Human Activity Recognition Final Report

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Introduction

The Human Activity Recognition (HAR) dataset classifies six activities—walking, walking upstairs, walking downstairs, sitting, standing, and laying—using data from a smartphone's accelerometer and gyroscope. Thirty participants, aged 19-48 wore a Samsung Galaxy S II on their waist, recording 3-axis acceleration and angular velocity at 50 Hz. Signals had a 0.3 Hz cutoff frequency as it was used to remove noise and was processed into a 2.56-second window with 50% overlap. The data was split into 70% for training and 30% for testing.

Data Description

The HAR dataset includes 561 features extracted from smartphone accelerometer and gyroscope readings. These features capture various aspects of the sensor signals, broken down as follows:

Features:

- Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration.
- Triaxial Angular velocity from the gyroscope.
- A 561-feature vector with time and frequency domain variables.
- Min, Max, Standard Deviation And Mean Of Data

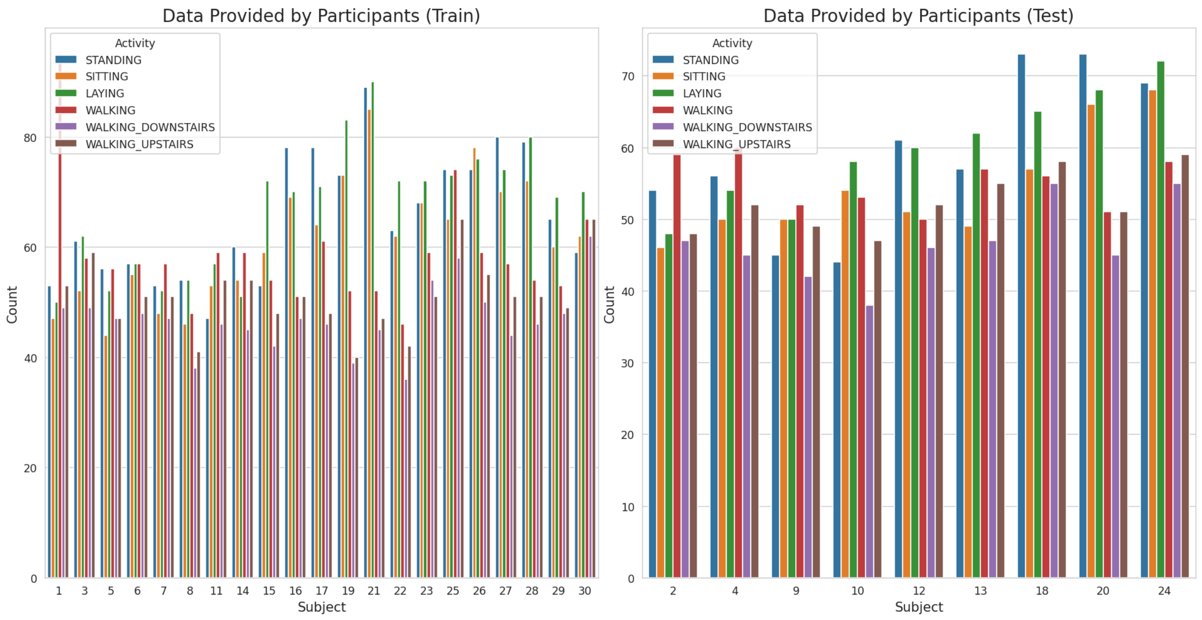
Attributes:

- Activity Labels (Sitting, Standing, Walking, Laying, Walking Upstairs, Walking Downstairs)

Exploratory Data Analysis

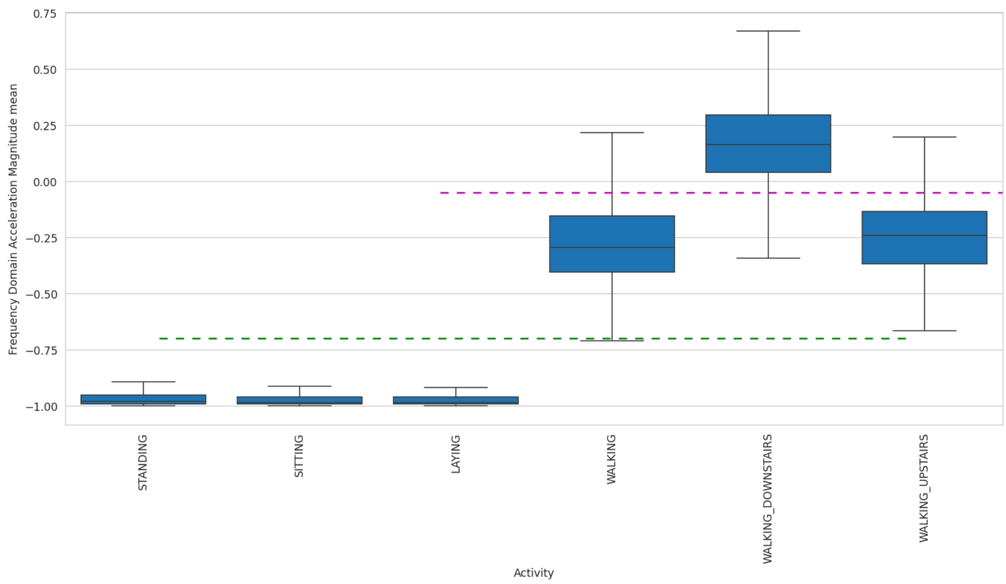
Missing value: None

Duplicate value: None



The data provided by each participant suggest a balance recording between all activities.

