32.5 x 8.9 (mm)
Weight	11g
Memory	1024Mb
Accelerometer Sample Rate	12.5Hz – 1600Hz Configurable
Battery Life	7+ days @ 100Hz, 31+ days @ 50Hz
Accelerometer Range	±2 / 4 / 8 / 16 g Configurable
Sensor Resolution	16 bit, Accel and Gyro

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Figure 4 Axivity AX6 IMU Sensor

Sensor Positioning and Battery

Axivity AX6 consists of a USB port on one side of the sensor puck, which can be used for charging and connecting the sensor to the OMGUI software to setup, configure and retrieve data. As per the Axivity company's recommendation, except for the left wrist, the USB port was configured to point towards the ground as shown in Figure 5.

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Figure 5 Axivity AX6 sensor position on different body parts.

As recommended by the Axivity company, the battery was kept above 85% while using the sensor s for data collection.

Sensor Placements and Directions

Placement of the Axivity AX6 sensors on the body

Figure 6 shows the accelerometer axes directions according to the Axivity company suggestion. Axivity AX6 sensors were placed at 10 different body locations, as shown in Figures 7 and 8, to find the ideal sensor placement for each type of activity performed as follows:

1. Wrist (2)
2. Knee (2)
3. Ankle (2)
4. Chest
5. Waist
6. Spine lumbar (Low back)
7. Spine Cervical (Neck)

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Figure 6 Axivity AX6 Axes Directions

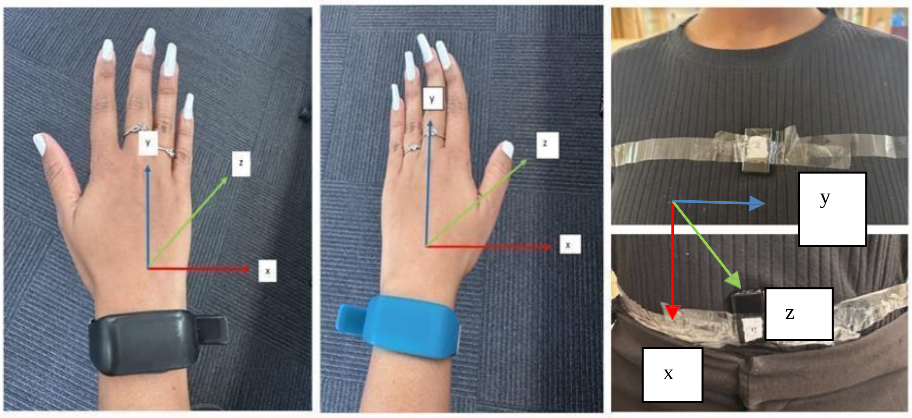

Figure 7 Axivity AX6 Sensor Placements at Right Wrist, Left Wrist, Chest, and Waist

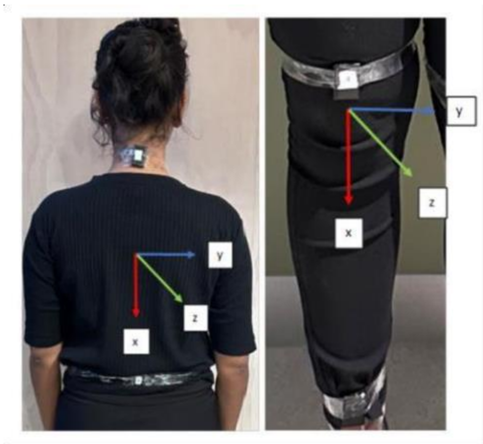

Figure 8 Axivity AX6 Sensor Placements at Neck, Low back, Knee, and Ankle

Sensor Accelerometer range

As the movements such as brisk walking was performed, the accelerometer range of the sensor was setup as +/- 8g according to the recommended range provided by the company as shown in Figure 9. A future extension of this project might include more complex high-level activities such as cycling, jumping, and running. Thus, a fixed and suitable accelerometer range was employed during this project, considering the possible future project directions.

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Figure 9 Axivity AX6 recommended accelerometer range.

Optimal Sampling Rate Selection

A comparison between using 25Hz and 100Hz sampling rates for collecting movement data was performed in this project. Two Axivity AX6 sensors were placed on top of each other on the dominant wrist as shown in Figure 10 and the reaching and grabbing activity was performed.

Figure 10 Axivity AX6 sensors worn on top of each other at right wrist for sampling rate comparison

The analysis for selecting a 25Hz sampling rate over 100Hz is detailed in Appendix A of this report. According to the Axivity OMGUI software, 25Hz sampling rate was setup as that was the available option near the required 20Hz (Figure 11).

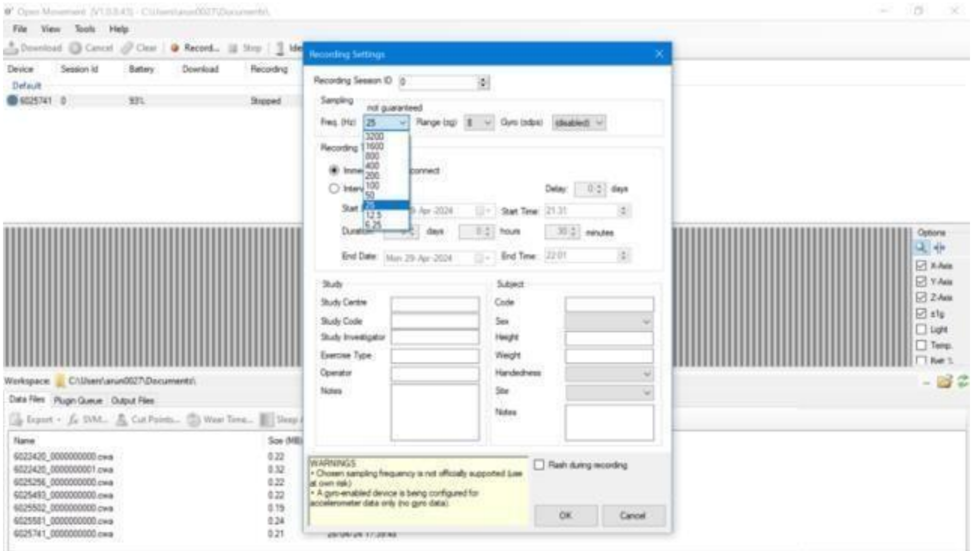

Figure 11 Available sampling rates in the Axivity AX6 OMGUI Software

Activities performed

The following four activities were performed in this project: sitting, walking, brisk walking, reaching and grabbing. Each of these four activities was performed for a duration of 2 minutes and repeated 5 times, with data collected over 5 consecutive days.

1. **Sitting:** Sitting on a flat surface without using a backrest, keeping the backbone straight, head facing straight towards front, both feet resting on the floor. Elbows, forearms, and palms resting comfortably on thighs. Knee and shank at 90 degrees. This posture is represented in Figure 12.
2. **Walking:** Natural, self-selected walking pace, hands and arms can swing naturally without holding anything. Head looking directly forward, aim to walk in a straight line, with no turning.
3. **Brisk walking:** Performed same as walking with increased maximum intensity in the walking speed as possible.
4. **Reaching and grabbing:** Reaching and grabbing a mobile phone placed in front of the person on a table using their dominant arm in the 'sitting' posture. The non-dominant arm was resting comfortably on its respective thigh.

¤ Step 1: Starting from the 'sitting' posture.

¤ Step 2: Reaching for the mobile phone placed on the table in front of the person their using dominant arm.

¤ Step 3: Grabbing the mobile phone using dominant arm and returning to the 'sitting' posture holding the mobile phone in the dominant arm and holding for 10 counts.

¤ Step 4: Placing back the mobile phone on the table at the same position using dominant arm and coming back to the 'sitting' posture and staying for 10 counts.

Figure 12 Sitting Posture

Axivity OMGUI Configuration and Analysis Tool

The AX6 Open Movement Graphical User Interface (OMGUI) Configuration and Analysis Tool is used as an interface to setup and configure the Axivity sensor puck to collect the raw accelerometer data that was recorded while performing the four different activities. An USB cable was used to connect the sensors to the computer. The raw accelerometer data is converted to readable data in .xlsx format and saved as excel files. Each activity has data recorded from five different excel files.

MATLAB Software: Data Preprocessing, Feature Extraction, and Classification.

The excel files were loaded as input in MATLAB software to plot the activity graphs, perform feature extraction, and classification. The data in the excel files were normalized and aligned to the same number of samples by trimming each dataset to the shortest length among them to ensure data from different excel files are in similar range. Data for each activity was read from the respective files and concatenated into 4 separate matrices corresponding to each activity. All concatenated activity data was then combined into a single matrix and labels were created for each activity. The raw accelerometer data is passed through a 25Hz low pass fourth order Butterworth filter to remove noise due to skin and cloth artefact (Liu et al, 2022). The data was divided into non-overlapping windows, having window size of 125 samples (equivalent to 5 seconds at a sampling rate of 25 samples per second).

For each window, the following features were extracted:

- ◊ Time-Domain Features: Mean, standard deviation, maximum, minimum, skewness, kurtosis, and root mean square values.
- ◊ Frequency-Domain Features: Mean and standard deviation of the FFT magnitudes.
- ◊ Energy Feature: Sum of the squares of the FFT magnitudes.
- ◊ Correlation Feature: Correlation coefficients among the three axes (X, Y, Z).

The dataset was split into training (80%) and testing (20%) sets using a holdout method. A multiclass SVM classifier using Error-Correcting Output Codes (ECOC) was used as the classifier. A confusion matrix along with accuracy, recall, and precision for each activity were generated to evaluate the model's performance. The classification accuracy was used to determine the ideal sensor placement on the body for each type of activity. Following the initial classification using data from a single sensor placement, further analysis was conducted by combining data from two and three sensor positions. The outcomes of these combined placements were then observed and analysed.

RESULTS

Activity Plots

Figures 13, 14, 15, and 16 illustrate the accelerometer plots corresponding to the sitting, reaching, and grabbing, walking, and brisk walking activities respectively.

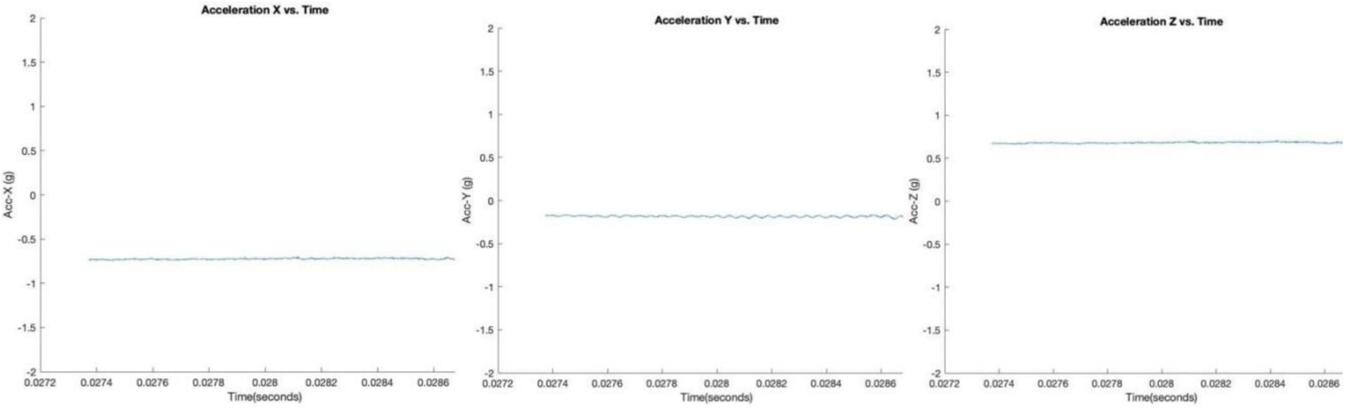

Figure 13 Accelerometer plot for 'sitting' activity along X, Y, and Z axes.

