Report on

IMU-Based Human Activity Recognition using Nicla Vision

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1. Introduction

Brief Overview of Human Activity Recognition (HAR)

Human Activity Recognition (HAR) is the process of identifying and classifying human actions based on data collected from sensors. In recent years, HAR using wearable sensors has gained significant attention due to its applicability in domains such as health monitoring, fitness tracking, rehabilitation, and human–computer interaction. IMU-based HAR systems aim to recognize activities by analysing motion patterns captured during daily movements.

Objective of the Assignment

The objective of this assignment is to design and implement an IMU-based human activity recognition system using a wrist-mounted Nicla Vision device. The task involves collecting raw IMU data for multiple activities, performing window-based feature extraction, training and evaluating a machine learning model, and deploying the trained model for real-time activity classification.

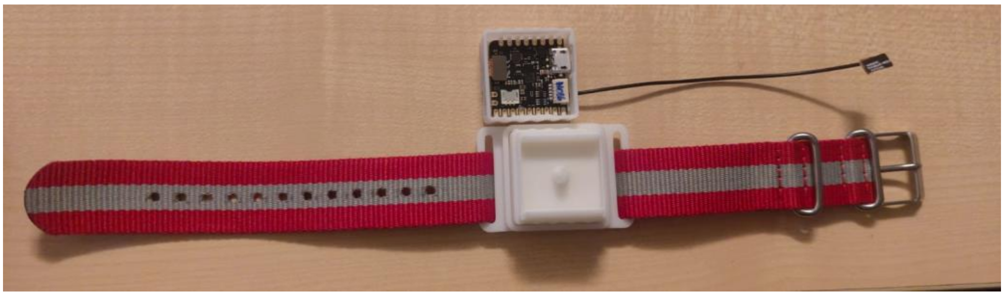
Overview of the Approach

The overall approach consists of four main stages. First, raw accelerometer and gyroscope data is collected from the Nicla Vision device at a fixed sampling rate for a set of predefined activities. Next, the continuous IMU signals are segmented into overlapping windows, and time-domain features are extracted from each window to represent the motion characteristics. A supervised machine learning model is then trained using the extracted features and evaluated using standard performance metrics. Finally, the trained model is deployed for real-time inference, where live IMU data streamed from the device is processed and classified to predict the ongoing human activity.

2. Sensor Setup and Data Collection

Description of Nicla Vision IMU

- The Nicla Vision development board is equipped with an onboard six-axis Inertial Measurement Unit (IMU).
- The IMU provides measurements of linear acceleration and angular velocity along three orthogonal axes.
- The compact form factor of the device makes it suitable for wearable, wrist-mounted data collection.



Sensors Used

- **Accelerometer:** Measures linear acceleration along three axes:
  - Ax (X-axis)
  - Ay (Y-axis)
  - Az (Z-axis)
- **Gyroscope:** Measures angular velocity along three axes:
  - Gx (X-axis)
  - Gy (Y-axis)
  - Gz (Z-axis)
- Together, these six channels capture both translational and rotational components of wrist motion.

Sampling Frequency

- IMU data was collected at a fixed sampling frequency of **50 Hz**.
- This corresponds to **50 samples per second**, which is sufficient to capture both slow and rapid human movements.

Duration per Activity

- Each activity was recorded continuously for a duration of **3 minutes**.
- This ensured adequate data coverage for capturing intra-activity variations.

Number of Samples per Activity

- At a sampling rate of 50 Hz and a duration of 3 minutes, approximately **9000 samples** were collected for each activity.
- Each sample consists of six IMU values corresponding to the accelerometer and gyroscope channels.

List of Activities Recorded

The following activities were recorded individually:

- Sitting
- Standing
- Walking (normal pace)
- Brisk walking
- Jogging
- Cycling
- Stair-up
- Stair-down
- Sit–stand–sit (transitional)
- Phone interaction (typing/scrolling)
- Eating with spoon
- Pick and place

Each activity was stored in a separate CSV file.

Wrist-Mounted Placement and Its Implications

- The Nicla Vision device was worn on the wrist during data collection.
- Wrist-mounted placement allows natural movement capture but introduces variability due to changes in hand orientation and motion style.
- Activities involving subtle or similar wrist movements can exhibit overlapping IMU patterns, which affects classification performance.
- Despite these challenges, wrist-based sensing remains practical and widely used for real-world HAR applications.

3. Exploratory Data Analysis and Signal Characteristics

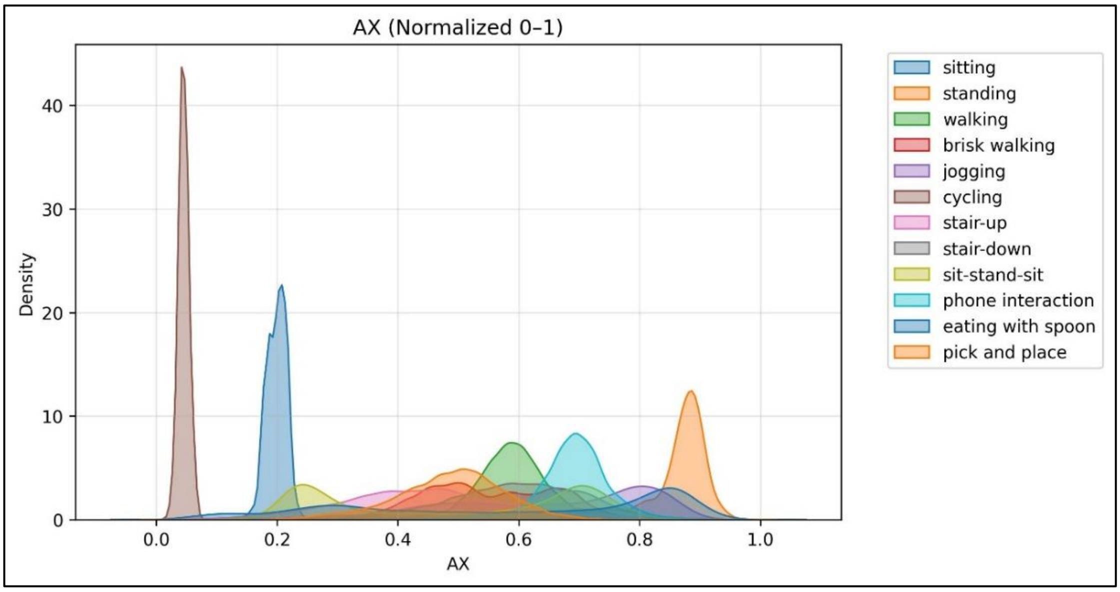
This section analyses the raw IMU signals to understand their statistical properties, activity-wise behaviour, and separability prior to model training.

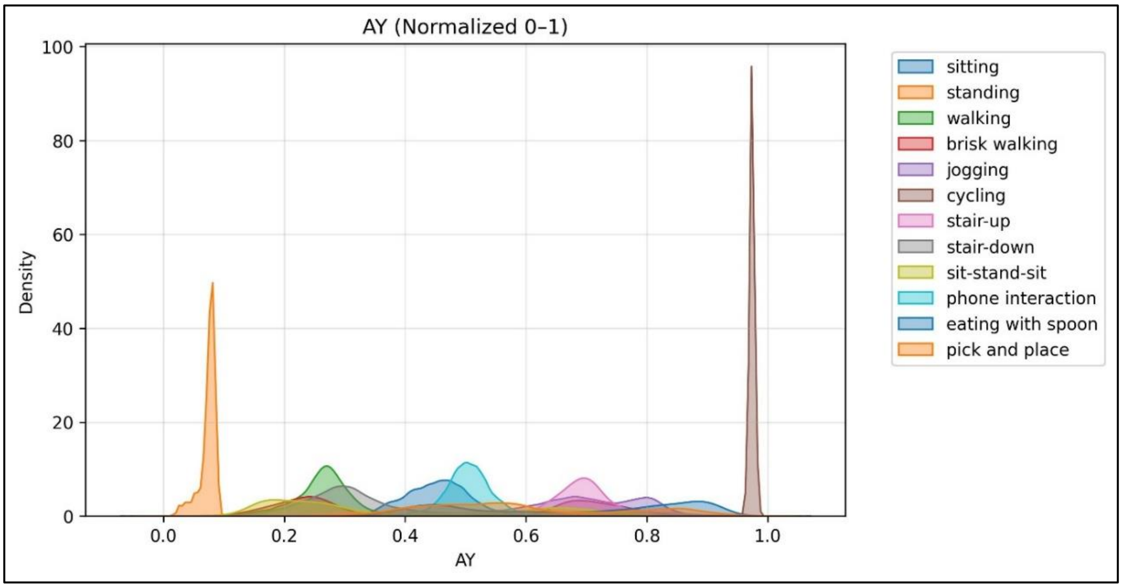
3.1 Raw Signal Characteristics

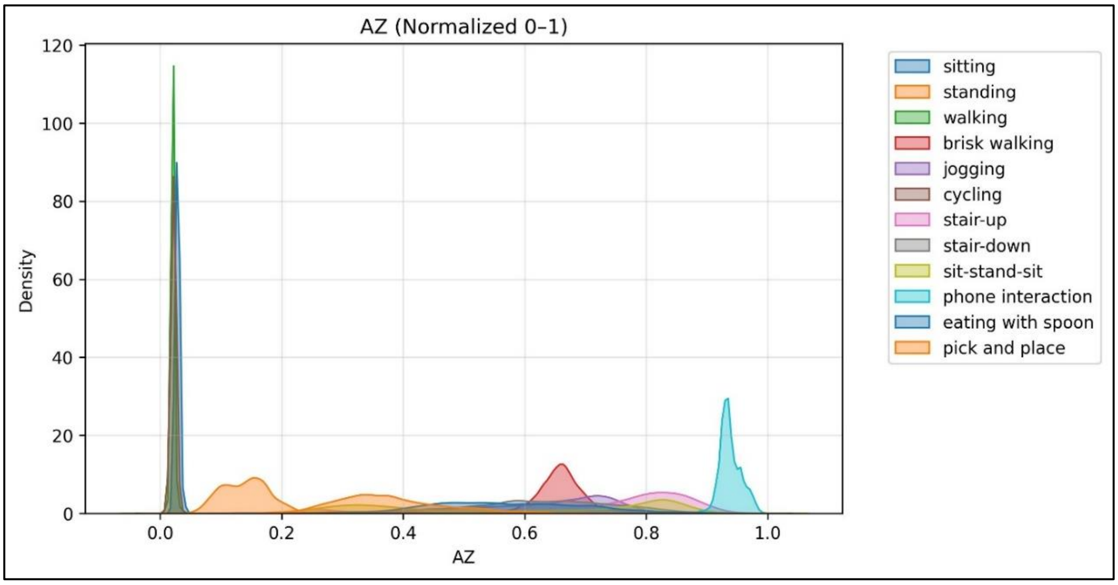
- The IMU provides **6 channels**: Accelerometer (Ax, Ay, Az) and Gyroscope (Gx, Gy, Gz).
- Accelerometer signals capture:
  - Static gravity component
  - Dynamic motion-induced acceleration
- Gyroscope signals capture:
  - Angular velocity due to wrist rotations and arm movements
- Static activities show:
  - Low signal amplitude
  - Near-constant mean values
- Dynamic activities show:
  - Larger signal fluctuations
  - Higher temporal variation
- Sensor noise is minimal but visible during:
  - Low-motion activities
  - Short-duration transitions