Accelerometer Frequency Domain in Magnitude Mean



By plotting the mean magnitude of each activity in the frequency domain, we observe a clear distinction between stationary and dynamic activities. Stationary activities typically exhibit lower mean magnitudes, ranging from approximately -0.75 to -1, while dynamic movements show significantly higher values, typically between -0.25 and 0.25. However, the plots also highlight challenges in classifying activities with similar movement patterns, as some dynamic activities may overlap with stationary ones in terms of their frequency characteristics. This overlap could make it difficult to differentiate between certain activities using just frequency-domain features.

Therefore, by visualizing these datasets through scatter plots, we can observe notable differences even among movements with similar patterns. For instance, the scatter plot comparing the activities “Sitting” and “Standing” provides valuable insights into this phenomenon, as both activities involve minimal motion.

Specifically, when comparing the mean 3-axis acceleration and gyroscope data for these two activities, a clear distinction emerges. In the acceleration domain, the patterns for "Sitting" and "Standing" on the X-axis and Z- axis are remarkably similar, making it challenging to differentiate between these two stationary activities. However, the gyroscope domain reveals significant differences. The scatter plot shows that the mean gyroscope values for "Sitting" exhibit substantial fluctuations along the X and Z axes compared to "Standing." In contrast, the accelerometer data displays only minor variations between these activities.

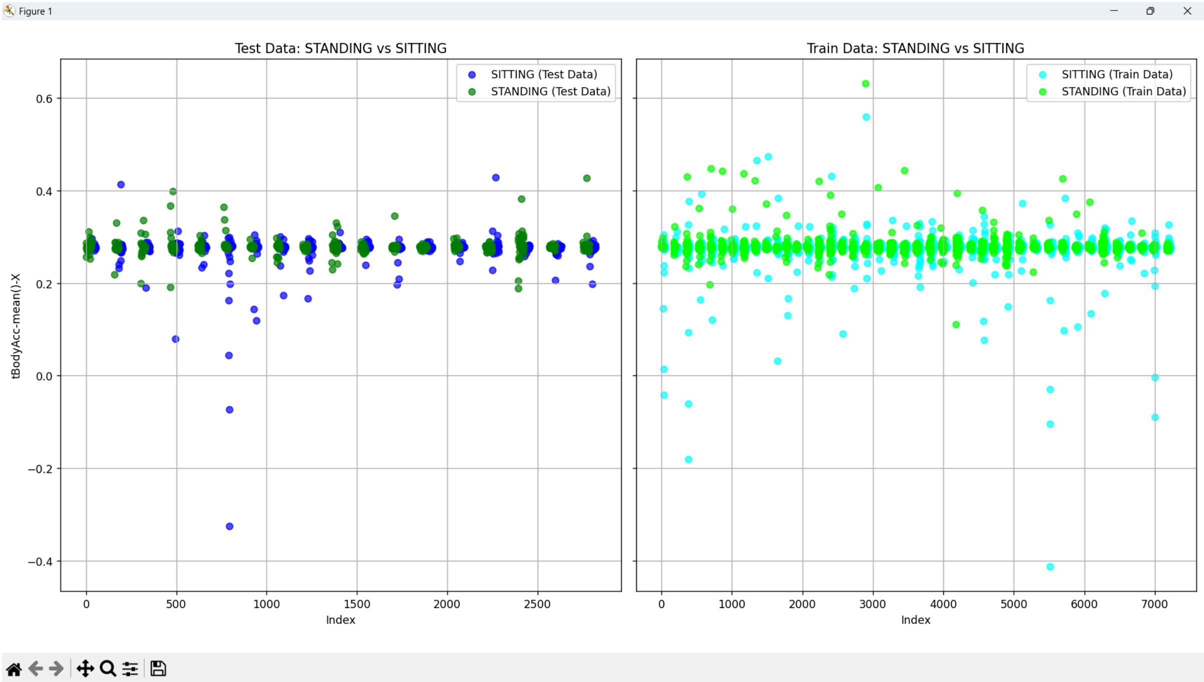
This analysis underscores the importance of gyroscopic data in distinguishing subtle differences between activities with limited movement.

The analysis of the activities “Walking Upstairs” and “Walking Downstairs” reveals relatively minimal dissimilarities, as both are classified as active movements. Due to their dynamic nature, these activities exhibit similar patterns in terms of acceleration behavior. Which implies that they are not sufficient to be used for classification alone. However, a closer examination of the Y-axis, which represents the mean acceleration values, suggests a subtle difference between the two activities.