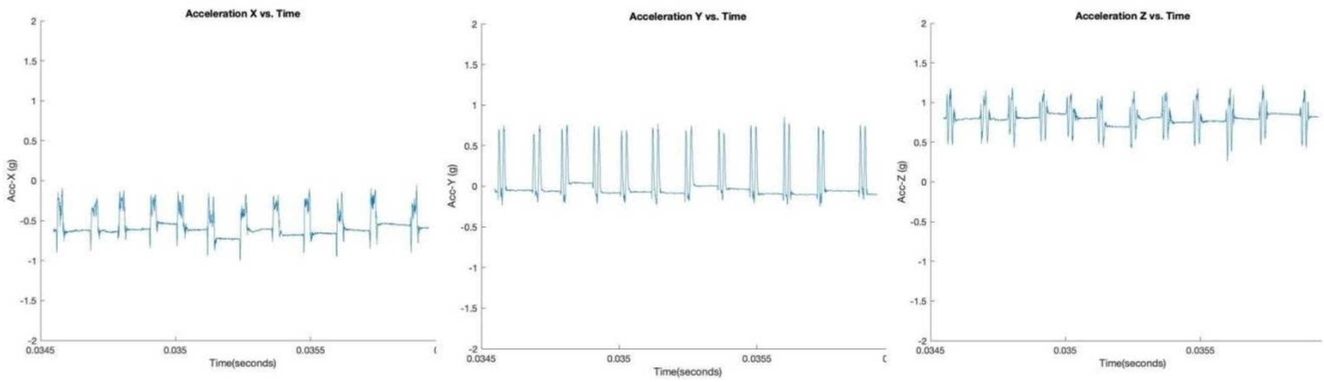

Figure 14 Accelerometer plot for 'reaching and grabbing' activity along X, Y, and Z axes.

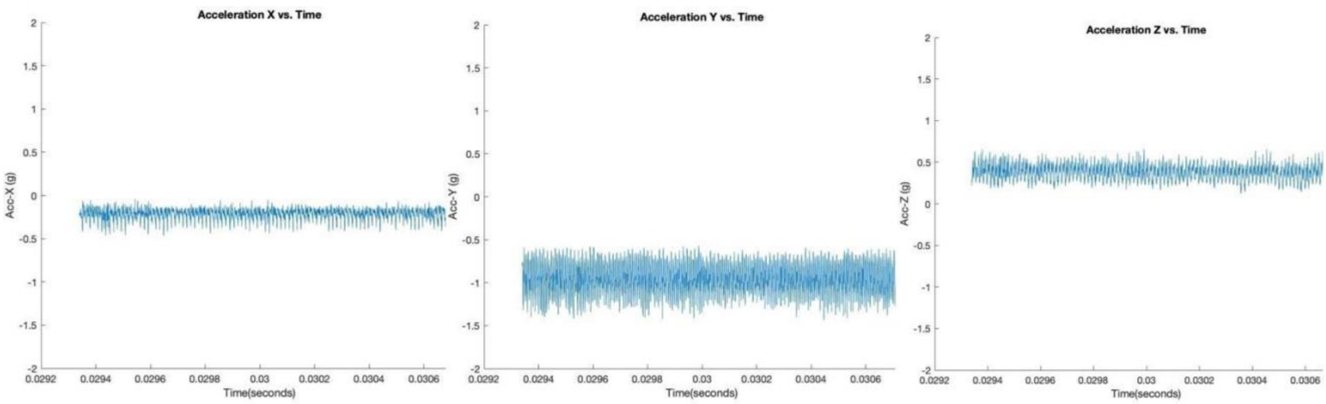

Figure 15 Accelerometer plot for 'walking' activity along X, Y, and Z axes.

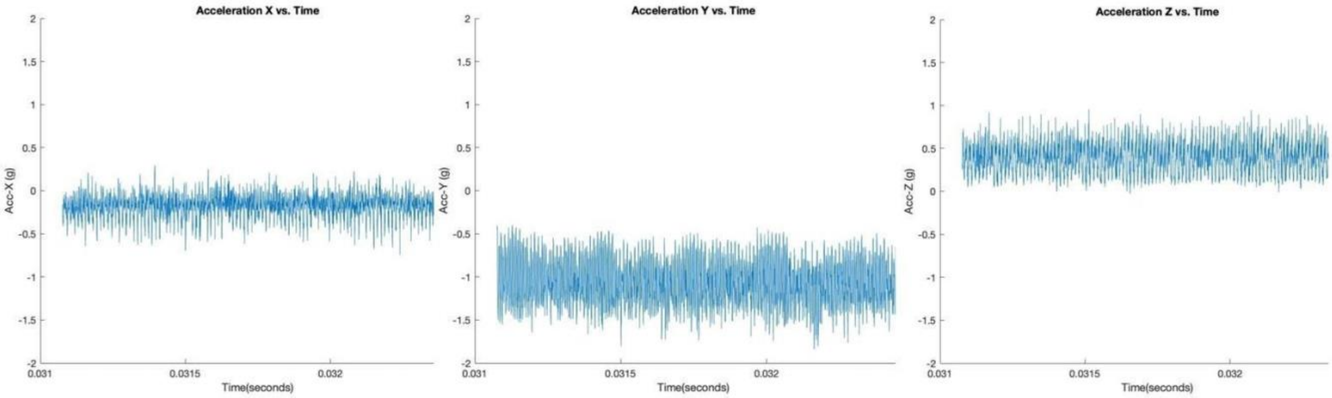

Figure 16 Accelerometer plot for 'brisk walking' activity along X, Y, and Z axes.

Classification Results

Sensor placement at right wrist

The highest classification accuracy of 96% was achieved at the right (dominant) wrist, making it the ideal sensor position among all the single sensor positions tested. There were minor mispredictions between the activities - sitting vs reaching/grabbing and walking vs brisk walking (Figure 17).

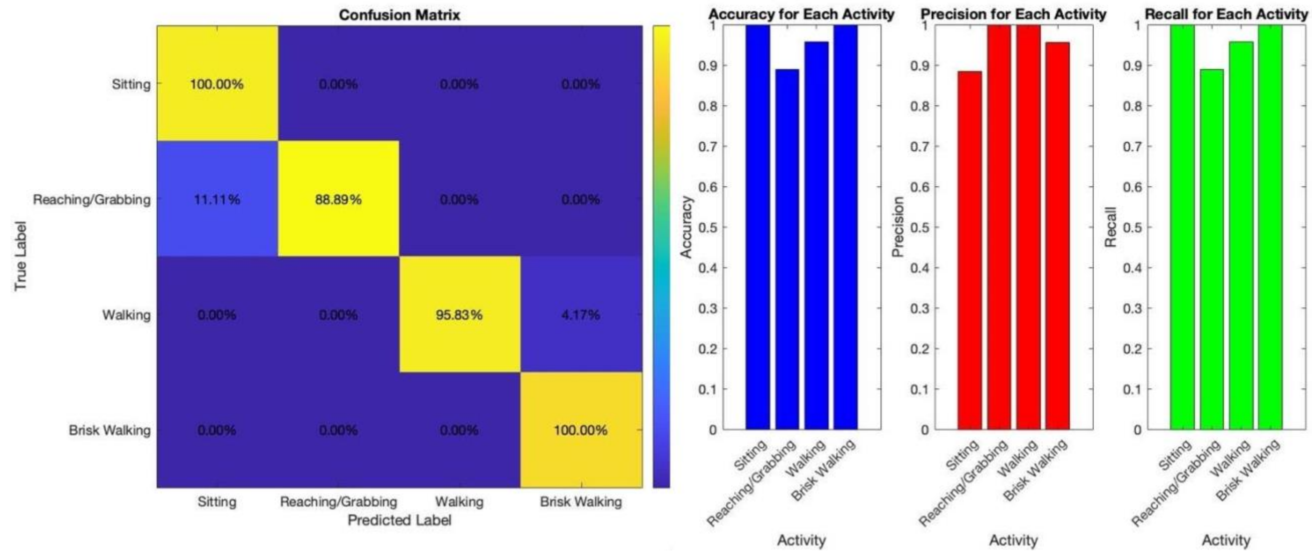

Figure 17 Confusion matrix and graphs of accuracy, recall, and precision for the right wrist sensor position.

Sensor placement at left wrist

The classification accuracy dropped to 88.5% at left (non-dominant) wrist as there was a higher misclassification between sitting vs reaching and grabbing activities (Figure 18). The outcomes of remaining single sensor positions have been included in the Appendix B of this report.

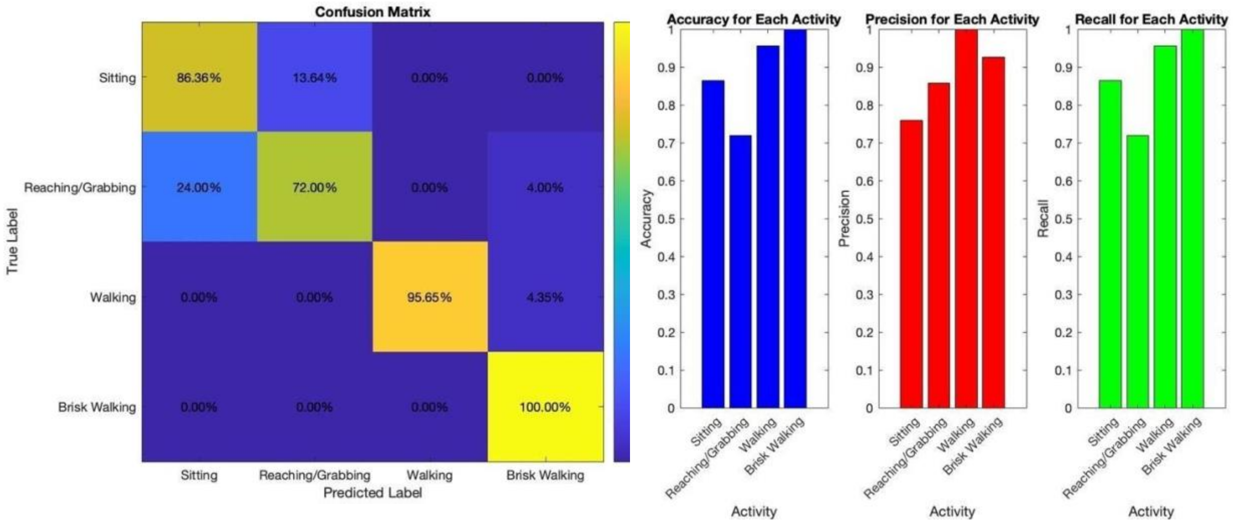

Figure 18 Confusion matrix and graphs of accuracy, recall, and precision for the left wrist sensor position.

Combination of 2 sensor placement positions: Right wrist and Low Back

These two positions had higher accuracies individually, and their combination improved the model's effectiveness and accuracy (Figure 19). Since the right wrist achieved the highest classification accuracy among all single positions, it was paired with the other remaining single sensor positions for performing combinations of 2 sensor positions. The classification outcomes for additional combinations of two sensor placements have been included in the Appendix C.

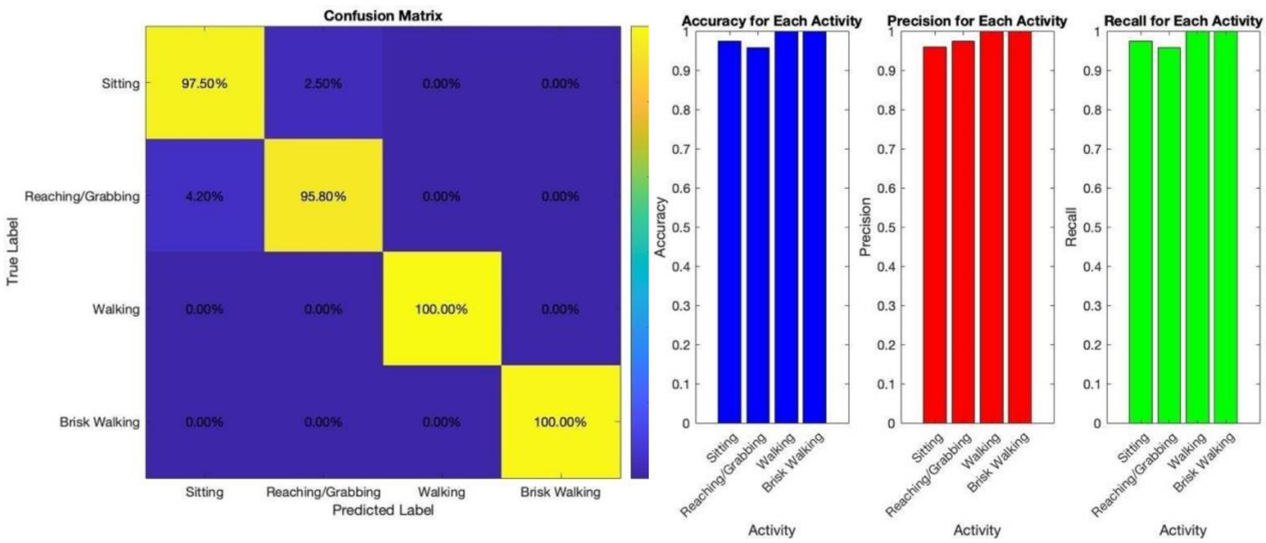

Figure 19 Confusion matrix and graphs of accuracy, recall, and precision for the combination of right wrist and low back sensor positions.