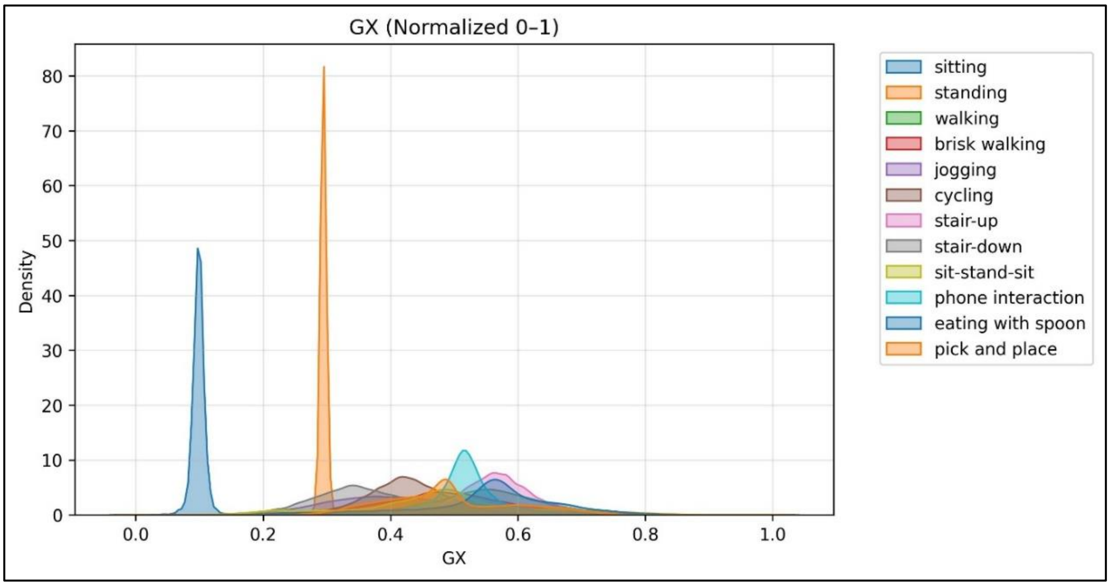
3.2 Distribution of IMU Signals (KDE / Density Analysis)

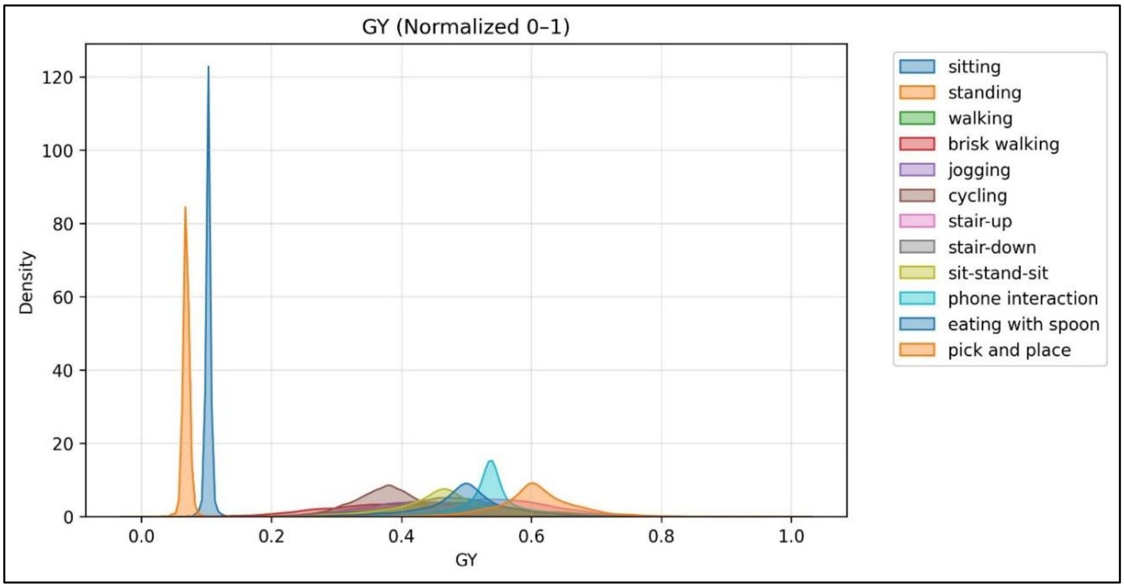
The statistical distribution of IMU signals provides insight into variability and overlap between activities. Table X summarizes the key distributional characteristics observed from kernel density estimates.

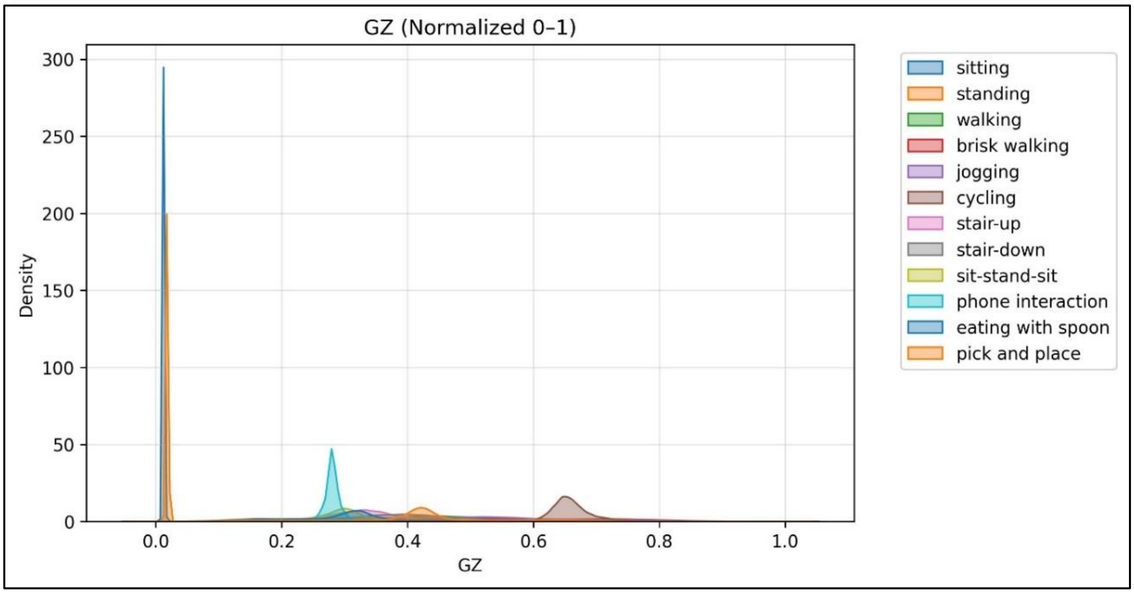

AX (Normalized 0–1)
Density
AX
0
10
20
30
40
0.0
0.2
0.4
0.6
0.8
1.0
sitting
standing
walking
brisk walking
jogging
cycling
stair-up
stair-down
sit-stand-sit
phone interaction
eating with spoon
pick and place


AY (Normalized 0–1)
Density
AY
0
20
40
60
80
100
0.0
0.2
0.4
0.6
0.8
1.0
sitting
standing
walking
brisk walking
jogging
cycling
stair-up
stair-down
sit-stand-sit
phone interaction
eating with spoon
pick and place


AZ (Normalized 0–1)
Density
AZ
0
20
40
60
80
100
120
0.0
0.2
0.4
0.6
0.8
1.0
sitting
standing
walking
brisk walking
jogging
cycling
stair-up
stair-down
sit-stand-sit
phone interaction
eating with spoon
pick and place


GX (Normalized 0–1)
Density
GX
sitting
standing
walking
brisk walking
jogging
cycling
stair-up
stair-down
sit-stand-sit
phone interaction
eating with spoon
pick and place


GY (Normalized 0–1)
Density
GY
sitting
standing
walking
brisk walking
jogging
cycling
stair-up
stair-down
sit-stand-sit
phone interaction
eating with spoon
pick and place


GZ (Normalized 0–1)
Density
GZ
sitting
standing
walking
brisk walking
jogging
cycling
stair-up
stair-down
sit-stand-sit
phone interaction
eating with spoon
pick and place

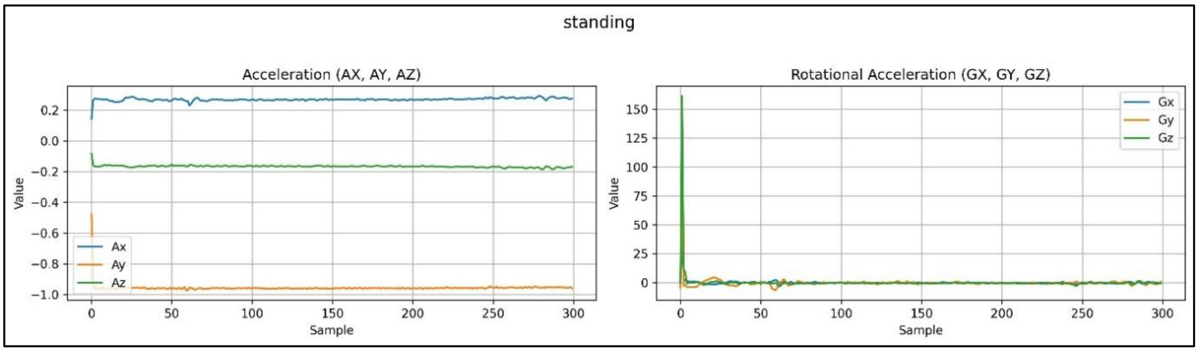
Feature	Key Observations Across Activities	Discriminative Insight
AX	Static activities (sitting, standing, cycling) show sharp narrow peaks at low values. Dynamic activities (walking, brisk walking, jogging, stair-up/down) spread toward mid–high range.	AX separates **static vs dynamic** activities well but overlaps among dynamic ones.
AY	Sitting and standing have very sharp, isolated peaks. Dynamic activities show broader distributions with partial overlap.	Good for **static posture detection**; limited for fine-grained motion separation.
AZ	Static activities cluster near zero. Phone interaction and brisk walking show higher peaks at upper range.	AZ captures **vertical motion and hand activity** distinctly.
GX	Sitting/standing show very sharp peaks near zero. Walking-related and stair activities spread in mid-range.	Strong indicator of **motion presence vs absence**.
GY	Static activities tightly clustered; dynamic actions (walking, jogging, pick-and-place) show broader distributions.	Helps distinguish **low vs moderate rotational movement**.
GZ	Sitting and standing zero variance. Cycling and brisk activities peak at higher values.	Highly effective for **rotational intensity discrimination**.