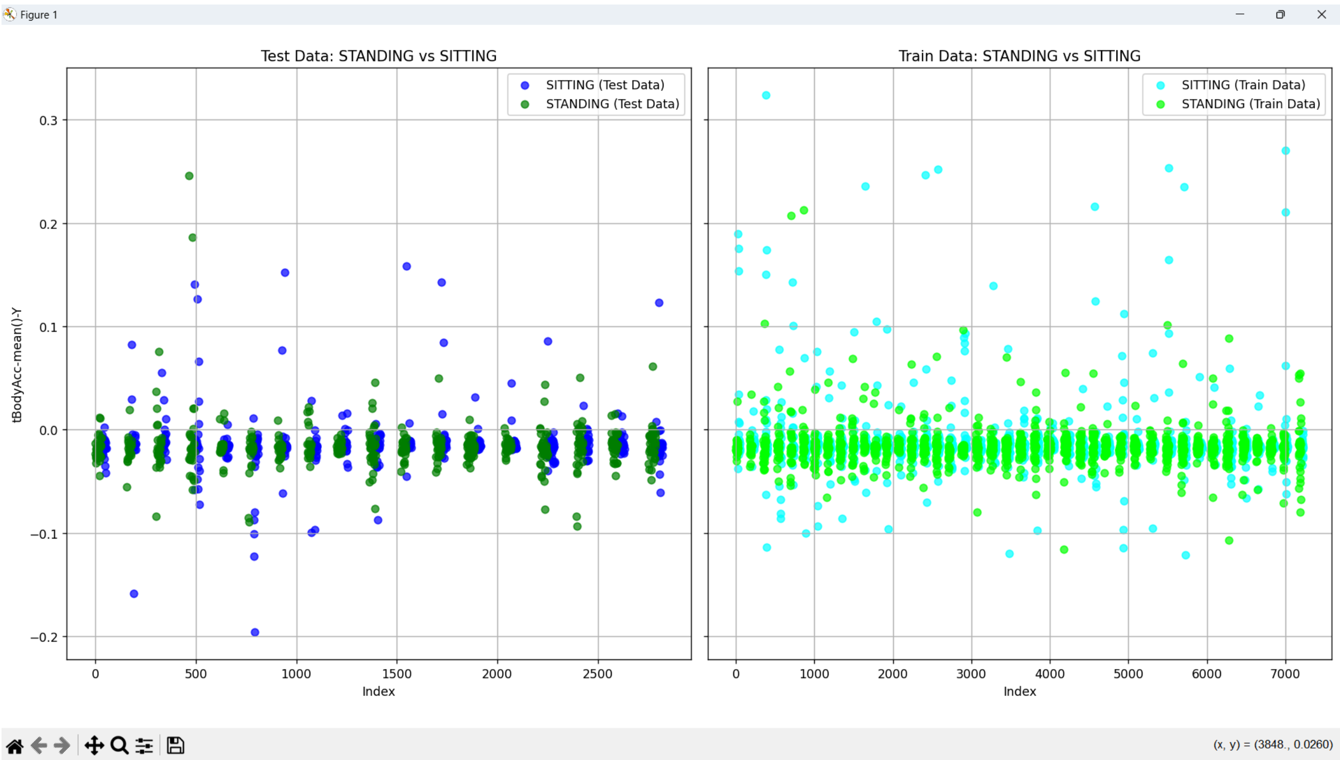
Specifically, the data for “Walking Upstairs” indicates a lower range of acceleration values, occasionally dropping below -0.10. In contrast, the activity “Walking Downstairs” does not exhibit any data points within this range. This observation highlights a potential distinction in the intensity or motion profile of these activities, with “Walking Upstairs” potentially involving more abrupt changes in acceleration due to factors like elevation gain.

Observations regarding different activities can assist with understanding the data further. We can see patterns formed in the data based on the amount of motion associated with that activity. Clear distinctions between high-motion and low-motion activities can be observed, in this case, we look at standing compared to walking. Increased deviation in the mean of walking when compared with standing fits with an understanding that walking requires more motion than standing when measured over a period of time. When compared with activities with similar levels of motion, such as walking and walking upstairs, we see data points that are far more closely related. This led us to wonder what the success of classifying high-motion activities (Walking, Walking-Upstairs, Walking-Downstairs) to low-motion activities (Laying, Sitting, Standing) would be. Additionally, we want to compare low-high motion classification with classification that occurs within the same level of motion (low-low and high-high motion)