Combination of 3 sensor placement positions: Right Wrist, Low Back, Neck

When another sensor position (neck) was combined with right wrist and low back, 98.95% classification accuracy was obtained. Additional results on other combinations of 3 sensor placements is provided in the Appendix D.

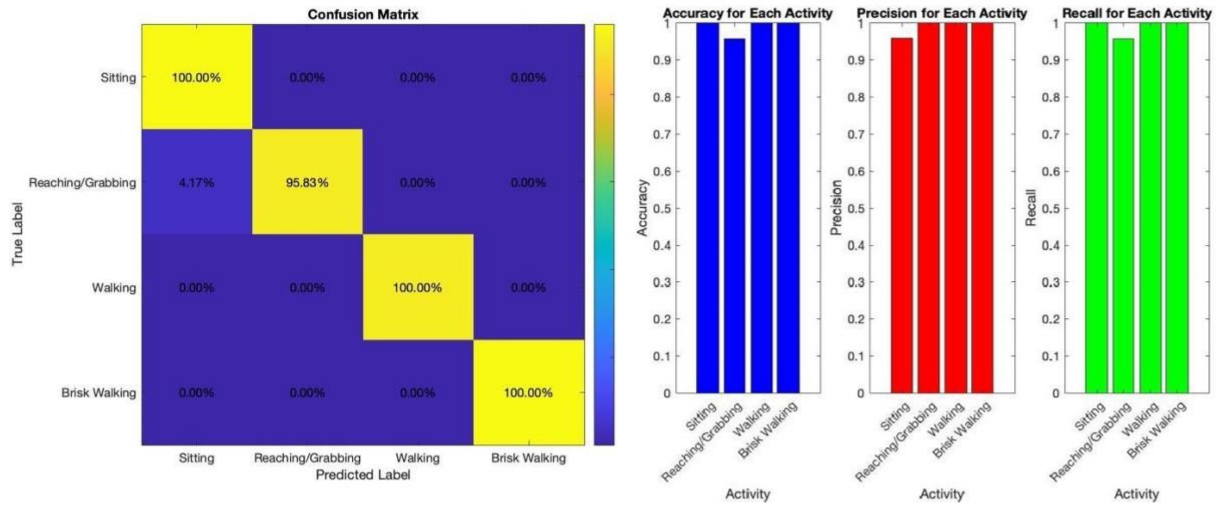

Figure 20 Confusion matrix and graphs of accuracy, recall, and precision for the combination of right wrist, low back, and neck sensor positions.

Comparison of classification accuracies obtained from different sensor placements and its combinations

The Figure 21 presents the overall classification accuracy for all sensor placement locations and their respective combinations. The accuracy significantly improved up to 5% compared to single sensor positions when 2 sensor positions were combined. The accuracy increased only slightly (from 0.5% up to 2% increase) while using combinations of 3 sensors when comparing with combinations of two sensors, indicating that wearing an additional sensor is not worthwhile. Comparing the results from different positions and their combinations shows that, for the four activities considered, the right wrist is ideal in the case of single sensor position, and the combination of the right wrist and low back is the best for sensor placement.

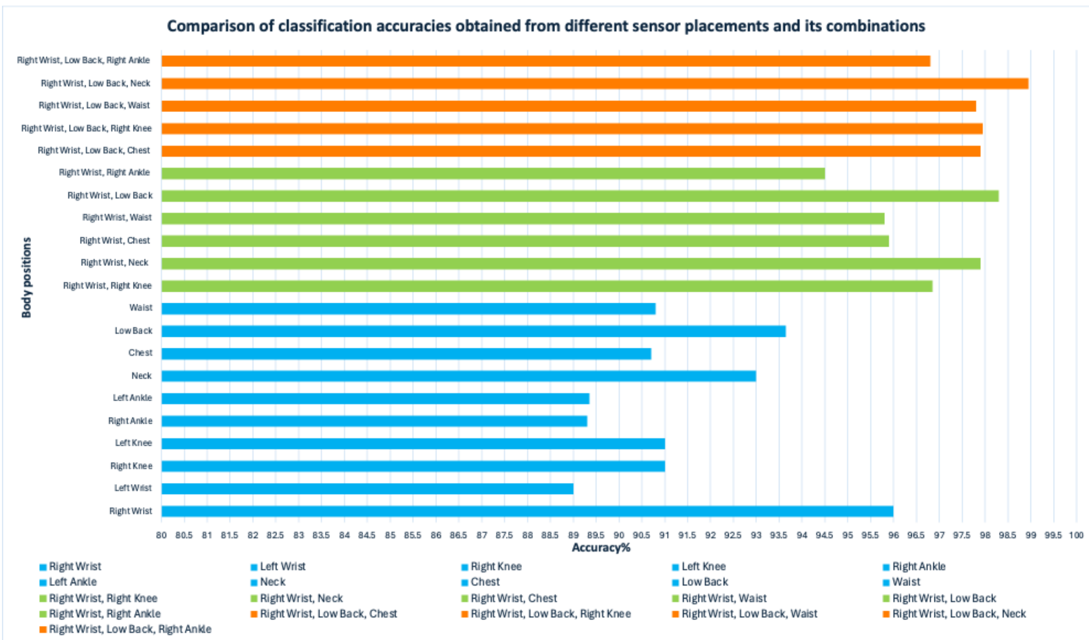

Figure 21 Overall classification accuracy for all considered sensor positions and its associated combinations.

DISCUSSION

Activity Acceleration Plots

Since there was no acceleration while sitting, the plot shows a consistent, stable line across all the three axes as expected (Figure 13). The difference in amplitude (Y axis) in the acceleration plots is because of the acceleration due to gravity. Acceleration was obtained whenever a movement was performed during reaching and grabbing (Figure 14). During walking, there was continuous movement and acceleration due to the swinging of arms and legs, with the entire body in motion (Figure 15). Brisk walking involved greater intensity in the 'walking' activity performed, resulting in increased amplitude of acceleration (Figure 16).

Right vs Left Wrist Positions

A significant difference in classifier prediction was observed between the sitting and reaching/grabbing activities at the left wrist, as the accuracy dropped by 7.5% compared to right wrist (Figure 18). This discrepancy arose because, while performing reaching and grabbing with the right wrist, the left wrist remained in the 'sitting' posture, which contributed to the similarity in data.

Walking vs Brisk Walking

In most cases, the classifier accurately distinguished between walking and brisk walking activities. The high accuracy is attributed to the increased intensity of brisk walking, which is evident from the acceleration amplitude observed in the graphs (Figure 16) compared to normal walking (Figure 15). The classifier effectively used the intensity and amplitude differences between the two activities to make accurate predictions. The feature extraction included time-domain and frequency-domain features that captured these variations, contributing to the classifier perfectly distinguishing between these 2 activities as in knee, ankle, low back, and waist positions (Appendix B).

Sitting vs Reaching and Grabbing

While performing the 'reaching and grabbing' activity, the subject periodically returned to the 'sitting' posture for 10 counts before resuming the next 'reaching and grabbing'. This periodic return to the 'sitting' posture made the data appear similar across both activities, leading to minor prediction inaccuracies and confusion between the two activities in the model. Thus, this overlap in data contributed to some inaccuracies in classifying 'reaching and grabbing' versus 'sitting'. The ability to distinguish between these 2 activities varies across different sensor positions and their combinations. Among the single sensor positions, the right wrist proved to be the most effective in predicting the four activities. When combining two sensors, the model's accuracy improved significantly in all sensor positions, as the additional sensor provided valuable data that enhanced classification performance.

Comparison with previous studies

The findings of this project correlate with that of previous studies. Earlier research identified activities like lying, sitting, walking, standing, cycling, running, ascending, and descending stairs, the lower back position was deemed more suitable when comparing to upper and middle backbone positions (Mehmood Khan, 2013). Similarly in this study, low back, knee, ankle, and waist are more recommended for lower body activities like walking and brisk walking than compared to upper body activities. Another study by Atallah et al. (2020) found that wrist-worn sensors are best for activities like wiping tables and vacuuming. This finding aligns with the results of this project, where the wrist sensor proved ideal for reaching/grabbing, a similar upper body activity.

Limitations of this research

1. The accelerometer data is collected from a single healthy adult. No elderly or clinical populations were involved in data collection. This limits the generalisability of the findings, as the data may not fully represent the variability in activity patterns and sensor performance across different age groups and health conditions.
2. The data was collected in a controlled environment, which may not accurately represent real-world conditions. In this setting, the individual was aware of and cautious during the activities, performing them perfectly. In a free environment, where the person is not mindful of the activities being performed, the model accuracy can decrease.
3. The study exclusively used the Axivity AX6, without evaluating other accelerometer models. This restriction limits the ability to generalize the findings to other types of accelerometers, which may have different performance characteristics and sensitivities.
4. Other types of activities (high-level like running, cycling and daily life activities) can be included, as expanding the range of activities beyond the four considered in this study could provide a more comprehensive understanding of the classifier's performance.

CONCLUSION

In conclusion, the ideal sensor position for the four activities considered (sitting, reaching and grabbing, walking, and brisk walking) was found in this project. This was determined from the sensor placement that yielded the highest classification accuracy using the multiclass SVM classifier. Compared to previous research, this project incorporated additional sensor positions that are novel to the research, such as the neck position, and an accuracy of 93% was obtained from the neck sensor when used as a single sensor position and the accuracy improved when combined with right wrist to 98.95%, making it a reliable position. Single sensor positions as well as combinations of 2 and 3 sensors were investigated in this project to observe how accuracy varied among the different placement positions and with greater number of sensors. For lower body activities like walking and brisk walking, wrist, low back, waist, knee, and ankle positions were found to be optimal. The right (dominant) wrist obtained 96% accuracy and found to be the best sensor position among single sensor placements. The accuracy improved significantly when two sensors were combined (due to maximum accuracy obtained from the right wrist position, it was paired with other positions). Among the combinations of 2 sensor positions, the dominant wrist and low back pair resulted the highest accuracy of 98.3%. However, there was little difference in accuracy when using combinations of three sensors (the accuracy increased in the range of 0.5% - 2%), and thus including an additional sensor above 2 sensors is not required, considering the preference for a minimal number of sensors. Thus, further combinations (4-10 sensors) were not attempted.

FUTURE WORKS

Further investigation involving more complex activities like running, cycling, and jumping, as well as a broader range of daily life activities, can be included to determine the most suitable sensor locations for these types of human activities. The study should be repeated with diverse adult populations, including clinical groups such as stroke survivors, to assess the applicability of the findings across different demographics and health conditions. The project could also be replicated using alternative accelerometers and machine learning models to assess the efficacy and reliability.

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APPENDICES

APPENDIX A – Sampling rate selection

Reaching and grabbing activity was performed using right wrist. The accelerometer data obtained using 100Hz sampling rate was 4 times larger than that of 25Hz sampling rate. Figure 12 shows accelerometer data along x, y, and z axes. By visual inspection from Figure (i), the peaks, and variations due to activities that were obtained using 100Hz sampling rate data were also obtained when using 25Hz sampling rate data.

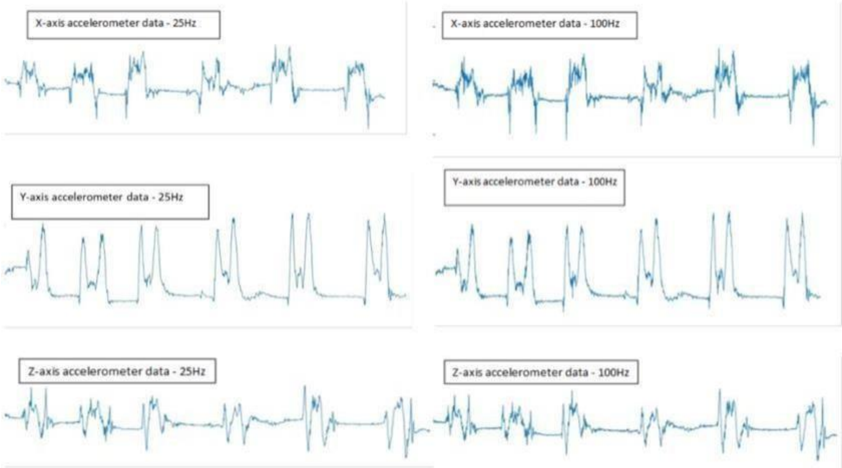


Figure (i) Accelerometer data of the 'reach and grab' activity performed at x, y, and z axes at 25Hz (left) and 100Hz (right) sampling rates with sensor placed at right wrist.