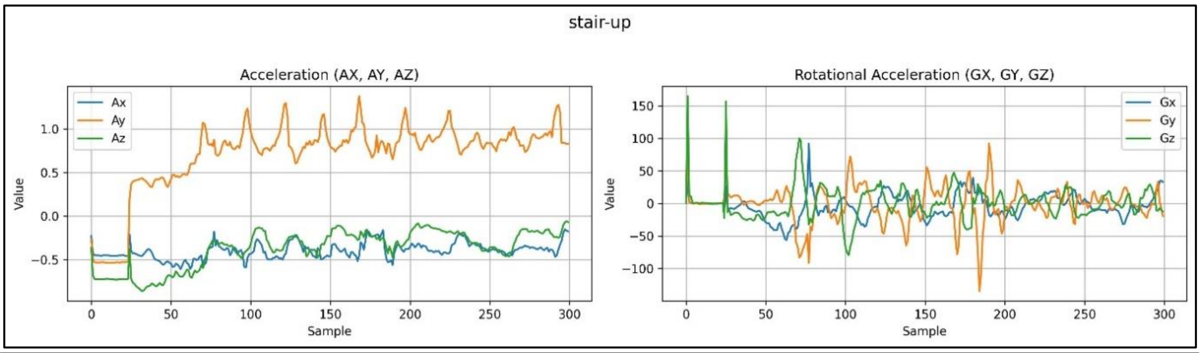
Key observations:

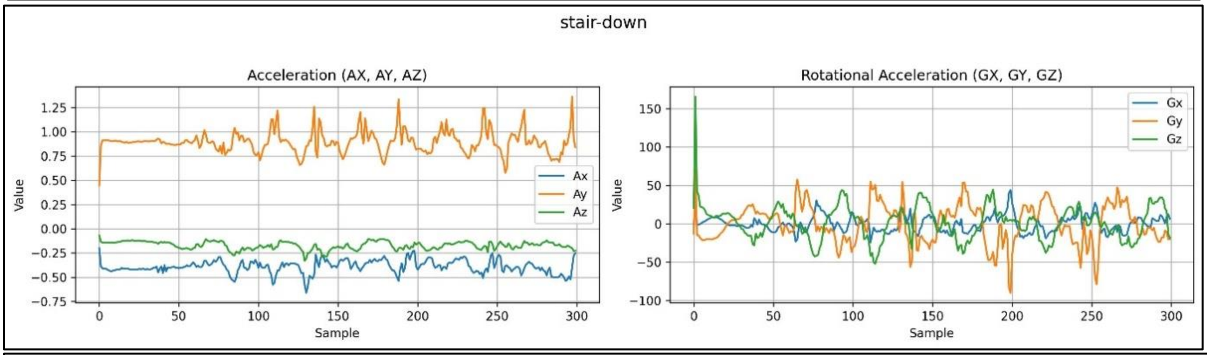
- **Accelerometer axes**:
  - Static activities (sitting, standing) have sharp, narrow peaks.
  - Dynamic activities show broader distributions.
- **Gyroscope axes**:
  - Static activities cluster near zero.
  - Dynamic activities show wider spread and higher density tails.
- **Axis sensitivity**:
  - Certain axes (e.g., Az, Gy) show stronger discrimination between activities.
- **Variance trends**:
  - Walking < brisk walking < jogging in terms of spread
- **Overlap observed**:
  - Walking and brisk walking distributions overlap significantly.
  - Stair-up and stair-down show similar density profiles

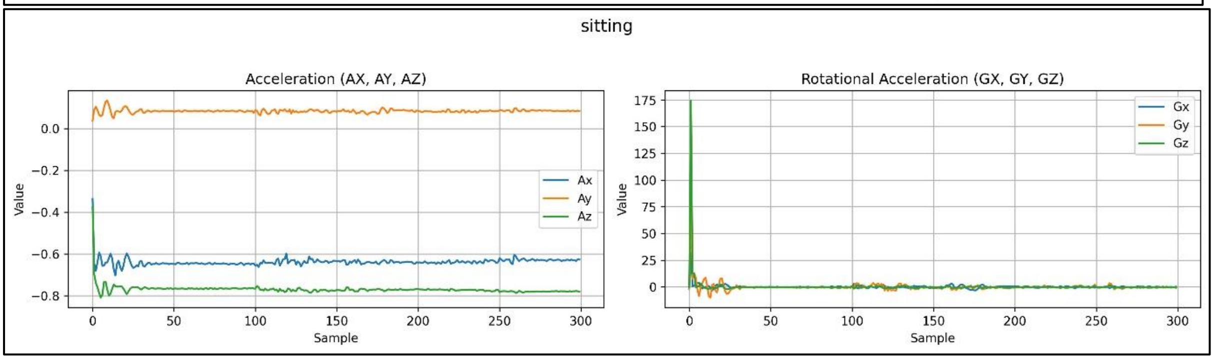
3.3 Activity-wise Signal behaviour (Interference / Time-Domain Plots)

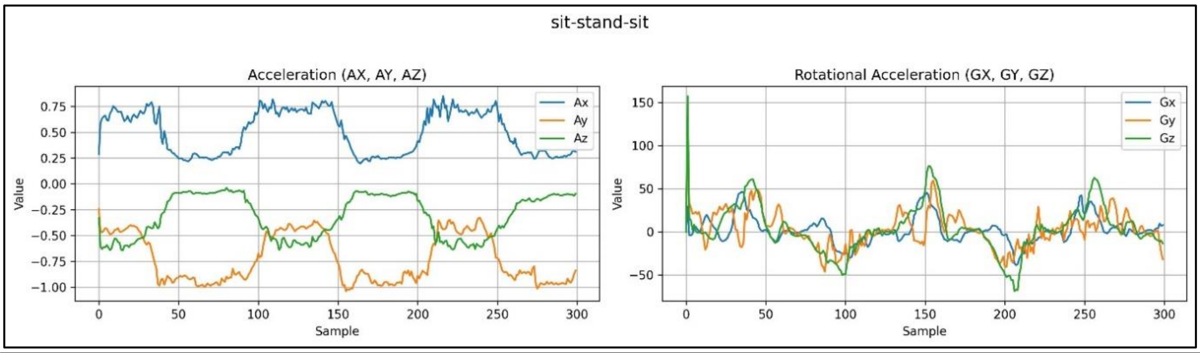
Understand the temporal behaviour of different activities, the raw accelerometer and gyroscope signals were analysed in the time domain. Table X summarizes the characteristic patterns observed across activities.

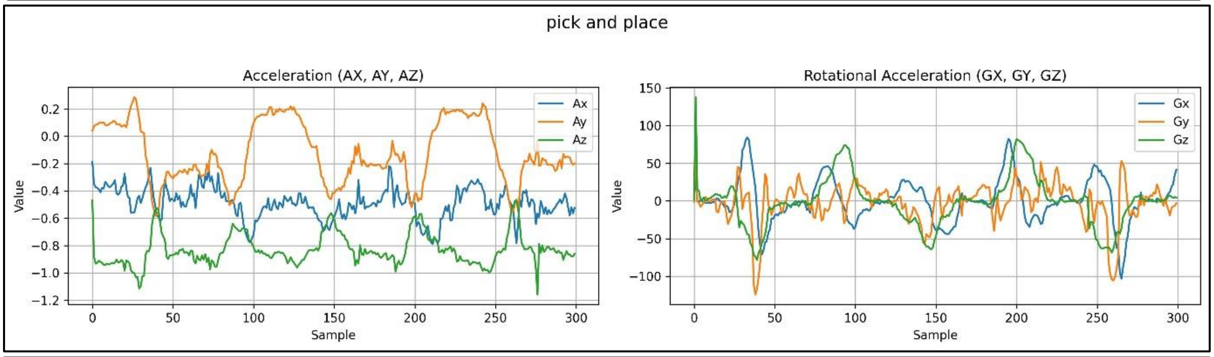


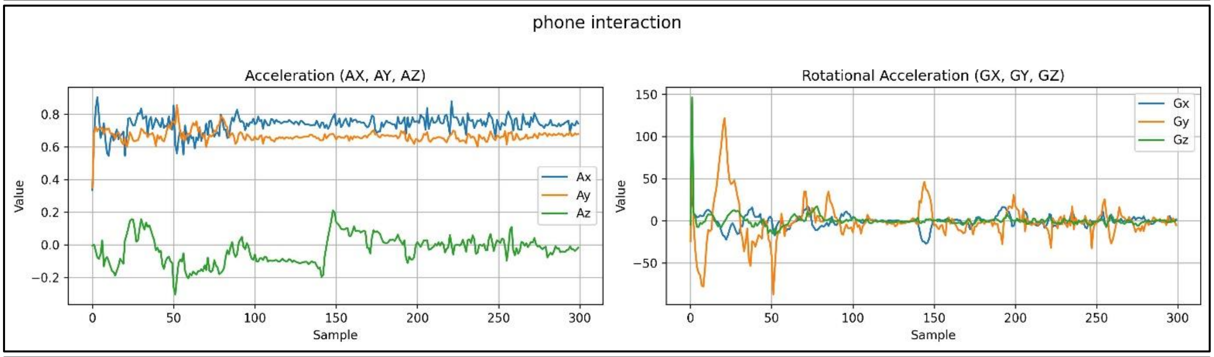


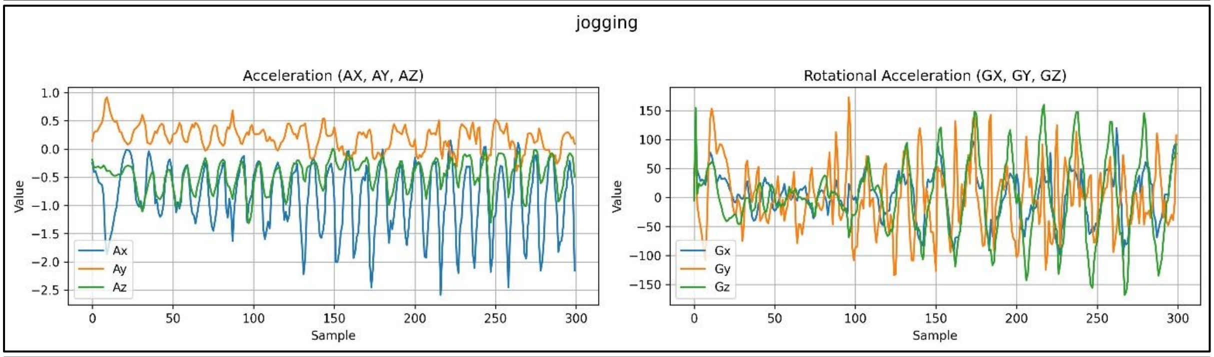


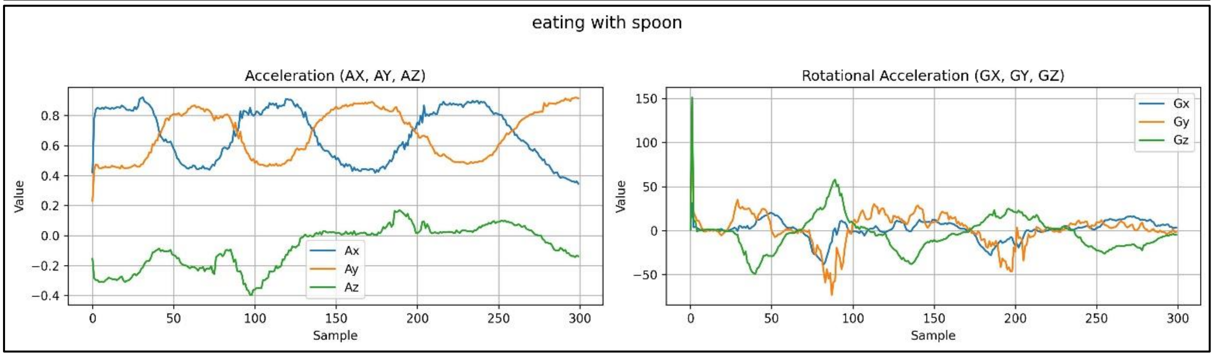


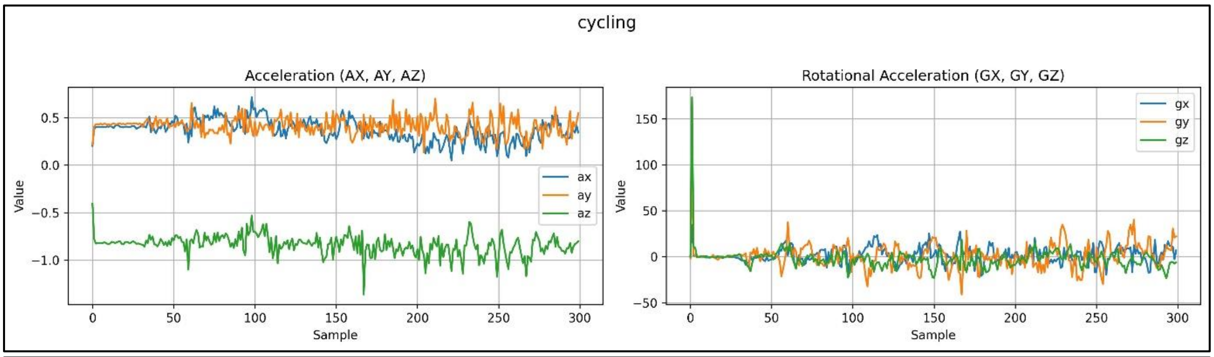

sit-stand-sit
Acceleration (AX, AY, AZ)
Ax
Ay
Az
Value
Sample
Rotational Acceleration (GX, GY, GZ)
Gx
Gy
Gz
Value
Sample