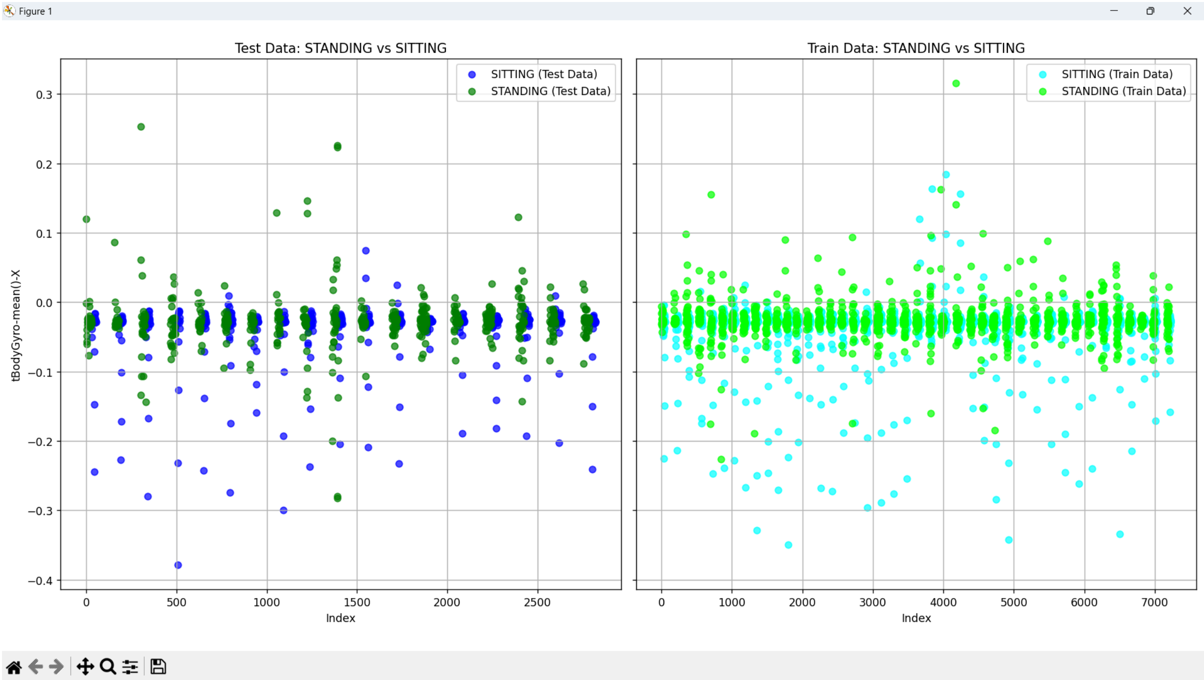
Accelerometer Time Domain in Standing vs Sitting (X)



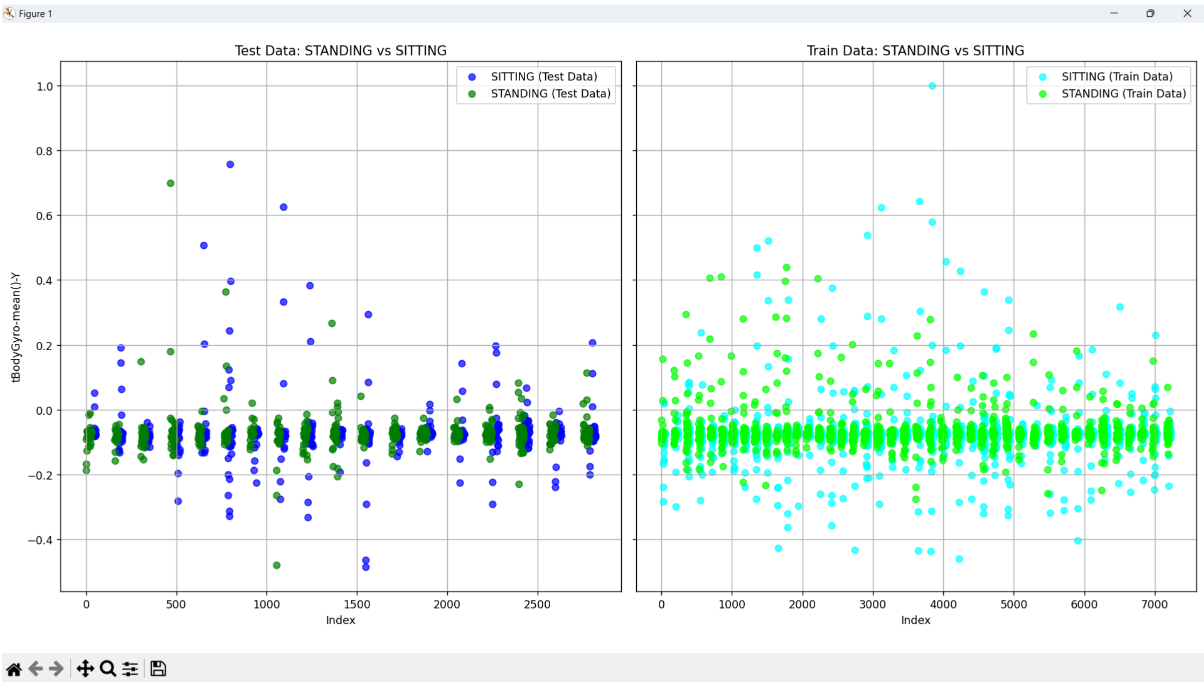
Gyroscope Time Domain in Standing vs Sitting (X)