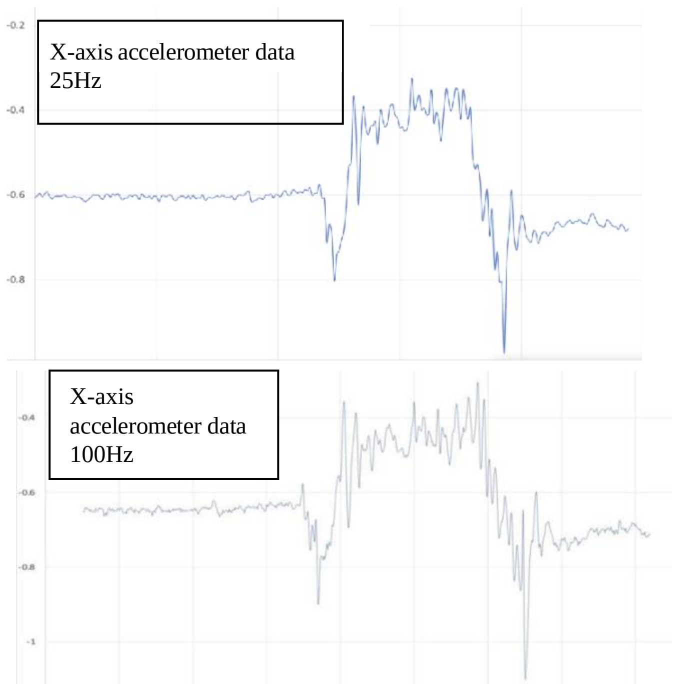


Figure (ii) A section of accelerometer data of the 'reach and grab' activity on x – axis using 25Hz and 100Hz sampling rates with sensor placed at right wrist.

MSE Calculation

Mean squared error is calculated to check for any data loss comparing 25Hz and 100Hz accelerometer data.

$$\text{MSE} = 1/n \sum_{i=1}^{n} (y2 - y1)^2$$

where:

- n is the number of samples considered from the activity plot
- y1 is the baseline value (-0.6 from figure (iii))
- y2 is the peak value (red points in the plot)

n = 5 (peaks selected as red points from figures(iii), (iv)).

n is selected, considering the points wherever peaks were obtained due to changes in acceleration in both 25Hz and 100Hz accelerometer data.

For 25Hz sampling rate,

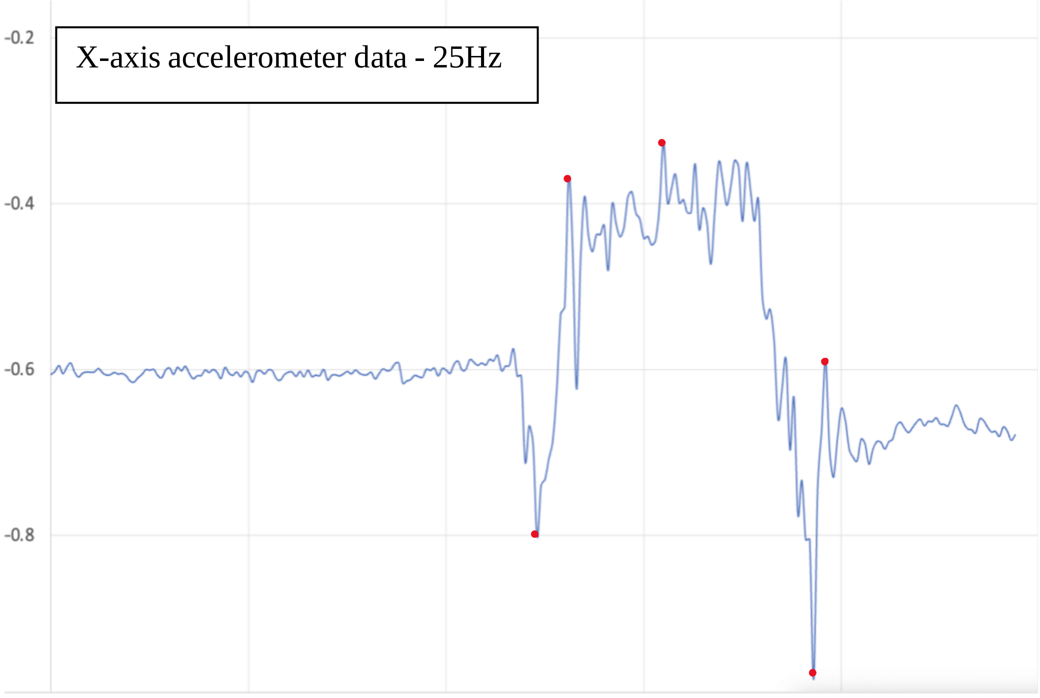


Figure (iii) Accelerometer data – 25Hz with peaks selected as red points

MSE_{25Hz} = 1/5 $[(-0.8-(-0.6))^2+(-0.38-(-0.6))^2+(-0.32-(-0.6))^2+(-0.61-(-0.6))^2+(-0.98-(-0.6))^2]\ g^2$

MSE_{25Hz} = 1/5 [0.31] g^2

MSE_{25Hz} = 0.062 g^2

For 100Hz sampling rate,

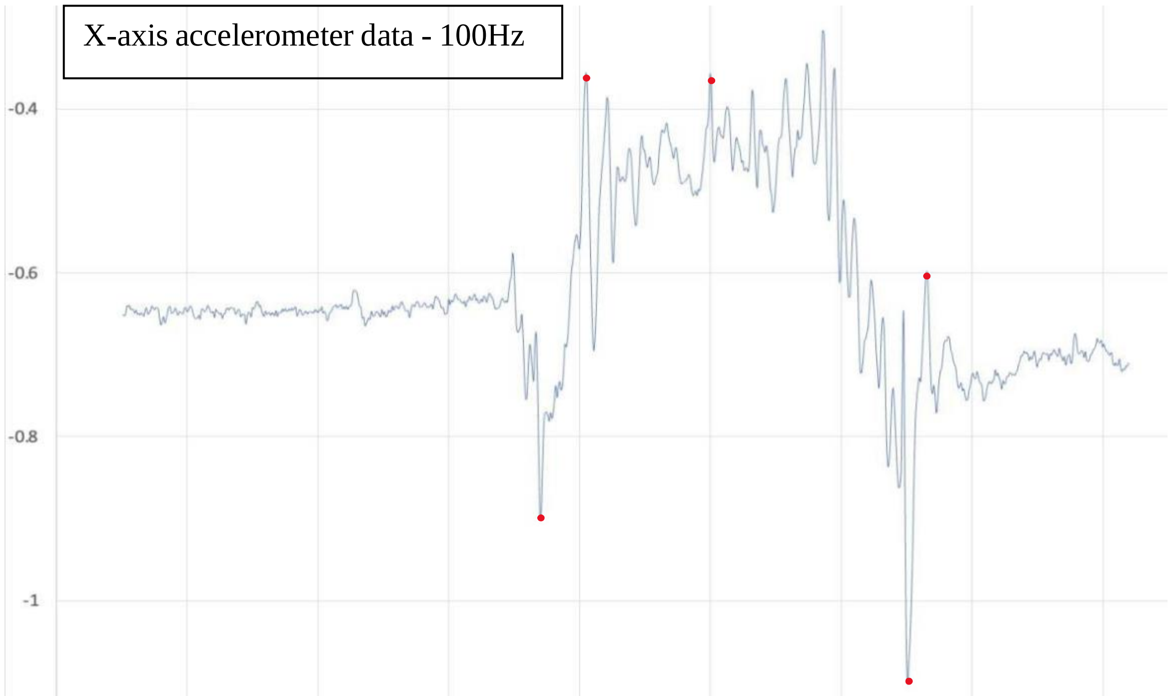


Figure (iv) Accelerometer data – 100Hz with peaks selected as red points

MSE_{100Hz} = 1/5 [$(-0.9-(-0.65))^2+(-0.38-(-0.65))^2+(-0.38-(-0.65))^2+(-0.6-(-0.65))^2+(-1.6-(-0.65))^2$] g^2

MSE_{100Hz} = 1/5 [1.113] g^2

MSE_{100Hz} = 0.222 g^2

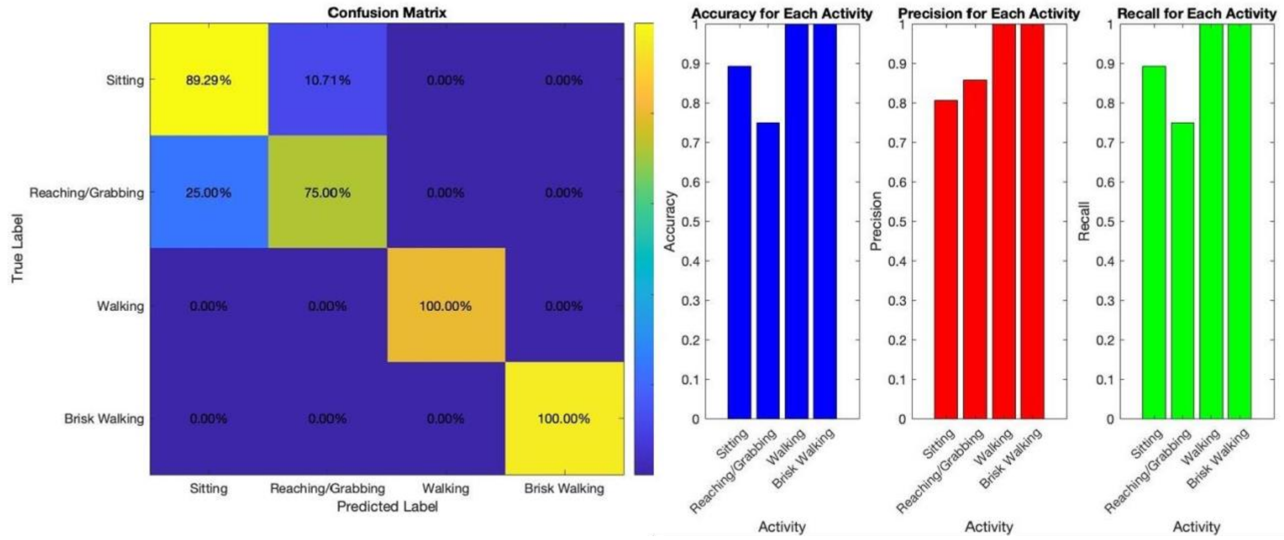
Taking the ratio between MSE_{25Hz} and MSE_{100Hz},

MSE_{25Hz}: MSE_{100Hz} = 1:3.6

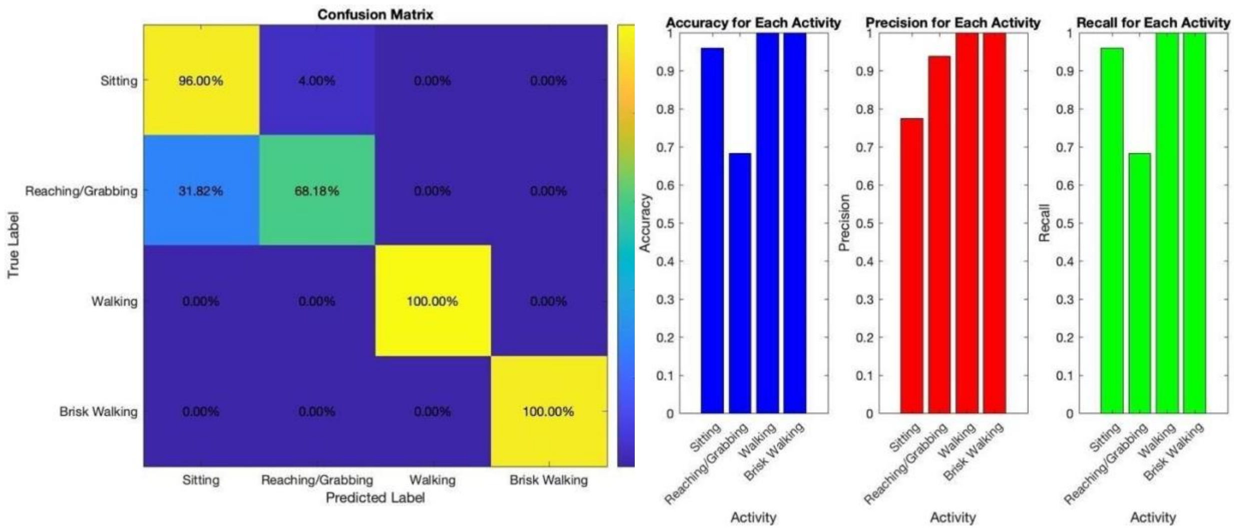
Comparing the obtained MSE ratio between 25Hz and 100Hz sampling rates, MSE_{100Hz} was about 3.6 (nearly 4) times higher than MSE_{25Hz}. There was no significant data loss when comparing data obtained using 25Hz with that of 100Hz.