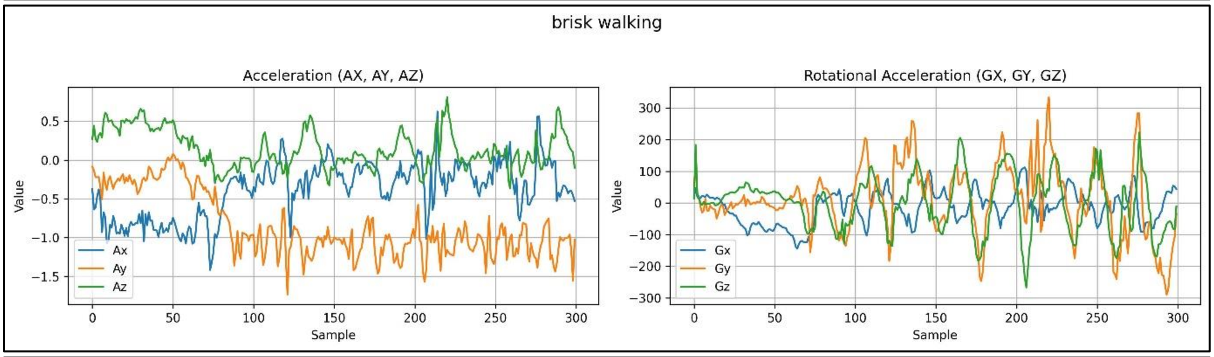

pick and place
Acceleration (AX, AY, AZ)
Ax
Ay
Az
Value
Sample
Rotational Acceleration (GX, GY, GZ)
Gx
Gy
Gz
Value
Sample

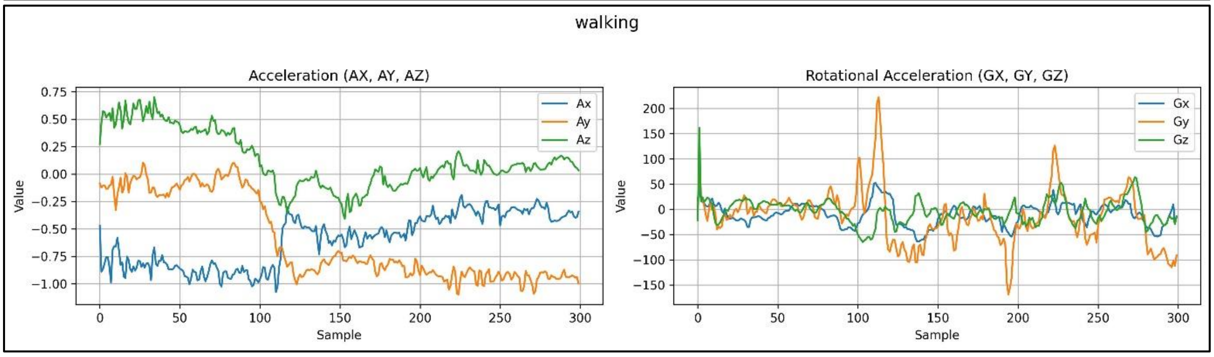

phone interaction
Acceleration (AX, AY, AZ)
Ax
Ay
Az
Value
Sample
Rotational Acceleration (GX, GY, GZ)
Gx
Gy
Gz
Value
Sample


jogging
Acceleration (AX, AY, AZ)
Ax
Ay
Az
Value
Sample
Rotational Acceleration (GX, GY, GZ)
Gx
Gy
Gz
Value
Sample


eating with spoon
Acceleration (AX, AY, AZ)
Ax
Ay
Az
Value
Sample
Rotational Acceleration (GX, GY, GZ)
Gx
Gy
Gz
Value
Sample







Activity	**Acceleration Characteristics (Ax, Ay, Az)**	**Gyroscope Characteristics (Gx, Gy, Gz)**	**Motion Intensity**	**Key Overlap / Remarks**
Sitting	Nearly constant values, very low variance	Gyro signals almost zero	Very Low	Can overlap with standing due to static posture
Standing	Stable acceleration with slightly higher noise than sitting	Minimal gyro activity	Very Low	Often confused with sitting
Walking	Periodic oscillations with moderate amplitude	Regular angular variations	Medium	Overlaps with brisk walking
Brisk Walking	Higher amplitude and faster oscillations than walking	Stronger and frequent gyro peaks	Medium–High	Distinguishable by higher variance

Jogging	Extremely high amplitude, high-frequency oscillations	Large, frequent gyro spikes	High	Most energetic activity; clearly separable
Cycling	Smooth, steady acceleration with low vertical impact	Low to moderate gyro variation	Medium	Less vertical motion than walking/jogging
Stair-Up	Strong vertical acceleration components	Large angular variations due to effort	High	Overlaps with stair-down
Stair-Down	Periodic impacts with slightly irregular pattern	Moderate gyro fluctuations	Medium–High	Lower intensity than stair-up
Sit–Stand–Sit	Step-like changes in acceleration during transitions	Short gyro peaks at transitions	Mixed (Static + Dynamic)	Transitional activity; overlaps with sitting/standing
Phone Interaction	Mostly constant acceleration with small variations	Irregular short gyro spikes	Low	Overlaps with sitting
Eating with Spoon	Smooth, slow cyclic acceleration	Controlled periodic gyro movement	Low–Medium	Like phone interaction but more rhythmic
Pick and place	Sudden changes, start–stop behaviour	Sharp gyro bursts during manipulation	Medium	Event-driven motion, non-periodic

Static activities (sitting, standing)

- Low variance across all axes
- Dominated by gravity component
- Minimal gyroscope activity
- Signals remain stable over time.

Dynamic activities (walking, brisk walking, jogging, cycling)

- Periodic patterns visible
- Increasing variance with activity intensity
- Higher energy content in gyroscope signals
- Cycling shows smoother periodicity compared to jogging.

Transitional activities (sit–stand–sit)

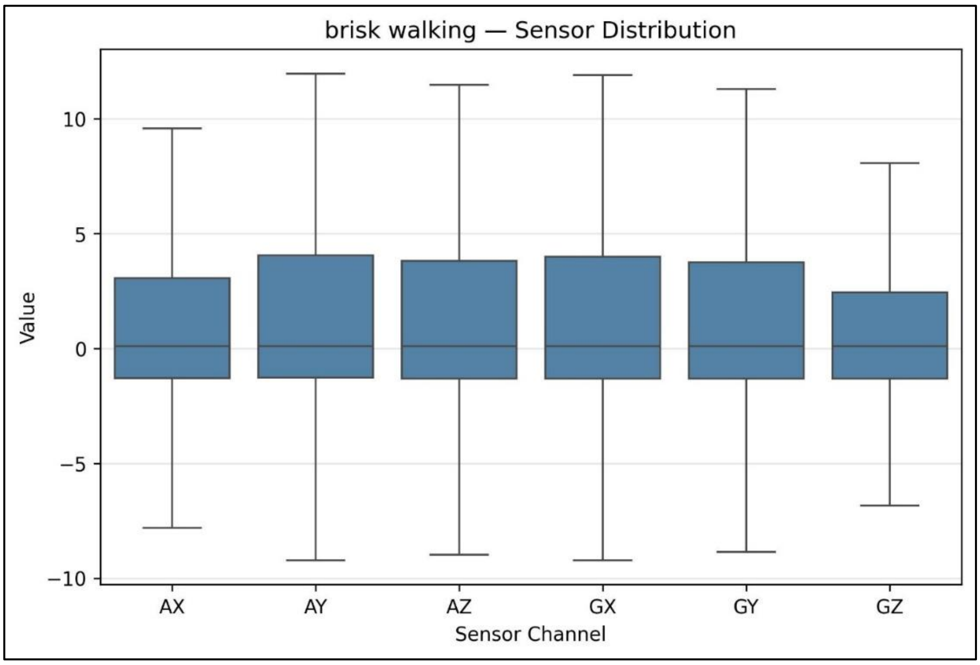
- Mixed characteristics:
    - Static segments
    - Short bursts of high motion
- Sudden peaks during posture change
- Causes overlap with both static and dynamic classes.

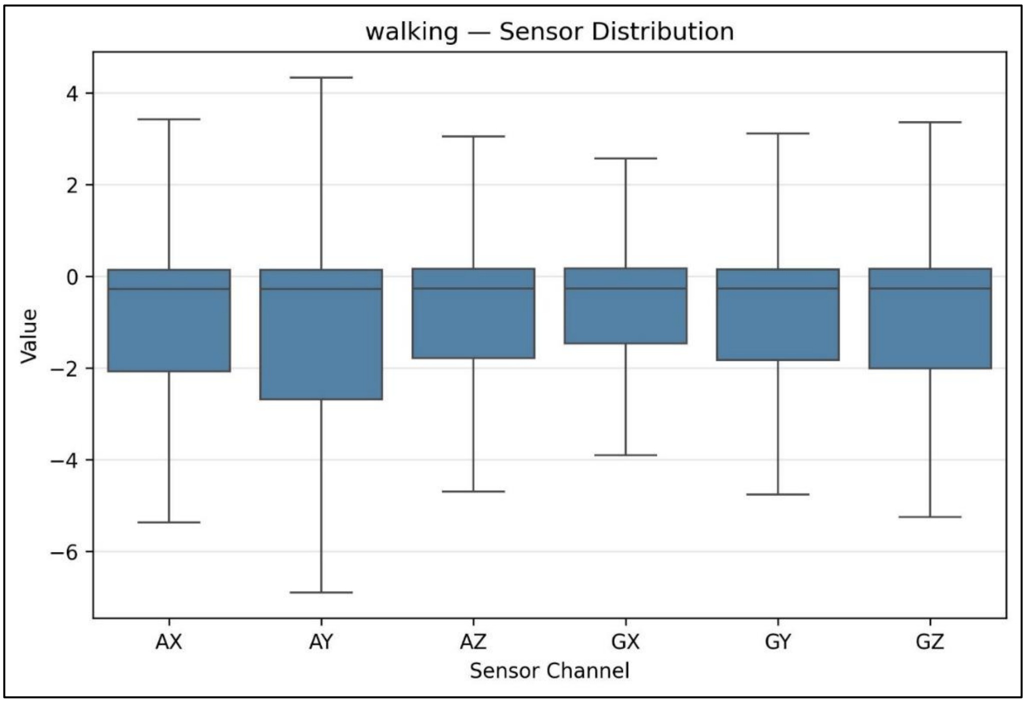
Fine motor activities (phone interaction, eating with spoon, pick and place)