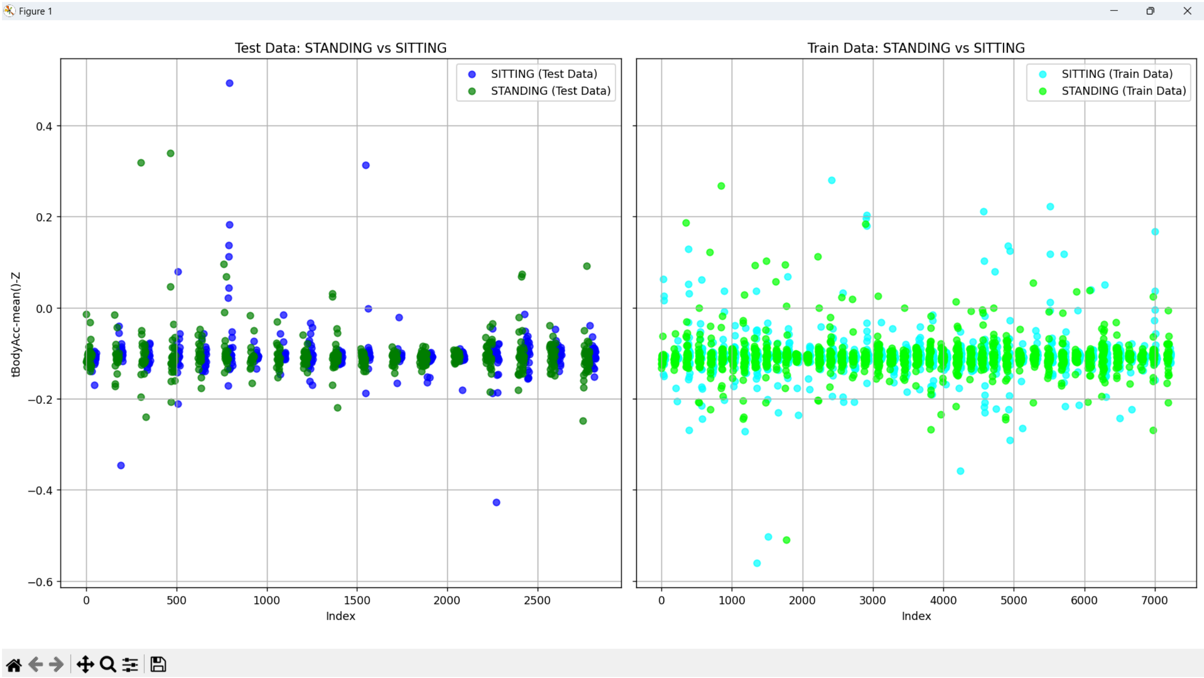
Accelerometer Time Domain in Standing vs Sitting (Y)



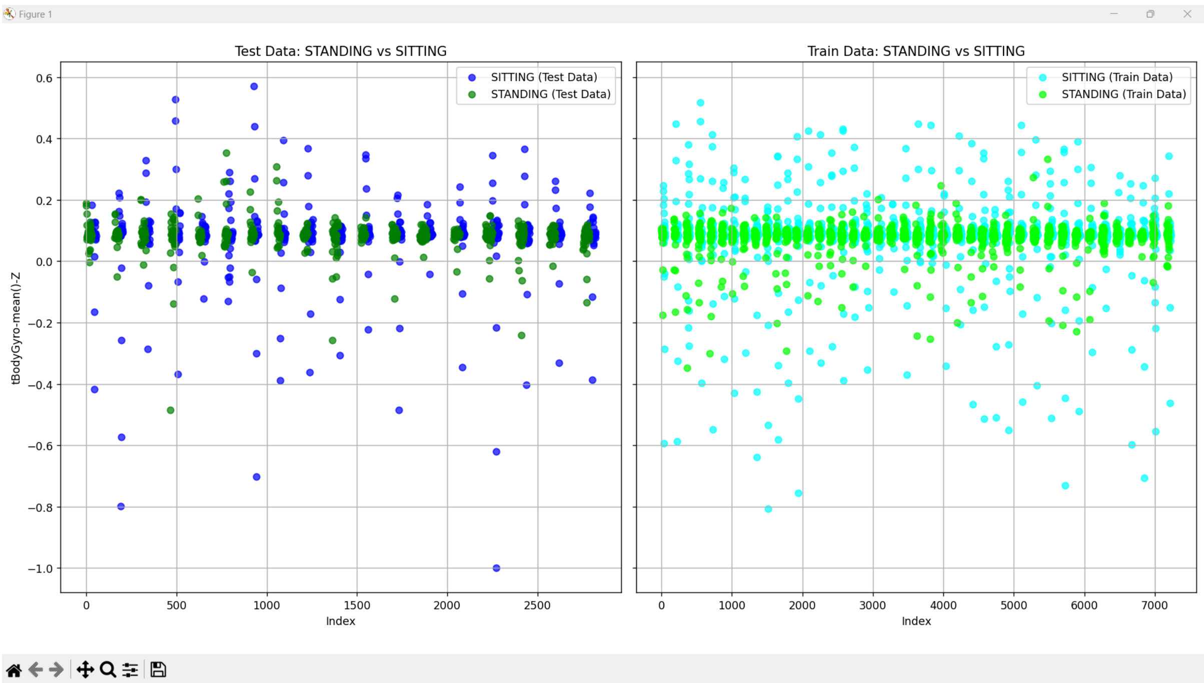
Gyroscope Time Domain in Standing vs Sitting (Y)