APPENDIX B – Results of remaining single sensor positions.

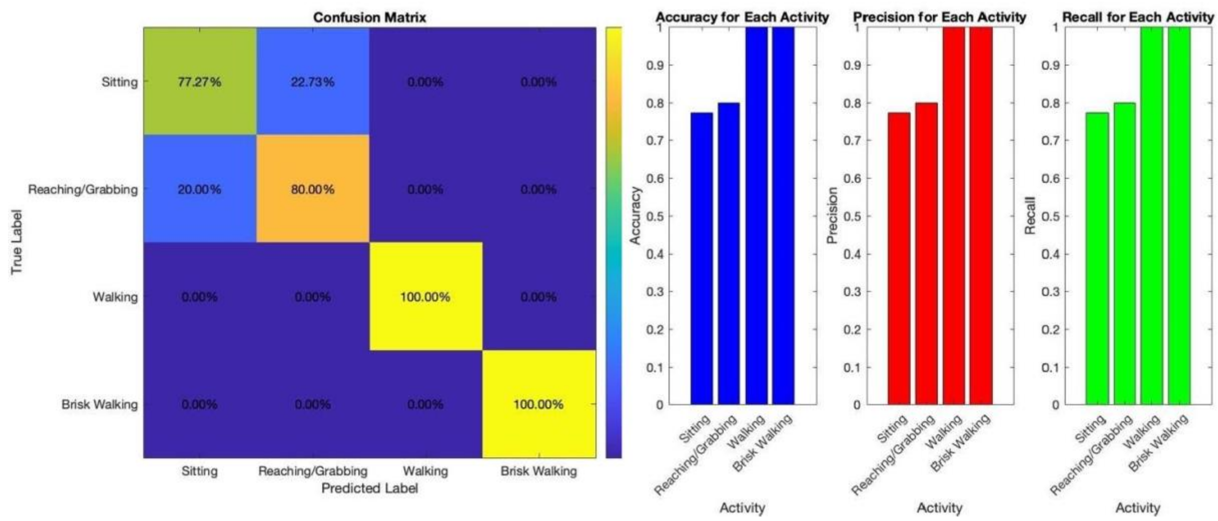
Right Knee – 91% Classification Accuracy



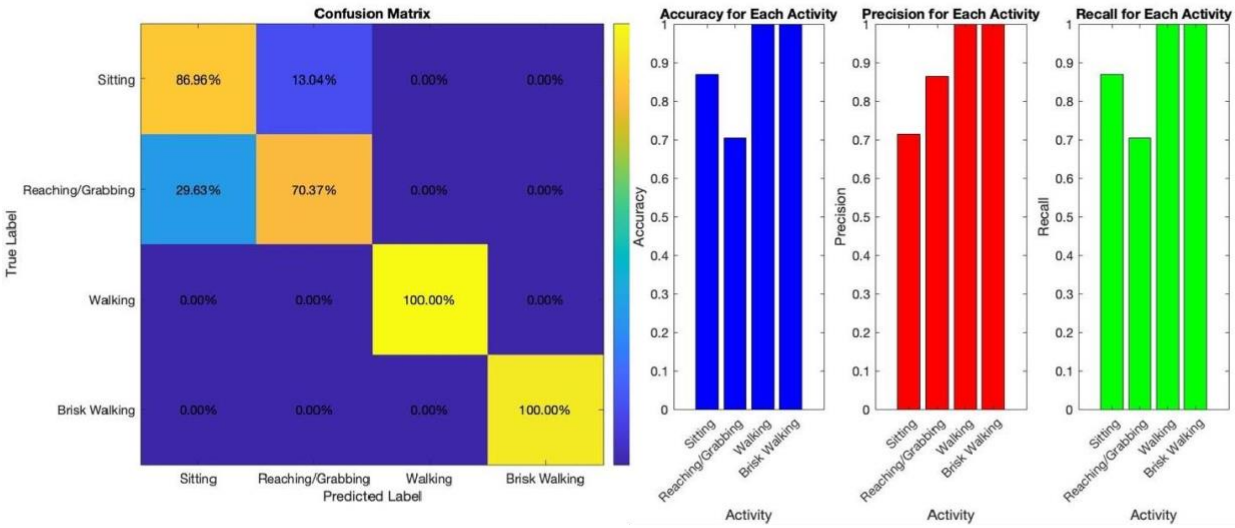
Left Knee – 91% Classification Accuracy



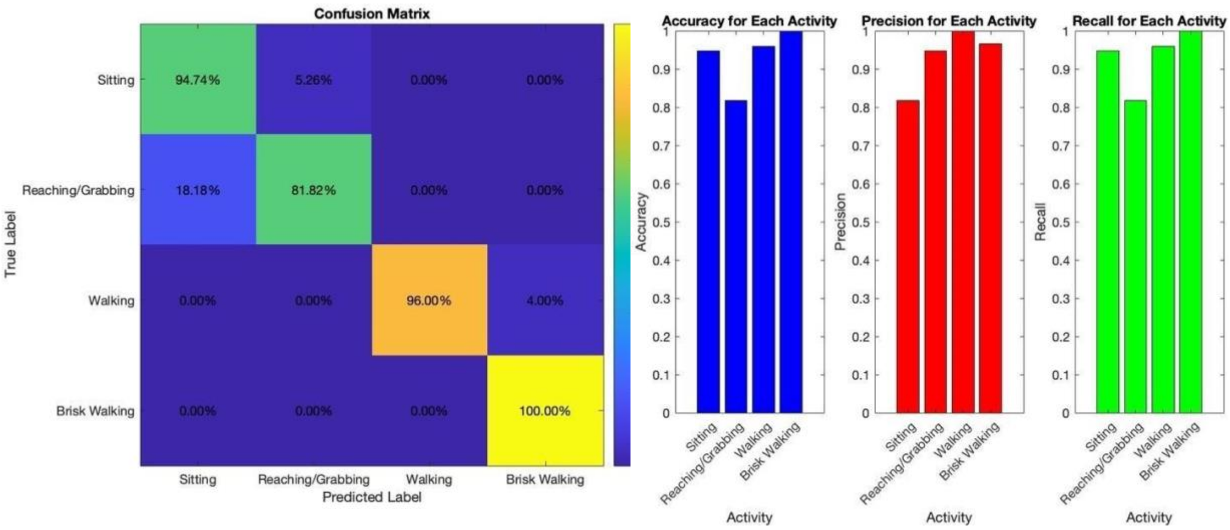
Right Ankle – 89.3% Classification Accuracy



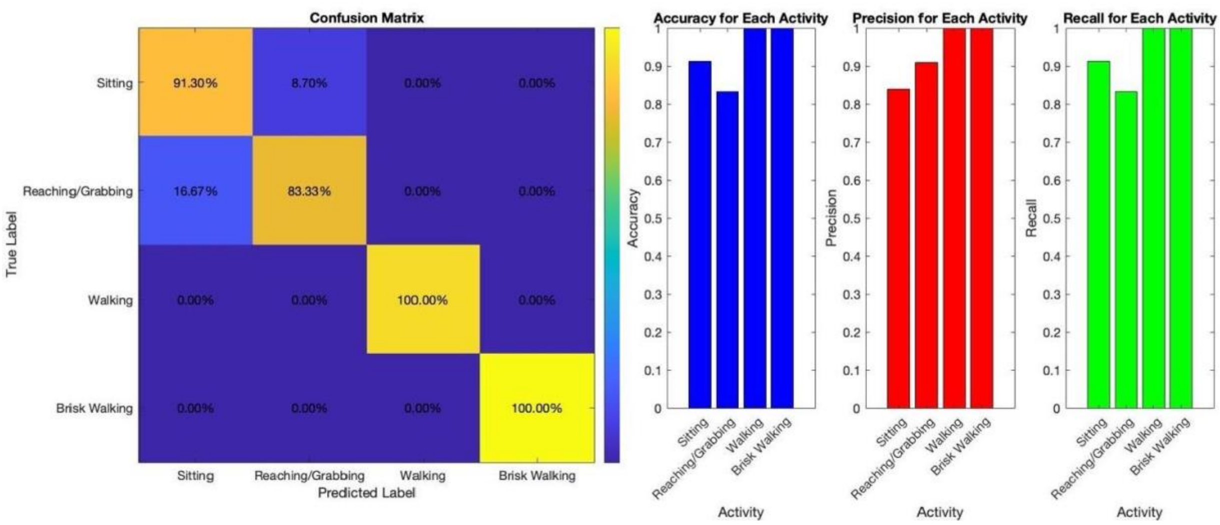
Left Ankle – 89.35% Classification Accuracy



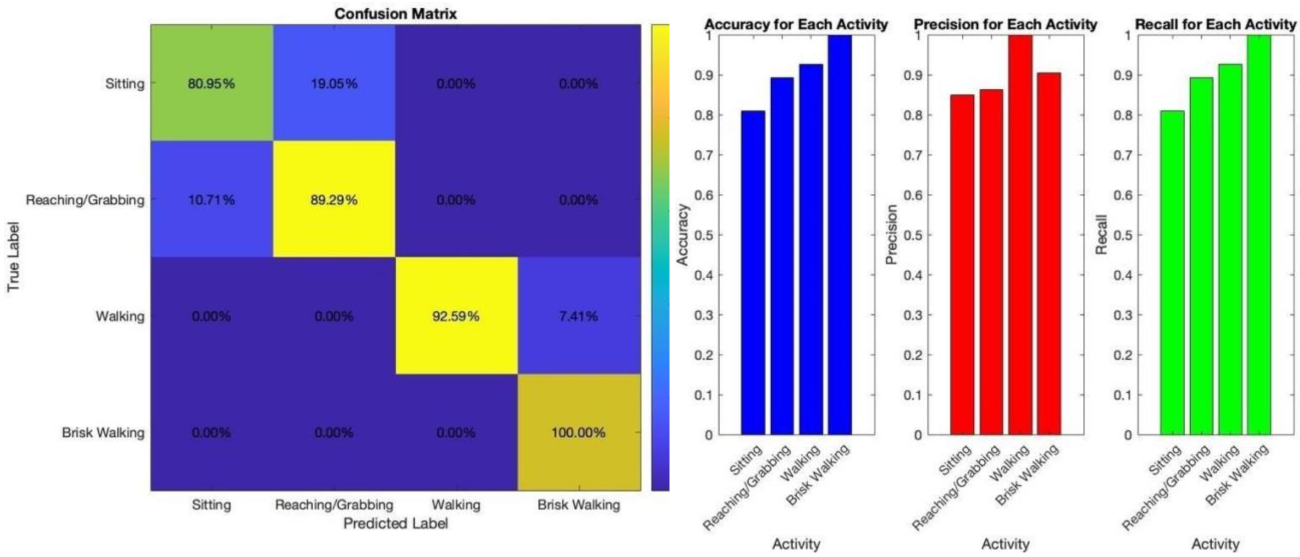
Neck – 93% Classification Accuracy



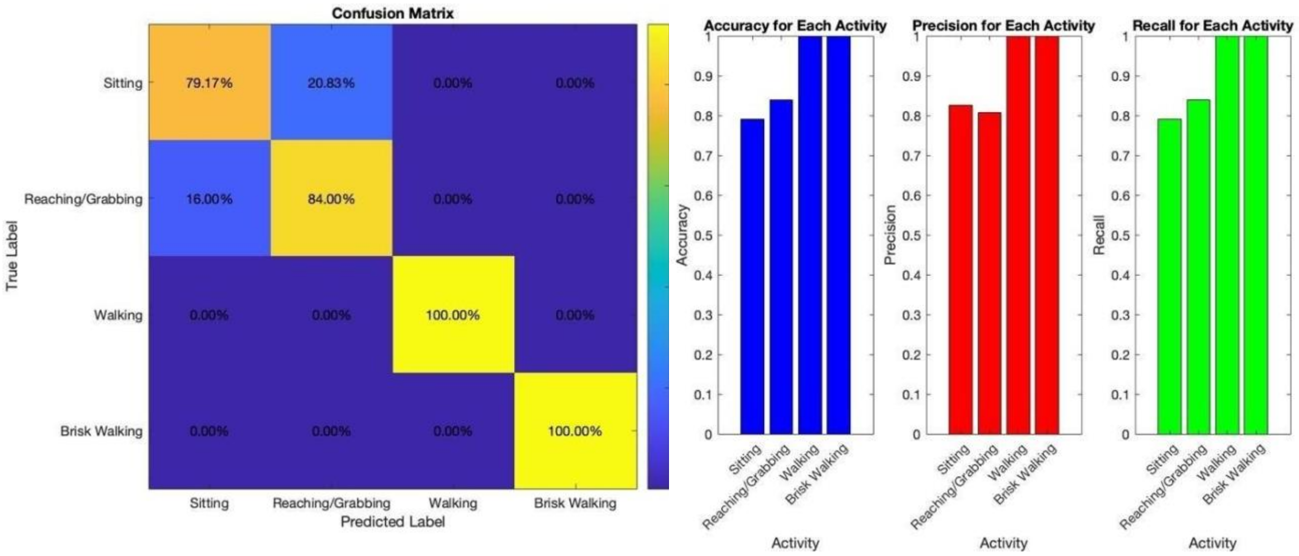
Low Back – 93.65% Classification Accuracy