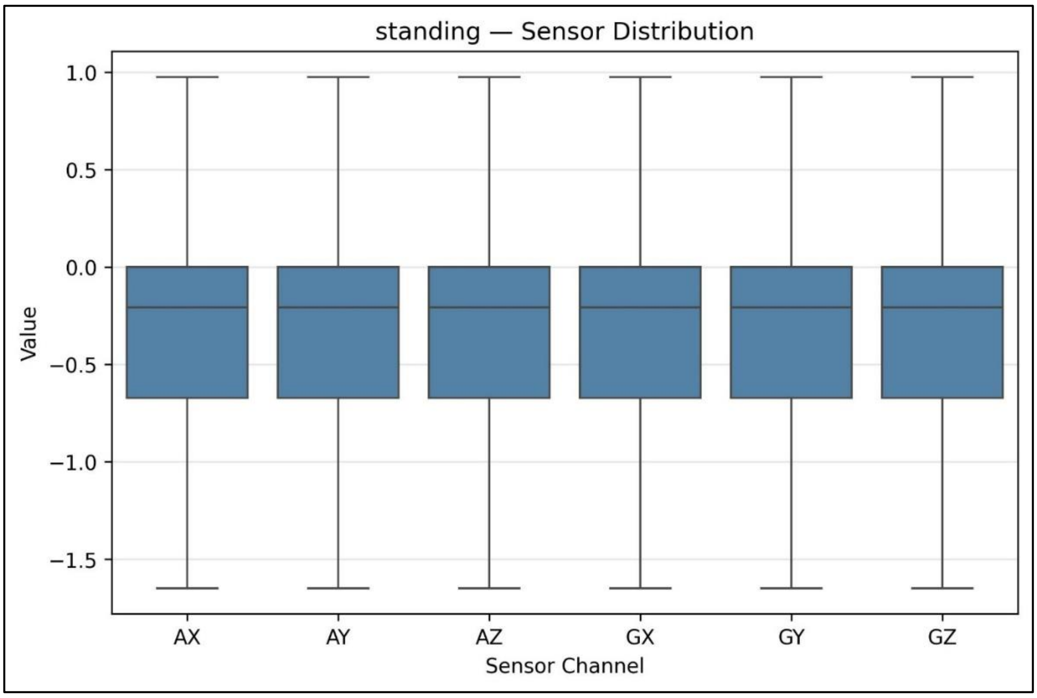
- Lower accelerometer magnitude
- Higher gyroscope sensitivity
- Subtle wrist rotations dominate the signal.
- Prone to overlap due to user-specific motion patterns.

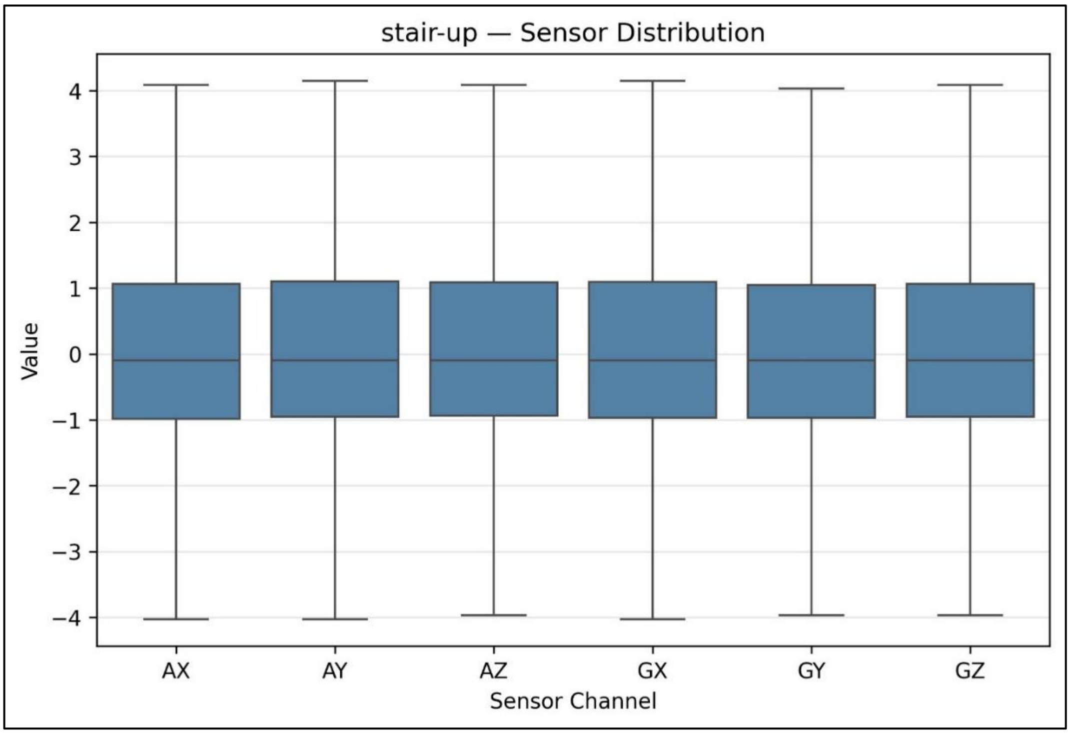
3.4 Box Plot Analysis (Spread and Outliers)

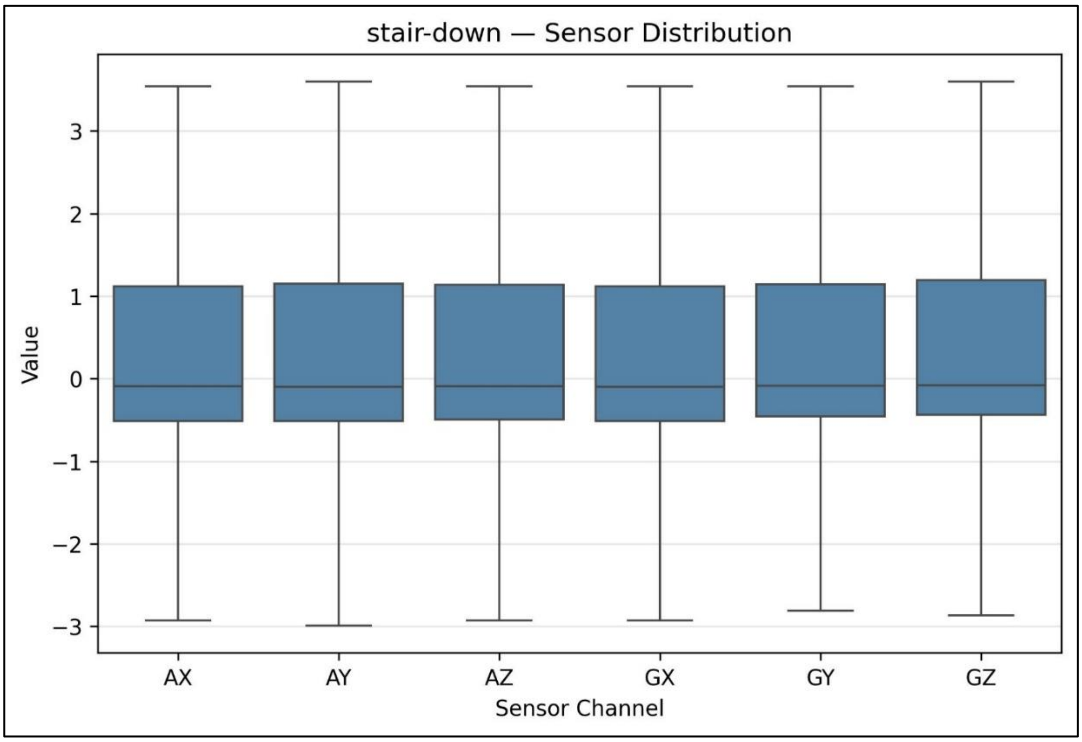
Box plots were used to analyse the spread, central tendency, and presence of outliers in IMU signals across activities. Table X provides a consolidated summary of these observations.

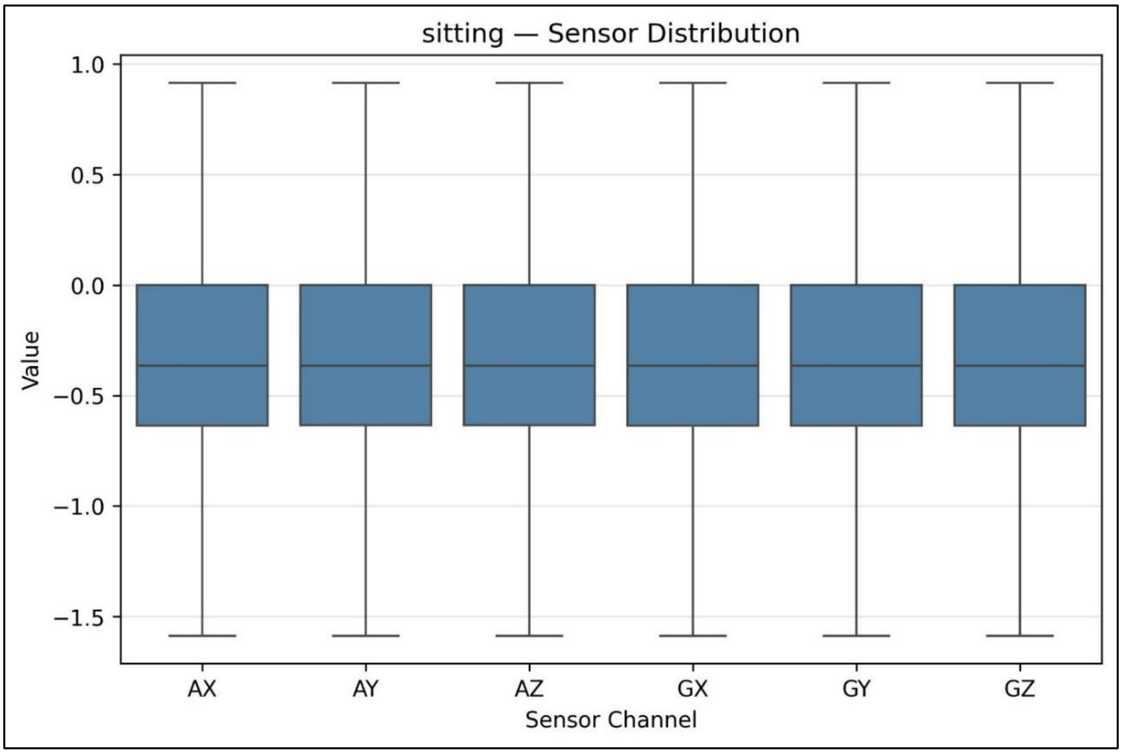


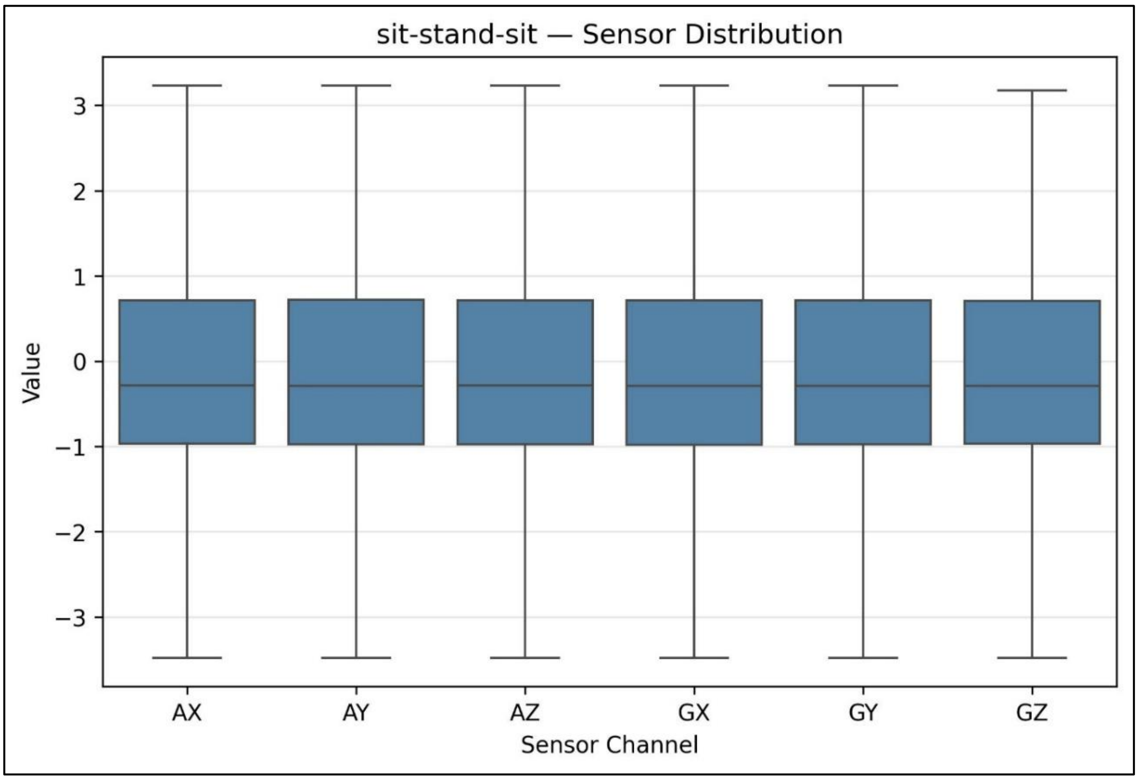

walking — Sensor Distribution
Value
4
2
0
−2
−4
−6
AX
AY
AZ
GX
GY
GZ
Sensor Channel