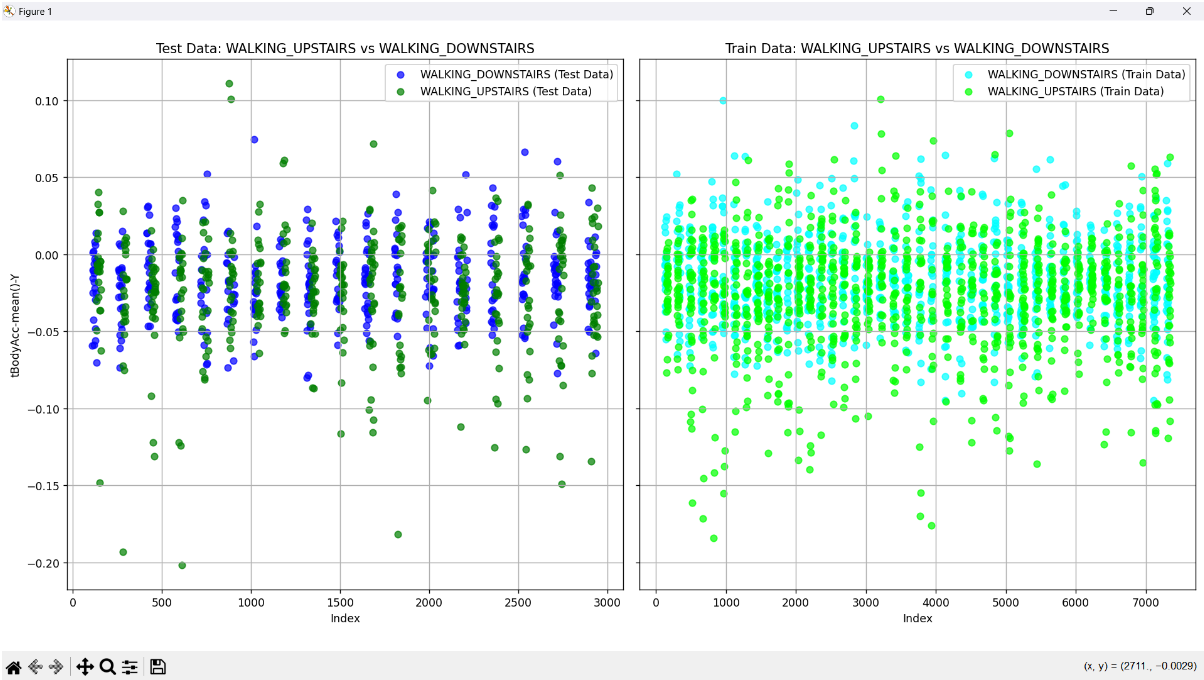
Accelerometer Time Domain in Standing vs Sitting (Z)



Gyroscope Time Domain in Standing vs Sitting (Z)



Accelerometer Time Domain in Walking_Upstairs vs Walking_Downstairs(Y)



Question Regarding Data

How accurately can we classify human activity based on accelerometer and gyroscope data using machine learning models (e.g., Decision Trees, KNN, Naive Bayes)?

Techniques Used to Answer Questions

1. **Data Preprocessing and Feature Engineering**
   - ***Feature Selection**:* Mean and standard deviation of accelerometer and gyroscope readings (X, Y, Z axes) were used to classify activities. These capture key movement variations.
   - ***Standardization**:* Applied StandardScaler to scale features for unbiased model performance, particularly for distance-based models like KNN.
   - ***Data Balancing***: Entropy, Balanced Weight, SMOTE to balance dataset

- ***Feature Additions:*** *Entropy and Correlation*
- ***Best k***: to be used for kNN classification

2. **Model Selection**
   - ***KNN****:* Instance-based learning using nearest neighbors; effective for close-class clusters.
   - ***Decision Tree****:* Splits data using decision rules; interpretable and handles non-linear relationships well.
   - ***Naive Bayes****:* Probabilistic model assuming feature independence; simple and computationally efficient.
3. **Model Training and Evaluation**
   - ***Training (70% of Data)****:* Models trained on accelerometer and gyroscope features.
   - ***Testing (30% of Data)****:* Tested on separate data to predict activity labels.
   - ***Metrics****:* Evaluated using accuracy (overall performance), precision (false positives), and recall (false negatives).
4. **Confusion Matrix**
   - Visualized matrices to identify misclassified activities, highlighting model strengths and weaknesses.
5. **Model Performance Comparison**
   - ***KNN****:* Performed well, especially with accelerometer data.
   - ***Decision Tree****:* Slightly lower accuracy but interpretable decision rules.
   - ***Naive Bayes****:* Least accurate, likely due to independence assumption mismatch.
6. **Scatterplot:**

  - A type of data visualization that displays points on a two-dimensional graph, representing the relationship between two variables.