Chest – 90.7% Classification Accuracy

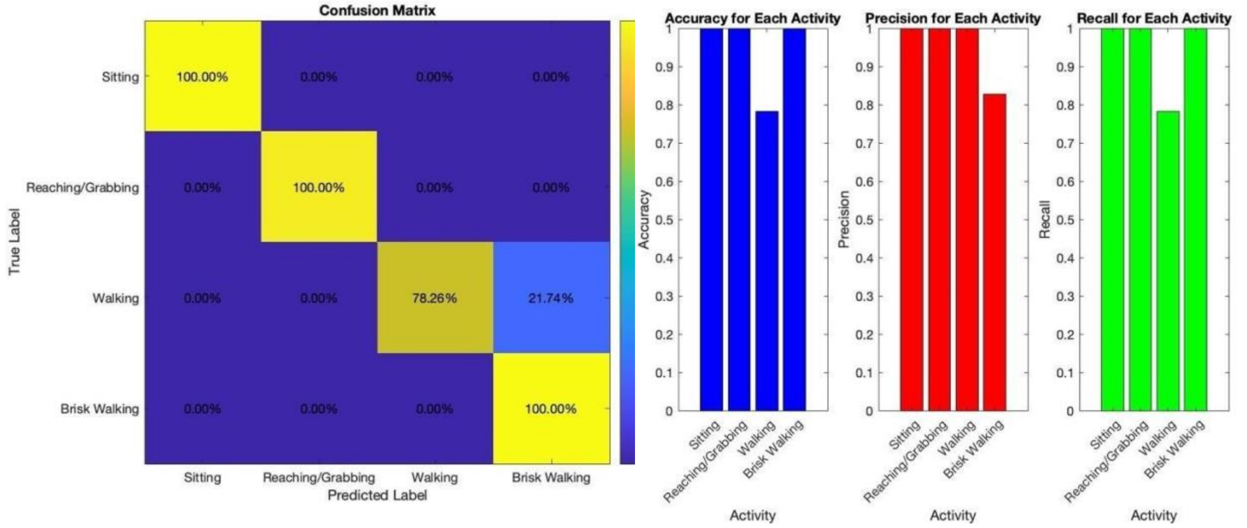


Waist – 90.8% Classification Accuracy

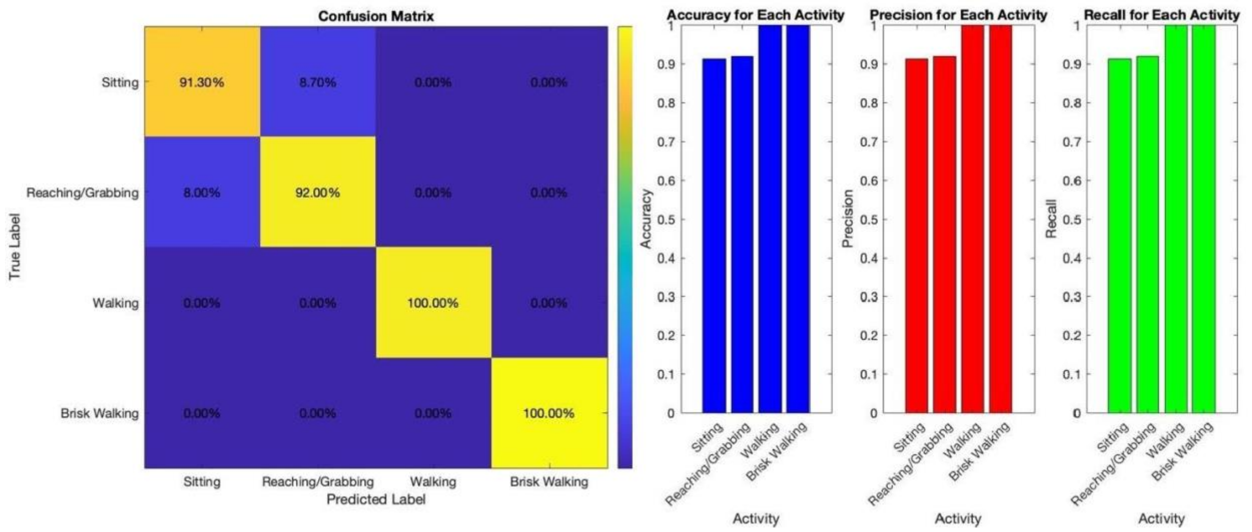


APPENDIX C – Results of remaining combinations of 2 sensor positions.

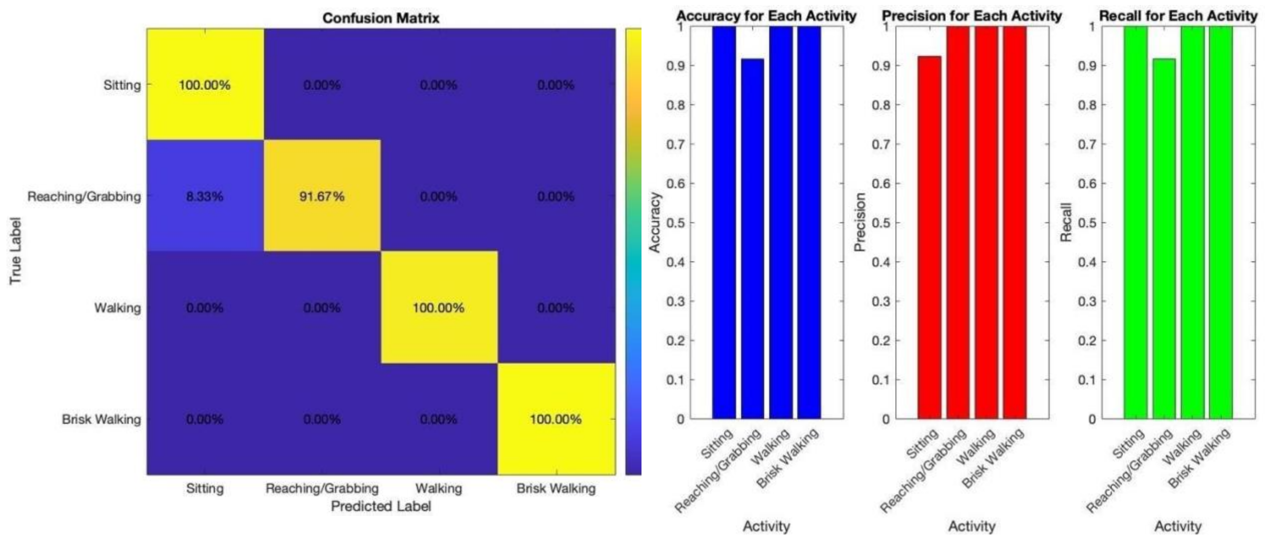
Right Wrist, Right Ankle – 94.5% Classification Accuracy.



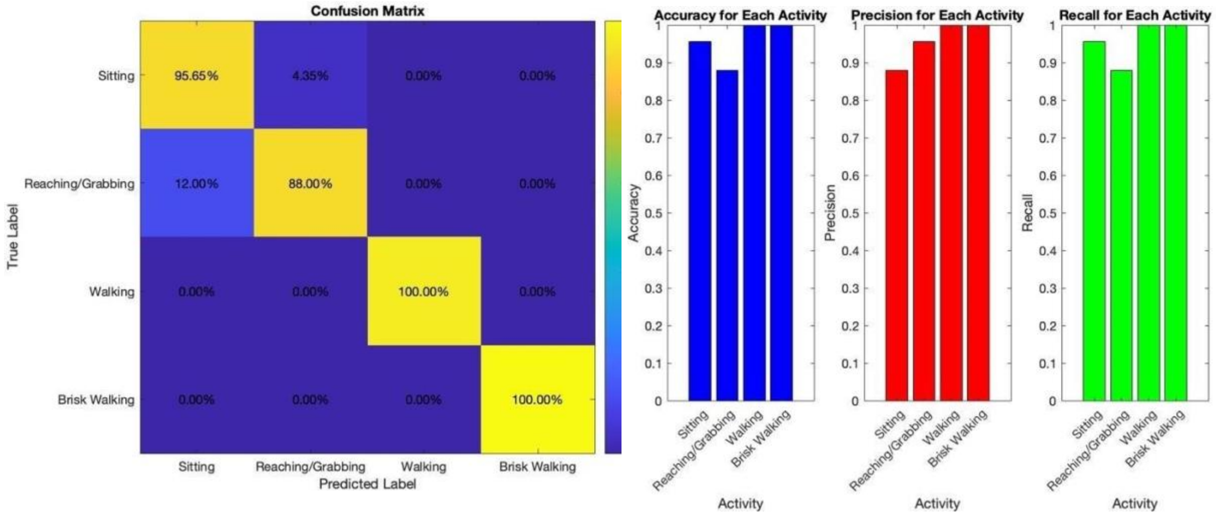
Right Wrist, Waist – 95.8% Classification Accuracy.



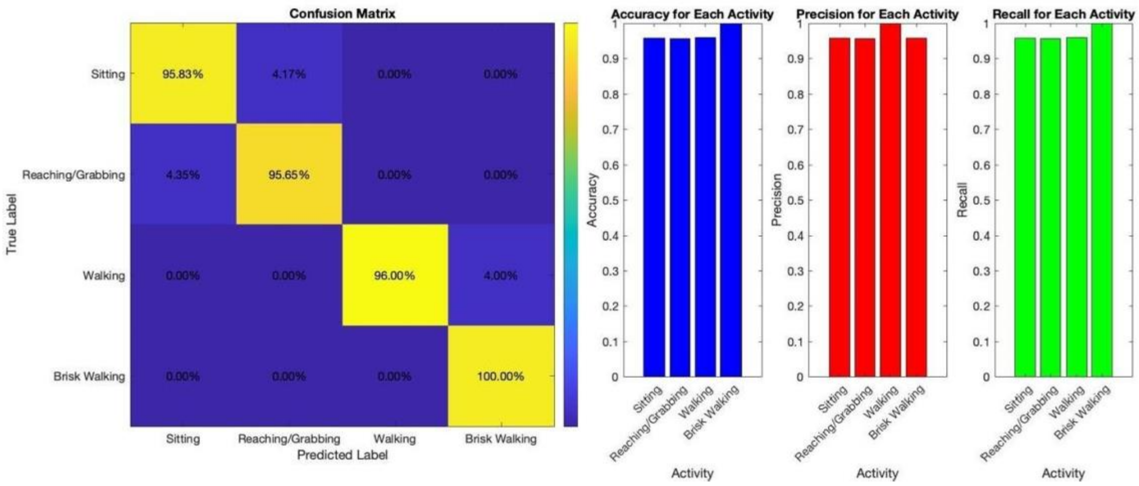
Right wrist, Neck – 97.9%



Right Wrist, Chest – 95.9% Classification Accuracy.