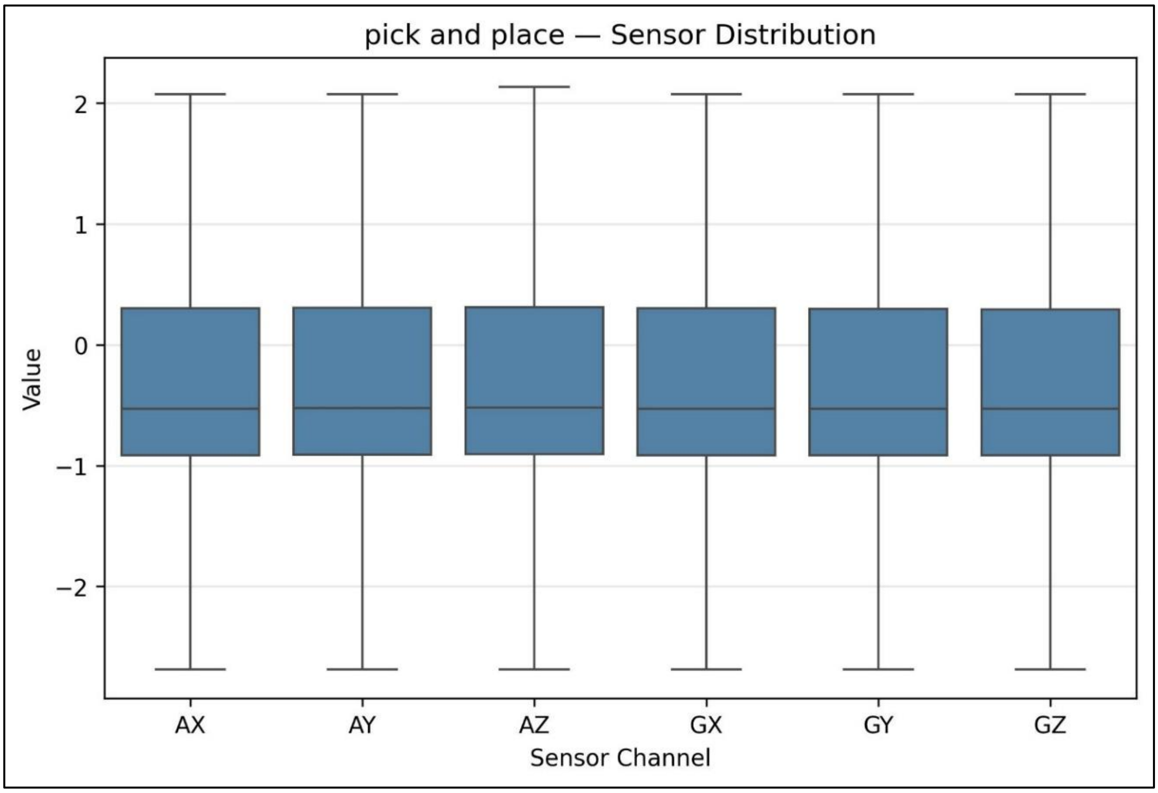

standing — Sensor Distribution
Value
1.0
0.5
0.0
−0.5
−1.0
−1.5
AX
AY
AZ
GX
GY
GZ
Sensor Channel

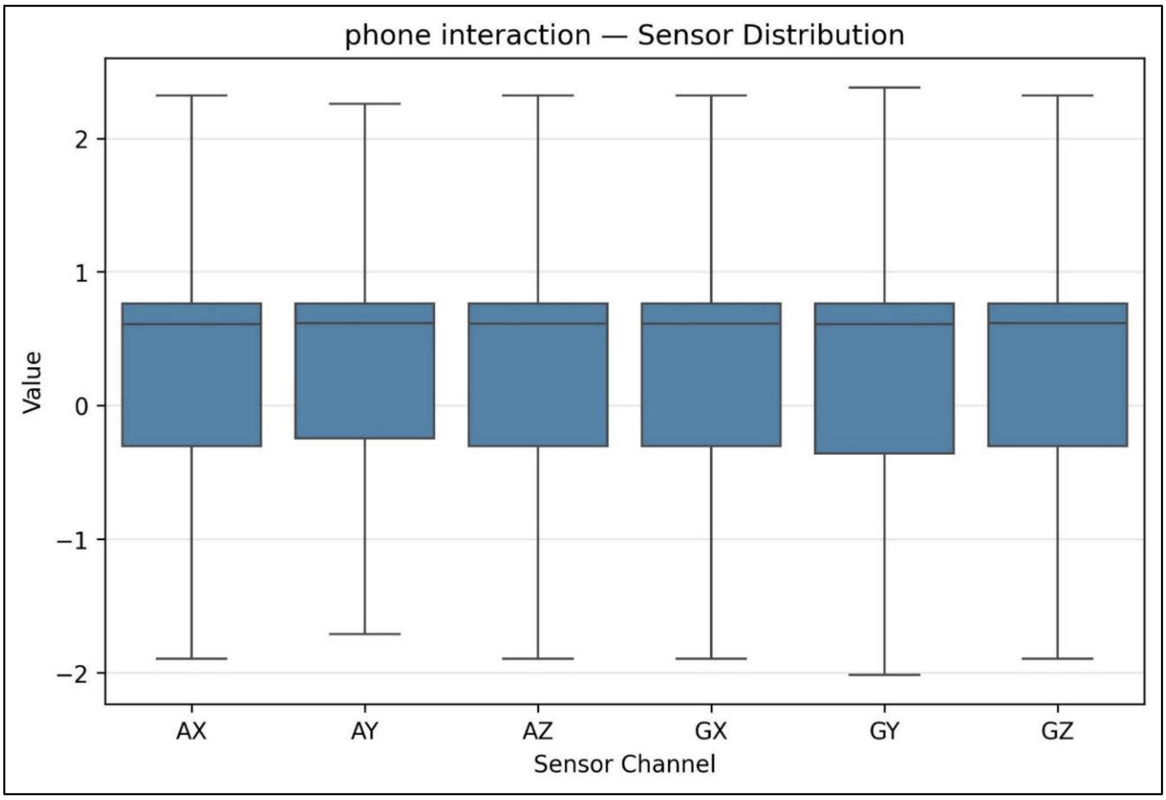

stair-up — Sensor Distribution
Value
4
3
2
1
0
−1
−2
−3
−4
AX
AY
AZ
GX
GY
GZ
Sensor Channel

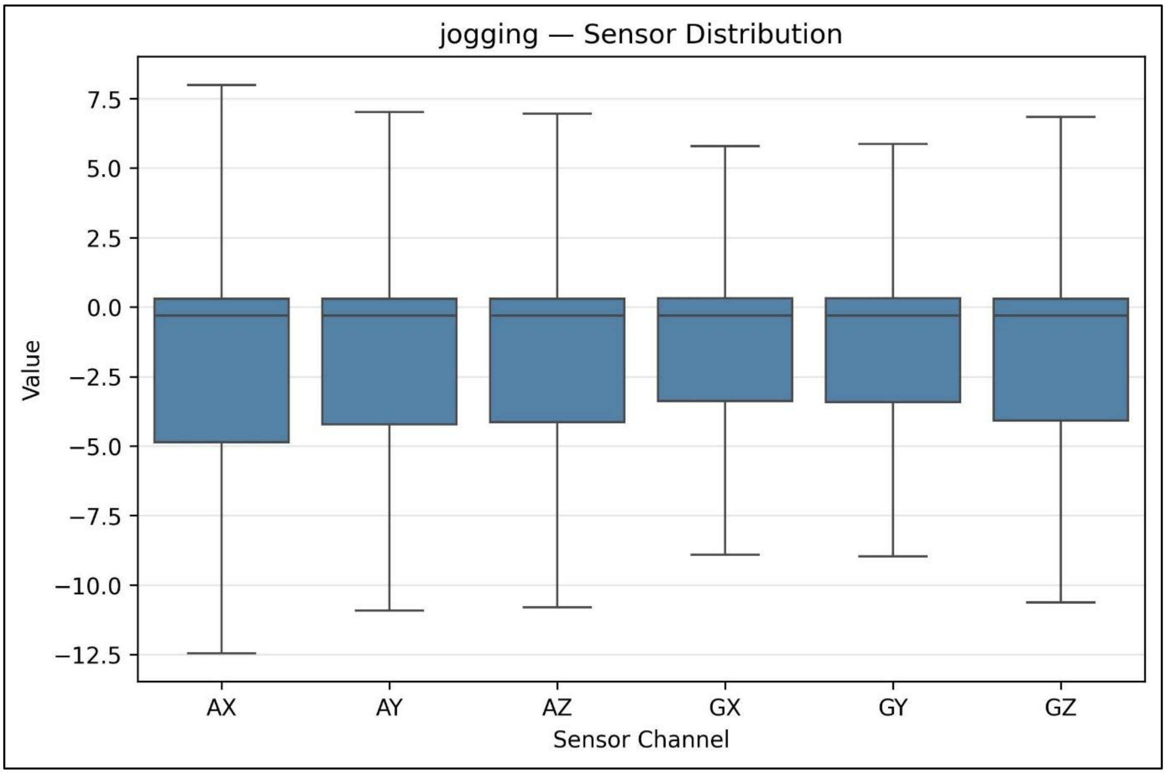

stair-down — Sensor Distribution
Value
3
2
1
0
−1
−2
−3
AX
AY
AZ
GX
GY
GZ
Sensor Channel