7. **Entropy:**
  - Using entropy to determine features with informative inputs to improve the accuracy of machine learning models.

Analysis

Accelerometer Data

KNN (k=19) Performance:

- Accuracy: 0.6349
- Macro Precision: 0.6526
- Macro Recall: 0.6296

Classification Report:

Class	Precision	Recall	F1-Score	Support
LAYING	0.82	0.76	0.79	537
SITTING	0.57	0.52	0.54	491
STANDING	0.64	0.72	0.68	532
WALKING	0.51	0.71	0.59	496
WALKING_DOWNSTAIRS	0.85	0.60	0.71	420
WALKING_UPSTAIRS	0.52	0.46	0.49	471
Accuracy			0.63	2947
Macro Avg	0.65	0.63	0.63	2947
Weighted Avg	0.65	0.63	0.64	2947

ID3 Performance:

- Accuracy: 0.5653
- Macro Precision: 0.5701
- Macro Recall: 0.5635

Classification Report:

Class	Precision	Recall	F1-Score	Support
LAYING	0.73	0.72	0.73	537
SITTING	0.48	0.49	0.48	491
STANDING	0.59	0.58	0.58	532
WALKING	0.51	0.52	0.52	496
WALKING_DOWNSTAIRS	0.71	0.63	0.67	420
WALKING_UPSTAIRS	0.40	0.44	0.42	471
Accuracy			0.57	2947
Macro Avg	0.57	0.56	0.57	2947
Weighted Avg	0.57	0.57	0.57	2947

Naive Bayes Performance:

- Accuracy: 0.4669
- Macro Precision: 0.4991
- Macro Recall: 0.4696

Classification Report:

Class	Precision	Recall	F1-Score	Support
LAYING	0.40	0.06	0.10	537
SITTING	0.31	0.06	0.10	491
STANDING	0.34	0.89	0.50	532
WALKING	0.52	0.85	0.64	496
WALKING_DOWNSTAIRS	0.80	0.62	0.70	420
WALKING_UPSTAIRS	0.63	0.35	0.45	471
Accuracy			0.47	2947
Macro Avg	0.50	0.47	0.41	2947
Weighted Avg	0.49	0.47	0.40	2947

Gyroscope Data

KNN (k=4) Performance

Accuracy: 0.6410

Macro Precision: 0.6387

Macro Recall: 0.6383

Classification Report:

Class	Precision	Recall	F1-Score	Support
LAYING	0.67	0.63	0.65	537
SITTING	0.62	0.66	0.64	491
STANDING	0.71	0.71	0.71	532
WALKING	0.67	0.70	0.68	496
WALKING_DOWNSTAIRS	0.54	0.60	0.56	420
WALKING_UPSTAIRS	0.63	0.54	0.58	471
Accuracy	**0.64**			**2947**
Macro Avg	**0.64**	**0.64**	**0.64**	**2947**
Weighted Avg	**0.64**	**0.64**	**0.64**	**2947**

ID3 Performance

Accuracy: 0.5765

Macro Precision: 0.5746

Macro Recall: 0.5738

Classification Report:

Class	Precision	Recall	F1-Score	Support
LAYING	0.59	0.57	0.58	537
SITTING	0.60	0.64	0.62	491
STANDING	0.67	0.67	0.67	532
WALKING	0.60	0.50	0.55	496
WALKING_DOWNSTAIRS	0.46	0.52	0.49	420
WALKING_UPSTAIRS	0.53	0.54	0.53	471
Accuracy	**0.58**			**2947**
Macro Avg	**0.57**	**0.57**	**0.57**	**2947**
Weighted Avg	**0.58**	**0.58**	**0.58**	**2947**

Naive Bayes Performance

Accuracy: 0.4530

Macro Precision: 0.4990

Macro Recall: 0.4497

Classification Report:

Class	Precision	Recall	F1-Score	Support
LAYING	0.49	0.10	0.17	537
SITTING	0.61	0.11	0.19	491
STANDING	0.35	0.86	0.50	532
WALKING	0.57	0.89	0.69	496
WALKING_DOWNSTAIRS	0.48	0.38	0.42	420
WALKING_UPSTAIRS	0.50	0.37	0.42	471
Accuracy	**0.45**			**2947**
Macro Avg	**0.50**	**0.45**	**0.40**	**2947**
Weighted Avg	**0.50**	**0.45**	**0.40**	**2947**

For accelerometer data, KNN achieved the highest cross-validation accuracy of 70.75% using k=19 and a test accuracy of 63.49%. It performed well for activities like "Laying" (precision: 82%) and "Walking Downstairs" (precision: 85%) but struggled with "Walking Upstairs" (precision: 52%). The Decision Tree model showed lower accuracy (50.79% cross-validation, 56.53% test) and macro precision of 57.01%. While effective for "Laying" and "Walking Downstairs," it struggled with "Walking Upstairs," likely due to overfitting. Naive Bayes had the lowest accuracy (46.69%), with significant difficulties in distinguishing activities like "Laying" (precision: 40%) and "Sitting" (precision: 31%).