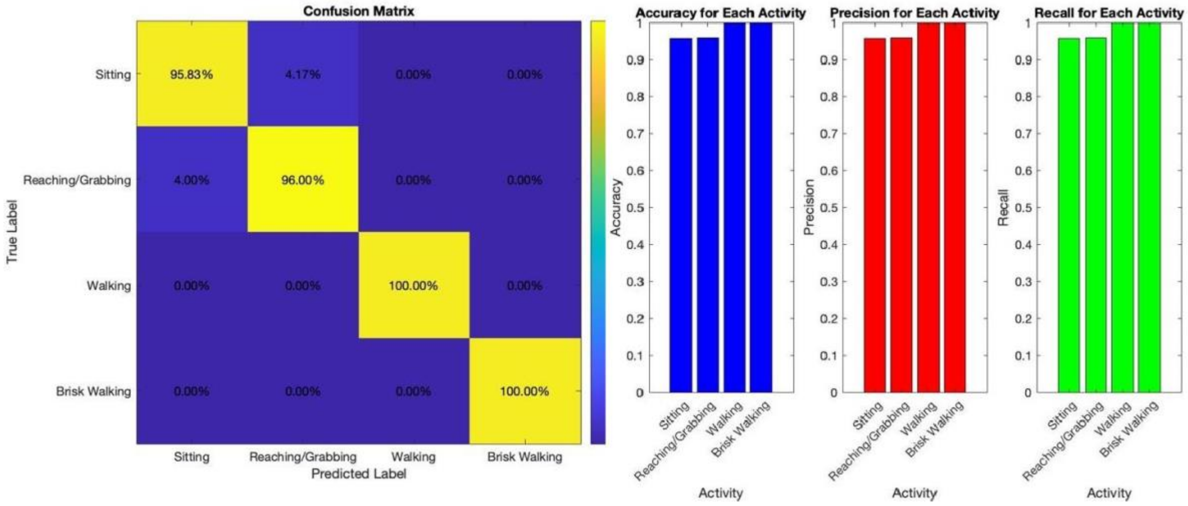


Right Wrist, Right Knee – 96.85% Classification Accuracy

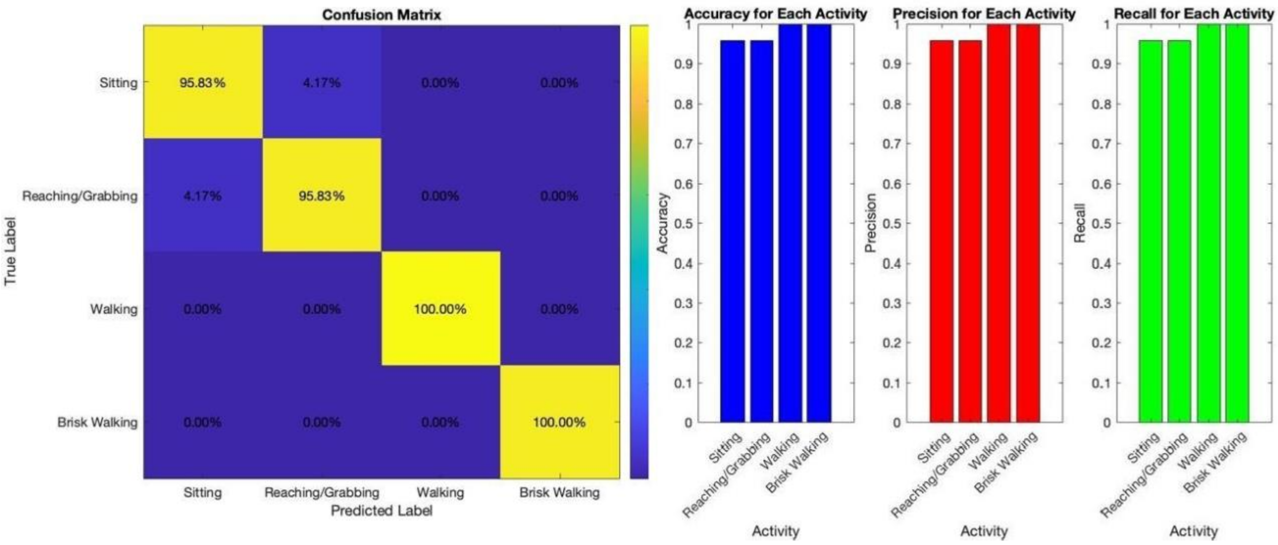


APPENDIX D – Results of remaining combinations of 3 sensor positions.

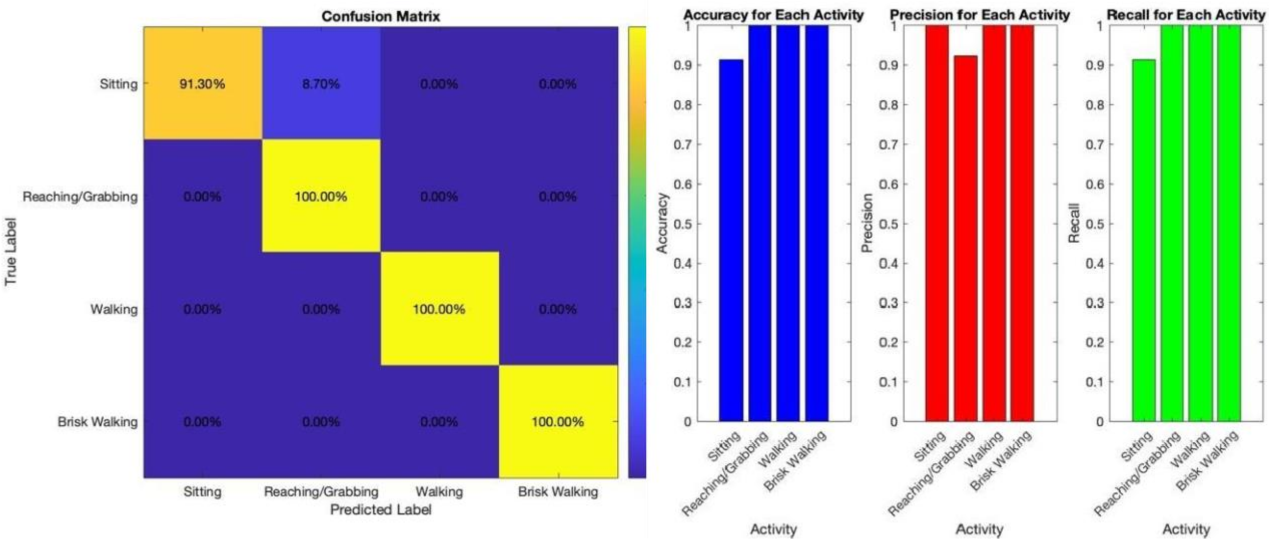
Right Wrist, Low Back, Right Knee – 97.95% Classification Accuracy.



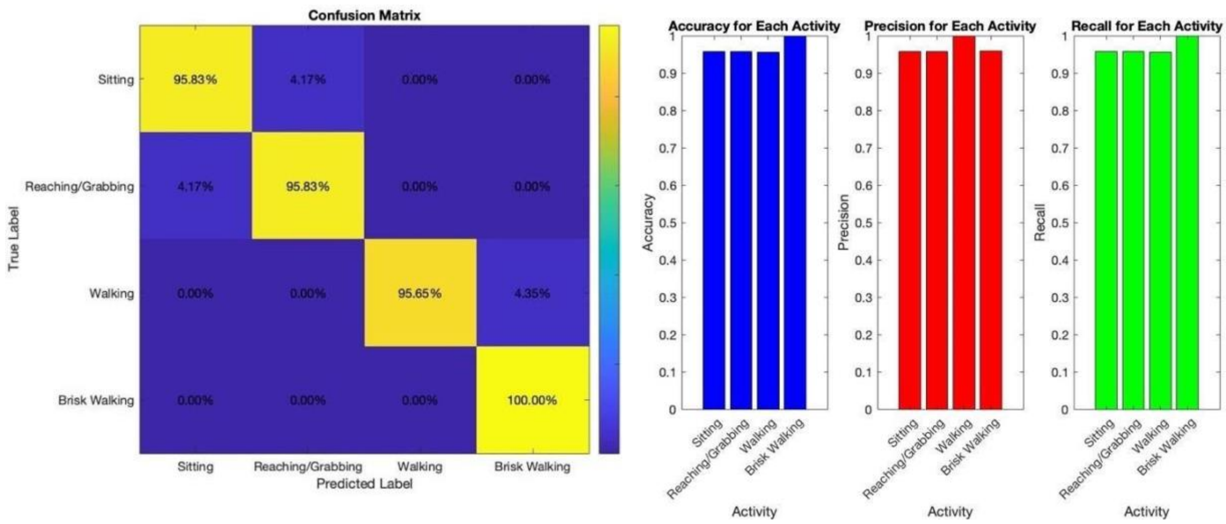
Right Wrist, Low Back, Chest – 97.9% Classification Accuracy.



Right Wrist, Low Back, Waist – 97.8% Classification Accuracy.



Right Wrist, Low Back, Right Ankle – 96.8% Classification Accuracy.