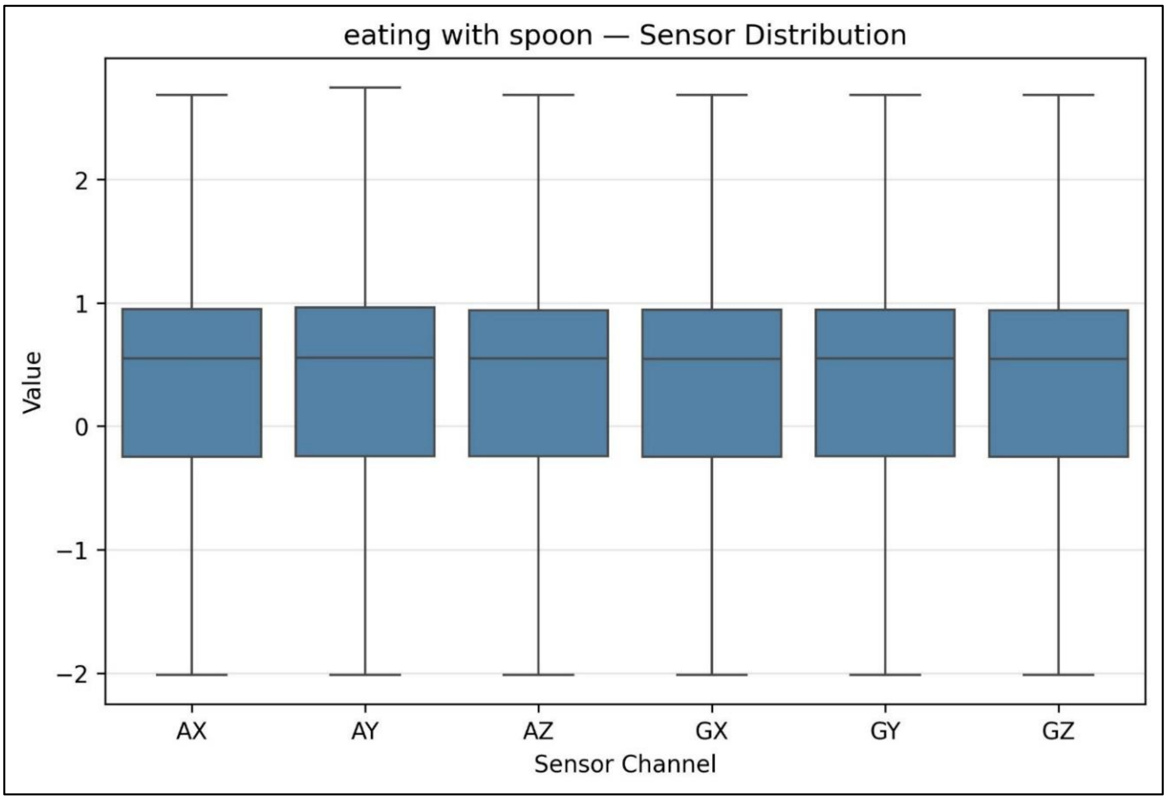

sitting — Sensor Distribution
1.0
0.5
0.0
−0.5
−1.0
−1.5
Value
AX
AY
AZ
GX
GY
GZ
Sensor Channel

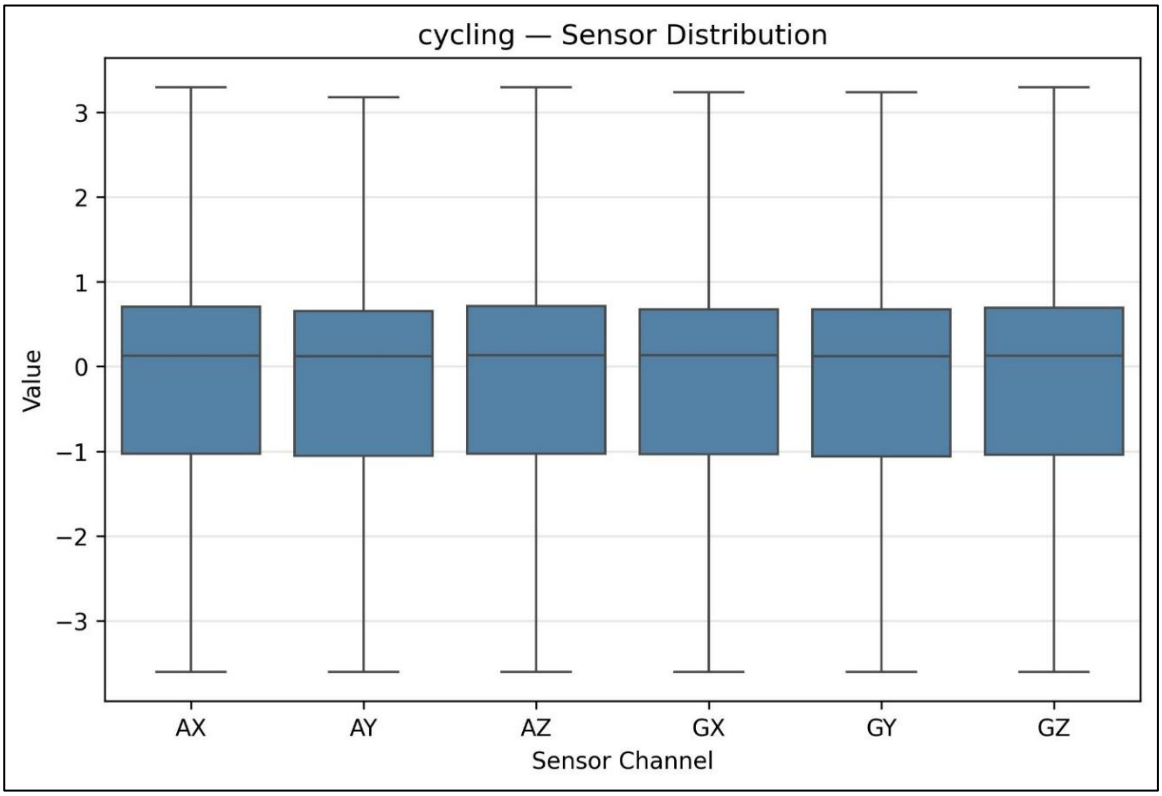

sit-stand-sit — Sensor Distribution
3
2
1
0
−1
−2
−3
Value
AX
AY
AZ
GX
GY
GZ
Sensor Channel


pick and place — Sensor Distribution
Value
Sensor Channel
AX
AY
AZ
GX
GY
GZ
2
1
0
−1
−2


phone interaction — Sensor Distribution
Value
Sensor Channel
AX
AY
AZ
GX
GY
GZ
2
1
0
−1
−2


jogging — Sensor Distribution
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−12.5
Value
AX
AY
AZ
GX
GY
GZ
Sensor Channel


eating with spoon — Sensor Distribution
2
1
0
−1
−2
Value
AX
AY
AZ
GX
GY
GZ
Sensor Channel



Activity Type	Observed Spread (IQR)	Outliers Presence	Key Box-Plot Insight
Sitting	Very low	Minimal	Stable signals dominated by gravity
Standing	Very low	Minimal	Similar distribution to sitting
Walking	Moderate	Few	Periodic motion with moderate variability
Brisk walking	High	Present	Increased acceleration and angular velocity
Jogging	Extremely high	Many	Large spread due to impact and arm swing
Cycling	Moderate	Few	Smooth periodic motion, less vertical impact
Stair-up	Moderate–high	Present	Repetitive upward motion with bursts
Stair-down	Moderate–high	Present	Controlled descent with similar spread
Sit–stand–sit	Mixed	Present	Sudden transitions cause broad range

Phone interaction	Low–moderate	Few	Wrist rotation dominates gyroscope
Eating with spoon	Low	Few	Fine motor movement, low acceleration
Pick and place	Moderate	Present	Short-duration abrupt movements

General observations from box plots:

- Static activities:
    - Narrow interquartile range (IQR)
    - Few outliers
- Dynamic activities:
    - Wider IQR across both accelerometer and gyroscope channels
    - Presence of extreme values due to sudden movements
- Jogging and brisk walking:
    - Largest spread among all activities
- Fine motor activities:
    - Moderate spread
    - Significant overlap across channels
- Consistency across channels:
    - Some activities show similar median shifts across all six axes.

3.5 Overlapping Patterns and Their Causes

- Standing vs sit–stand–sit:
    - Shared static posture phases.
- Walking vs brisk walking:
    - Similar motion patterns differing in intensity.
- Stair-up vs stair-down:
    - Comparable limb movement frequencies

Primary reasons for overlap:

- Wrist-based sensing limitation
- Short analysis window duration
- Natural variability in human motion
- Similar biomechanical patterns across activities

3.6 Key Takeaways from Data Analysis

- Raw signals show clear trends but limited separability for similar activities.
- Statistical features are required to enhance discrimination.
- Overlaps justify the use of:
  - Windowing
  - Feature extraction
  - Supervised learning models

4. Windowing Strategy

A fixed-length sliding window approach was used to segment continuous IMU data into meaningful temporal units suitable for feature extraction and classification.

- **Window size:** Fixed number of samples per window (as constrained by deployment requirements)
- **Overlap:** Partial overlap between consecutive windows to preserve temporal continuity
- **Rationale:**
  - Ensures sufficient temporal context for capturing motion patterns.
  - Maintains responsiveness for real-time prediction.
  - Balances computational cost and classification accuracy

This windowing strategy enables consistent feature extraction while supporting real-time inference.

5. Feature Engineering

Feature engineering was performed to convert raw IMU signals into compact, informative representations suitable for lightweight machine learning models.

5.1 Raw Features

The following raw sensor values were directly included:

- Accelerometer: **Ax, Ay, Az**
- Gyroscope: **Gx, Gy, Gz**

Purpose:

- Preserve instantaneous motion and orientation information.
- Provide baseline signal characteristics for the classifier.

5.2 Time-Domain Feature Extraction

Time-domain statistical features were computed over each window to capture signal behaviour.

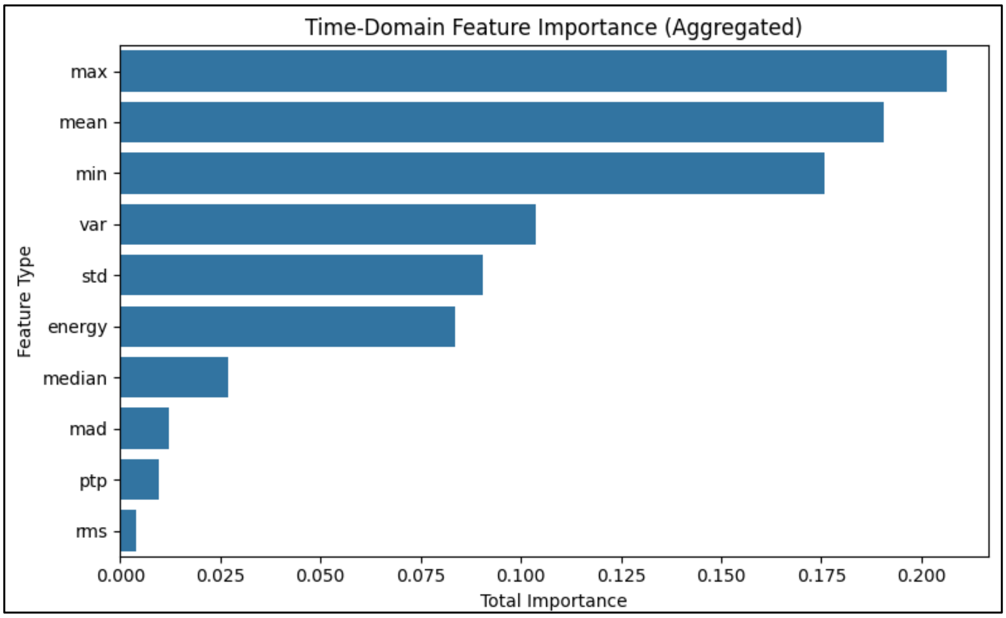
Extracted features included:

- Mean
- Standard deviation
- Minimum and maximum
- Signal energy
- Range

Justification:

- Time-domain features are computationally efficient.
- Well-suited for embedded and TinyML style deployment
- Effective in distinguishing static vs dynamic activities

5.3 Feature Relevance Observation



Feature importance analysis from the trained decision tree revealed:

- A small subset of features contributed disproportionately to classification performance.
- Both accelerometer- and gyroscope-derived features appeared among the most influential
- Dynamic activity discrimination relied heavily on variance- and energy-based features.

This observation guided confidence in using a compact feature set for deployment.

6. Dataset Preparation

The dataset was prepared as follows:

- Windowed samples were labelled according to activity class.
- Features were normalized to ensure consistent scale.
- Dataset was split into training and testing sets.

Goal:
Ensure fair evaluation while maintaining representativeness of real-world motion patterns.

7. Model Development

7.1 Model Choice

A **Decision Tree classifier** was selected due to:

- Interpretability (explicit if–else rules)
- Low inference latency
- Suitability for embedded deployment
- No requirement for floating-point heavy operations

7.2 Hyperparameter Exploration

Key parameters explored included:

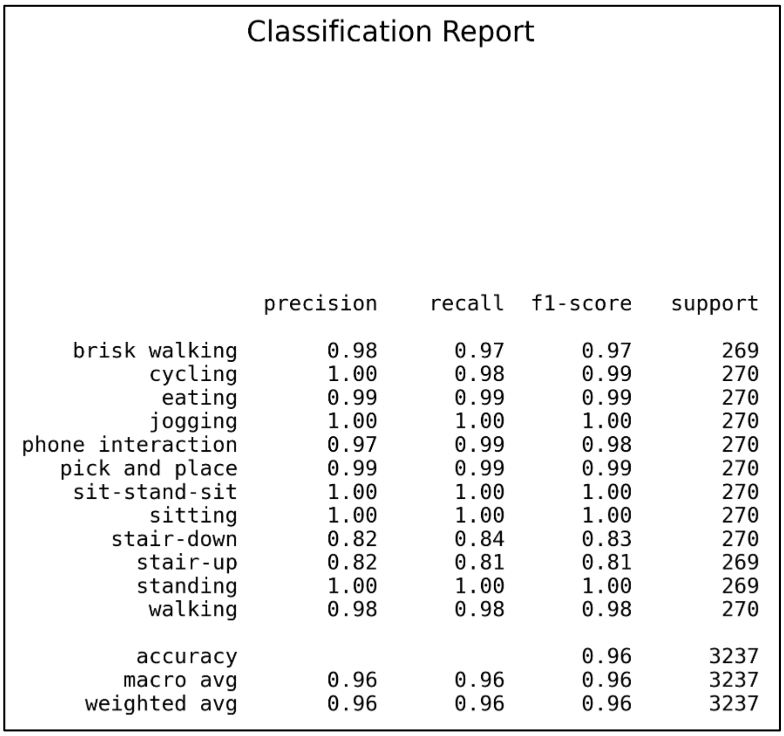
- Maximum tree depth
- Minimum samples per split
- Minimum samples per leaf

Objective:

- Avoid overfitting.
- Maintain generalization.
- Keep model complexity manageable.

8. Model Evaluation

8.1 Quantitative Evaluation Metrics



Classification Report

	precision	recall	f1-score	support
brisk walking	0.98	0.97	0.97	269
cycling	1.00	0.98	0.99	270
eating	0.99	0.99	0.99	270
jogging	1.00	1.00	1.00	270
phone interaction	0.97	0.99	0.98	270
pick and place	0.99	0.99	0.99	270
sit-stand-sit	1.00	1.00	1.00	270
sitting	1.00	1.00	1.00	270
stair-down	0.82	0.84	0.83	270
stair-up	0.82	0.81	0.81	269
standing	1.00	1.00	1.00	269
walking	0.98	0.98	0.98	270
accuracy			0.96	3237
macro avg	0.96	0.96	0.96	3237
weighted avg	0.96	0.96	0.96	3237

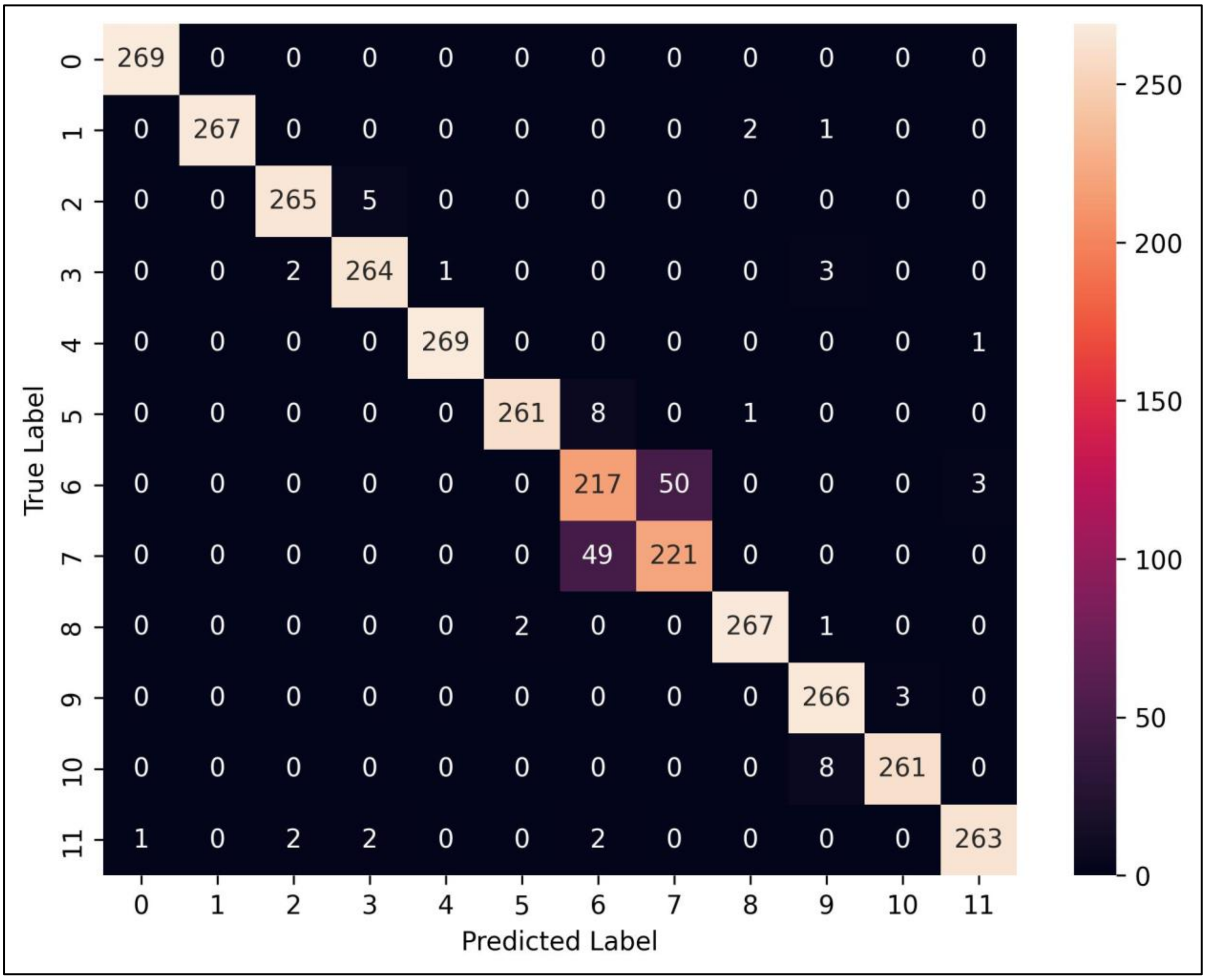
The model was evaluated using:

- Accuracy
- Precision
- Recall
- F1-score (macro and weighted)

Observations:

- High overall accuracy and F1-score
- Robust performance for static and high-motion activities
- Slightly reduced performance for transitional activities.

8.2 Misclassification Analysis



Analysis of the confusion matrix showed:

- Confusion between standing and sit–stand–sit
- Overlap between stair-up and stair-down
- Occasional misclassification between walking and brisk walking

These errors align with observed feature overlap in earlier analysis.

8.3 Optimal Model Selection

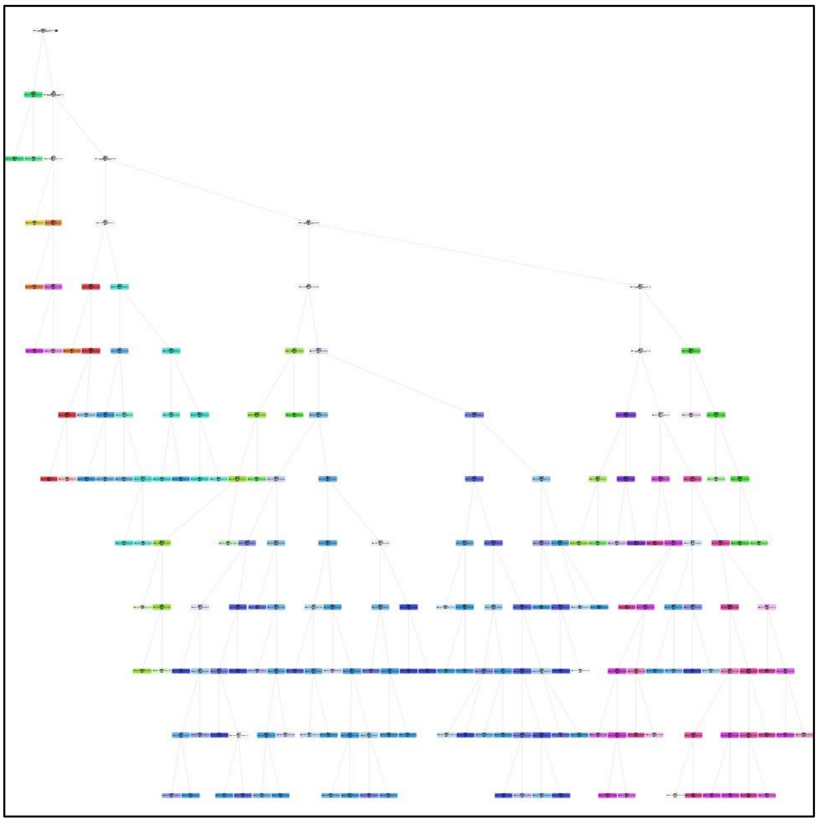
The final model was selected based on:

- Balanced accuracy and F1-score
- Stable real-time behaviour
- Simplicity and deploy ability.

This model achieved the best trade-off between performance and practical constraints.

9. Real-Time Deployment

9.1 Deployment Pipeline



The deployment pipeline consisted of:

1. Real-time IMU data acquisition
2. Window buffering
3. Feature extraction
4. Model inference
5. Temporal smoothing of predictions

The explicit decision tree structure allows direct mapping to embedded logic.

9.2 Live Prediction Behaviour

During live deployment:

- Predictions were responsive to activity changes.
- Minor frame-to-frame fluctuations were observed.
- Majority voting over recent predictions significantly improved stability

This highlights the difference between offline evaluation and real-time inference.

10. Challenges and Limitations

- Wrist orientation variability introduced noise.
- Overlapping motion patterns between similar activities
- Short windows limited discrimination of slow transitions
- Wireless data transmission caused minor timing jitter.

These limitations are inherent to real-world wearable sensing systems.

11. Key Observations and Learnings

- Time-domain features are effective for lightweight activity recognition.
- Transitional activities are inherently harder to classify.
- Feature overlap analysis is crucial for interpreting misclassifications.
- Deployment-time smoothing improves user-perceived performance.

12. Conclusion

This work demonstrates a complete IMU-based activity recognition pipeline from data collection to real-time deployment. By combining efficient feature engineering, interpretable modelling, and practical deployment strategies, the system achieves robust performance while remaining suitable for embedded and TinyML applications. The insights gained from misclassification and real-time behaviour analysis provide a solid foundation for future improvements.