APPENDIX E – MATLAB Code

MATLAB Code for performing multiclass SVMclassification using single sensor position.

```
% Define files to input data from excel files
walking_files = {'rwwalking.xlsx', '2rwwalking.xlsx', '3rwwalking.xlsx', '4rwwalking.xlsx', '5rwwalking.xlsx'};
brisk_walking_files = {'rwbriskwalking.xlsx', '2rwbriskwalking.xlsx', '3rwbriskwalking.xlsx',
'4rwbriskwalking.xlsx', '5rwbriskwalking.xlsx'};
sitting_files = {'rwsitting.xlsx', '2rwsitting.xlsx', '3rwsitting.xlsx', '4rwsitting.xlsx', '5rwsitting.xlsx'};
reaching_grabbing_files = {'rwreach.xlsx', '2rwreach.xlsx', '3rwreach.xlsx', '4rwreach.xlsx', '5rwreach.xlsx'};

% Initialise empty matrices to store concatenated data
walking_data = [];
brisk_walking_data = [];
sitting_data = [];
reaching_grabbing_data = [];

% Function to align data by trimming
align_data = @(data1, data2) deal(data1(1:min(size(data1, 1), size(data2, 1)), :), data2(1:min(size(data1, 1),
size(data2, 1)), :));

% Read and concatenate data for walking
for i = 1:length(walking_files)
   file_data = read_and_trim(walking_files{i}, num_samples);
   walking_data = [walking_data; file_data];
end

% Read and concatenate data for brisk walking
for i = 1:length(brisk_walking_files)
   file_data = read_and_trim(brisk_walking_files{i}, num_samples);
   brisk_walking_data = [brisk_walking_data; file_data];
end

% Read and concatenate data for sitting
for i = 1:length(sitting_files)
   file_data = read_and_trim(sitting_files{i}, num_samples);
   sitting_data = [sitting_data; file_data];
```

```
end

% Read and concatenate data for reaching/grabbing
for i = 1:length(reaching_grabbing_files)
    file_data = read_and_trim(reaching_grabbing_files{i}, num_samples);
    reaching_grabbing_data = [reaching_grabbing_data; file_data];
end

% Combine all data into one matrix
X = [sitting_data; reaching_grabbing_data; walking_data; brisk_walking_data];

% Create labels for each activity
labels = [1 * ones(size(sitting_data, 1), 1);  % sitting
          2 * ones(size(reaching_grabbing_data, 1), 1);   % reaching/grabbing
          3 * ones(size(walking_data, 1), 1);  % walking
          4 * ones(size(brisk_walking_data, 1), 1)];  % brisk walking

% Apply lowpass filter
Fs = 25; % Sampling frequency (Hz)
Fc = 25; % Cut-off frequency (Hz)
[b, a] = butter(4, Fc/(Fs/2), 'low'); % 4th order Butterworth filter
X = filtfilt(b, a, X);

% Define window size in samples (5 seconds * 25 samples/second)
window_size = 5 * 25; % 125 samples

% Feature extraction with 5-second non-overlapping windows
features = [];
feature_labels = [];

for i = 1:window_size:length(X)-window_size+1
    window = X(i:i+window_size-1, :);

    % Time-domain features
    mean_val = mean(window);
    std_val =  std(window);
    max_val = max(window);
    min_val = min(window);
    rms_val = rms(window);
    skew_val = skewness(window);
    kurt_val = kurtosis(window);


    % Frequency-domain features
    fft_val = fft(window);
    fft_mag = abs(fft_val);
    fft_mean = mean(fft_mag);
    fft_std = std(fft_mag);

    % Energy feature
    energy_val = sum(fft_mag(:).^2); % Ensure energy_val is a scalar

    % Correlation feature
    corr_val = corrcoef(window);
```

```
    corr_val = corr_val(tril(true(size(corr_val)), -1)); % Extract lower triangular part of correlation matrix
    corr_val = corr_val(:)'; % Ensure it's a row vector

    % Combine all features into a fixed-size vector
    feature_vector = [mean_val, std_val, max_val, min_val, rms_val, skew_val, kurt_val, fft_mean, fft_std,
energy_val, corr_val];

    features = [features; feature_vector];

    % Label for the current window
    window_label = mode(labels(i:i+window_size-1));
    feature_labels = [feature_labels; window_label];
end

% Train-test split (80% train, 20% test)
cv = cvpartition(feature_labels, 'HoldOut', 0.2);
X_train = features(training(cv), :);
y_train = feature_labels(training(cv));

X_test = features(test(cv), :);
y_test = feature_labels(test(cv));

% Train multiclass SVM classifier using ECOC
svmModel = fitcecoc(X_train, y_train);

% Predict labels for test data
predicted_labels = predict(svmModel, X_test);

% Evaluate the model
confMat = confusionmat(y_test, predicted_labels);

% Compute accuracy, recall, and precision
accuracy = sum(diag(confMat)) / sum(confMat(:));
recall = diag(confMat) ./ sum(confMat, 2);
precision = diag(confMat) ./ sum(confMat, 1)';

% Create confusion matrix plot
figure;
imagesc(confMat);
title('Confusion Matrix');
xlabel('Predicted Label');
ylabel('True Label');
colorbar;

% Set axis labels
xticks(1:size(confMat, 2));
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
yticks(1:size(confMat, 1));
yticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});

% Add percentage values to confusion matrix
for i = 1:size(confMat, 1)
    for j = 1:size(confMat, 2)
        text(j, i, sprintf('%.2f%%', 100 * confMat(i, j) / sum(confMat(i, :))), ...
```

```
        'HorizontalAlignment', 'center', 'VerticalAlignment', 'middle', 'Color', 'k');
    end
end

% Create subplots for accuracy, precision, and recall
figure;
subplot(1, 3, 1);
bar(1:size(confMat, 1), diag(confMat) ./ sum(confMat, 2), 'b');
xlabel('Activity');
ylabel('Accuracy');
title('Accuracy for Each Activity');
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
xtickangle(45);

subplot(1, 3, 2);
bar(1:size(confMat, 1), precision, 'r');
xlabel('Activity');
ylabel('Precision');
title('Precision for Each Activity');
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
xtickangle(45);

subplot(1, 3, 3);
bar(1:size(confMat, 1), recall, 'g');
xlabel('Activity');
ylabel('Recall');
title('Recall for Each Activity');
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
xtickangle(45);

% Display metrics
fprintf('Accuracy: %.2f\n', accuracy);
disp('Precision:');
disp(precision);
disp('Recall:');
disp(recall);
```

MATLAB Code – to classify using combination of two sensor positions.

```
% Define the file lists for each activity and each sensor position
walking_files_pos1 = {'rwwalking.xlsx', '2rwwalking.xlsx', '3rwwalking.xlsx', '4rwwalking.xlsx',
'5rwwalking.xlsx'};
brisk_walking_files_pos1 = {'rwbriskwalking.xlsx', '2rwbriskwalking.xlsx', '3rwbriskwalking.xlsx',
'4rwbriskwalking.xlsx', '5rwbriskwalking.xlsx'};
sitting_files_pos1 = {'rwsitting.xlsx', '2rwsitting.xlsx', '3rwsitting.xlsx', '4rwsitting.xlsx', '5rwsitting.xlsx'};
reaching_grabbing_files_pos1 = {'rwreach.xlsx', '2rwreach.xlsx', '3rwreach.xlsx', '4rwreach.xlsx',
'5rwreach.xlsx'};

walking_files_pos2 = {'rightanklewalking.xlsx', '2rightanklewalking.xlsx', '3rightanklewalking.xlsx',
'4rightanklewalking.xlsx', '5rightanklewalking.xlsx'};
brisk_walking_files_pos2 = {'rightanklebriskwalking.xlsx', '2rightanklebriskwalking.xlsx',
'3rightanklebriskwalking.xlsx', '4rightanklebriskwalking.xlsx', '5rightanklebriskwalking.xlsx'};
sitting_files_pos2 = {'rightanklesitting.xlsx', '2rightanklesitting.xlsx', '3rightanklesitting.xlsx',
'4rightanklesitting.xlsx', '5rightanklesitting.xlsx'};
```

```
reaching_grabbing_files_pos2 = {'rightanklereach.xlsx', '2rightanklereach.xlsx', '3rightanklereach.xlsx',
'4rightanklereach.xlsx', '5rightanklereach.xlsx'};

% Initialize empty matrices to store concatenated data
walking_data = [];
brisk_walking_data = [];
sitting_data = [];
reaching_grabbing_data = [];

% Function to align data by trimming
align_data = @(data1, data2) deal(data1(1:min(size(data1, 1), size(data2, 1)), :), data2(1:min(size(data1, 1),
size(data2, 1)), :));

% Read and concatenate data for walking
for i = 1:length(walking_files_pos1)
    file_data_pos1 = xlsread(walking_files_pos1{i}, 'B:D');
    file_data_pos2 = xlsread(walking_files_pos2{i}, 'B:D');
    if size(file_data_pos1, 1) ~= size(file_data_pos2, 1)
        % Trim the longer file to match the shorter one
        [file_data_pos1, file_data_pos2] = align_data(file_data_pos1, file_data_pos2);
    end
    combined_data = [file_data_pos1, file_data_pos2]; % Combine data from both positions
    walking_data = [walking_data; combined_data];
end

% Read and concatenate data for brisk walking
for i = 1:length(brisk_walking_files_pos1)
    file_data_pos1 = xlsread(brisk_walking_files_pos1{i}, 'B:D');
    file_data_pos2 = xlsread(brisk_walking_files_pos2{i}, 'B:D');
    if size(file_data_pos1, 1) ~= size(file_data_pos2, 1)
        % Trim the longer file to match the shorter one
        [file_data_pos1, file_data_pos2] = align_data(file_data_pos1, file_data_pos2);
    end
    combined_data = [file_data_pos1, file_data_pos2]; % Combine data from both positions
    brisk_walking_data = [brisk_walking_data; combined_data];
end

% Read and concatenate data for sitting
for i = 1:length(sitting_files_pos1)
    file_data_pos1 = xlsread(sitting_files_pos1{i}, 'B:D');
    file_data_pos2 = xlsread(sitting_files_pos2{i}, 'B:D');
    if size(file_data_pos1, 1) ~= size(file_data_pos2, 1)
        % Trim the longer file to match the shorter one
        [file_data_pos1, file_data_pos2] = align_data(file_data_pos1, file_data_pos2);
    end
    combined_data = [file_data_pos1, file_data_pos2]; % Combine data from both positions
    sitting_data = [sitting_data; combined_data];
end

% Read and concatenate data for reaching/grabbing
for i = 1:length(reaching_grabbing_files_pos1)
    file_data_pos1 = xlsread(reaching_grabbing_files_pos1{i}, 'B:D');
    file_data_pos2 = xlsread(reaching_grabbing_files_pos2{i}, 'B:D');
    if size(file_data_pos1, 1) ~= size(file_data_pos2, 1)
```

```
        % Trim the longer file to match the shorter one
        [file_data_pos1, file_data_pos2] = align_data(file_data_pos1, file_data_pos2);
    end
    combined_data = [file_data_pos1, file_data_pos2]; % Combine data from both positions
    reaching_grabbing_data = [reaching_grabbing_data; combined_data];
end

% Combine all data into one matrix
X = [sitting_data; reaching_grabbing_data; walking_data; brisk_walking_data];

% Create labels for each activity
labels = [1 * ones(size(sitting_data, 1), 1);  % sitting
          2 * ones(size(reaching_grabbing_data, 1), 1);   % reaching/grabbing
          3 * ones(size(walking_data, 1), 1);  % walking
          4 * ones(size(brisk_walking_data, 1), 1)];  % brisk walking

% Apply lowpass filter
Fs = 25; % Sampling frequency (Hz)
Fc = 25; % Cut-off frequency (Hz)
[b, a] = butter(4, Fc/(Fs/2), 'low'); % 4th order Butterworth filter
X = filtfilt(b, a, X);

% Define window size in samples (5 seconds * 25 samples/second)
window_size = 5 * 25; % 125 samples

% Feature extraction with 5-second non-overlapping windows
features = [];
feature_labels = [];

for i = 1:window_size:length(X)-window_size+1
    window = X(i:i+window_size-1, :);

    % Time-domain features
    mean_val = mean(window);
    std_val =  std(window);
    max_val = max(window);
    min_val = min(window);
    rms_val = rms(window);
    skew_val = skewness(window);
    kurt_val = kurtosis(window);


    % Frequency-domain features
    fft_val = fft(window);
    fft_mag = abs(fft_val);
    fft_mean = mean(fft_mag);
    fft_std = std(fft_mag);

    % Energy feature
    energy_val = sum(fft_mag(:).^2); % Ensure energy_val is a scalar

    % Correlation feature
    corr_val = corrcoef(window);
    corr_val = corr_val(tril(true(size(corr_val)), -1)); % Extract lower triangular part of correlation matrix
```

```
    corr_val = corr_val(:)'; % Ensure it's a row vector

    % Combine all features into a fixed-size vector
    feature_vector = [mean_val, std_val, max_val, min_val, rms_val, skew_val, kurt_val, fft_mean, fft_std,
energy_val, corr_val];

    features = [features; feature_vector];

    % Label for the current window
    window_label = mode(labels(i:i+window_size-1));
    feature_labels = [feature_labels; window_label];
end

% Train-test split (80% train, 20% test)
cv = cvpartition(feature_labels, 'HoldOut', 0.2);
X_train = features(training(cv), :);
y_train = feature_labels(training(cv));

X_test = features(test(cv), :);
y_test = feature_labels(test(cv));

% Train multiclass SVM classifier using ECOC
svmModel = fitcecoc(X_train, y_train);

% Predict labels for test data
predicted_labels = predict(svmModel, X_test);

% Evaluate the model
confMat = confusionmat(y_test, predicted_labels);

% Compute accuracy, recall, and precision
accuracy = sum(diag(confMat)) / sum(confMat(:));
recall = diag(confMat) ./ sum(confMat, 2);
precision = diag(confMat) ./ sum(confMat, 1)';

% Create confusion matrix plot
figure;
imagesc(confMat);
title('Confusion Matrix');
xlabel('Predicted Label');
ylabel('True Label');
colorbar;

% Set axis labels
xticks(1:size(confMat, 2));
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
yticks(1:size(confMat, 1));
yticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});

% Add percentage values to confusion matrix
for i = 1:size(confMat, 1)
    for j = 1:size(confMat, 2)
        text(j, i, sprintf('%.2f%%', 100 * confMat(i, j) / sum(confMat(i, :))), ...
            'HorizontalAlignment', 'center', 'VerticalAlignment', 'middle', 'Color', 'k');
```

```
    end
end

% Create subplots for accuracy, precision, and recall
figure;
subplot(1, 3, 1);
bar(1:size(confMat, 1), diag(confMat) ./ sum(confMat, 2), 'b');
xlabel('Activity');
ylabel('Accuracy');
title('Accuracy for Each Activity');
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
xtickangle(45);

subplot(1, 3, 2);
bar(1:size(confMat, 1), precision, 'r');
xlabel('Activity');
ylabel('Precision');
title('Precision for Each Activity');
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
xtickangle(45);

subplot(1, 3, 3);
bar(1:size(confMat, 1), recall, 'g');
xlabel('Activity');
ylabel('Recall');
title('Recall for Each Activity');
xticklabels({'Sitting', 'Reaching/Grabbing', 'Walking', 'Brisk Walking'});
xtickangle(45);

% Display metrics
fprintf('Accuracy: %.2f\n', accuracy);
disp('Precision:');
disp(precision);
disp('Recall:');
disp(recall);
```