On gyroscope data, KNN also performed best, achieving 70.99% cross-validation accuracy and 64.10% test accuracy. It excelled in recognizing "Standing" (precision: 71%) and "Walking" (precision: 67%). The Decision Tree performed moderately, achieving 57.65% test accuracy, but struggled with similar activities like "Walking Upstairs" and "Walking Downstairs." Naive Bayes again underperformed, with a test accuracy of 45.30% and challenges in recognizing "Laying" and "Sitting."

Comparing both datasets, KNN consistently outperformed the other models, while Decision Trees exhibited moderate but less stable results. Naive Bayes struggled across both datasets due to its inability to handle feature dependencies. All models found it challenging to distinguish between "Walking Upstairs" and "Walking Downstairs," likely due to overlapping motion patterns, despite the use of SMOTE to address class imbalances.

In summary, KNN was the most effective model for human activity recognition in this study, particularly when optimized for k. Decision Trees demonstrated moderate accuracy, while Naive Bayes was unsuitable due to its simplifying assumptions. Future work should focus on enhanced sampling techniques and ensemble methods to improve the classification of overlapping activities.

Therefore, entropy was taken into consideration to choose the best correlative columns to enhance the accuracy rate for both Accelerometer and Gyroscope data. After calculating the top 50 informative data attributes by using entropy, there were major increases in the accuracy rates of all models.

Accelerometer Data (with entropy)

KNN (k=19) Performance

Accuracy: 0.8246

Macro Precision: 0.8428

Macro Recall: 0.8175

Classification Report:

Class	Precision	Recall	F1-Score	Support
STANDING	1.00	0.97	0.99	537
SITTING	0.86	0.64	0.73	491
LAYING	0.72	0.91	0.80	532
WALKING	0.71	0.97	0.82	496
WALKING_DOWNSTAIRS	0.87	0.72	0.79	420
WALKING_UPSTAIRS	0.90	0.69	0.78	471
Accuracy			**0.82**	**2947**
Macro Avg	**0.84**	**0.82**	**0.82**	**2947**
Weighted Avg	**0.84**	**0.82**	**0.82**	**2947**

ID3 Performance

Accuracy: 0.7788

Macro Precision: 0.7822

Macro Recall: 0.7718

Classification Report:

Class	Precision	Recall	F1-Score	Support
STANDING	1.00	1.00	1.00	537
SITTING	0.72	0.71	0.71	491
LAYING	0.73	0.74	0.74	532
WALKING	0.69	0.83	0.75	496
WALKING_DOWNSTAIRS	0.84	0.63	0.72	420
WALKING_UPSTAIRS	0.71	0.72	0.72	471
Accuracy			0.78	**2947**
Macro Avg	**0.78**	**0.77**	**0.77**	**2947**
Weighted Avg	**0.78**	**0.78**	**0.78**	**2947**

Naive Bayes Performance

Accuracy: 0.8222

Macro Precision: 0.8252

Macro Recall: 0.8161

Classification Report:

Class	Precision	Recall	F1-Score	Support
STANDING	0.93	1.00	0.96	537
SITTING	0.90	0.62	0.73	491
LAYING	0.74	0.89	0.81	532
WALKING	0.80	0.83	0.81	496
WALKING_DOWNSTAIRS	0.75	0.72	0.74	420
WALKING_UPSTAIRS	0.83	0.84	0.84	471
Accuracy			0.82	**2947**
Macro Avg	**0.83**	**0.82**	**0.81**	**2947**
Weighted Avg	**0.83**	**0.82**	**0.82**	**2947**

Gyroscope Data (with entropy)

KNN (k=4) Performance

Accuracy: 0.6603

Macro Precision: 0.66653

Macro Recall: 0.6555

Classification Report:

Class	Precision	Recall	F1-Score	Support
STANDING	0.66	0.70	0.68	537
SITTING	0.62	0.60	0.61	491
LAYING	0.67	0.64	0.75	532
WALKING	0.61	0.83	0.71	496
WALKING_DOWNSTAIRS	0.63	0.48	0.55	420
WALKING_UPSTAIRS	0.79	0.68	0.73	471
Accuracy			**0.66**	**2947**
Macro Avg	**0.67**	**0.66**	**0.65**	**2947**
Weighted Avg	**0.67**	**0.66**	**0.66**	**2947**

ID3 Performance

Accuracy: 0.6746

Macro Precision: 0.6789

Macro Recall: 0.6783

Classification Report:

Class	Precision	Recall	F1-Score	Support
STANDING	0.60	0.56	0.58	537
SITTING	0.55	0.57	0.56	491
LAYING	0.64	0.66	0.65	532
WALKING	0.81	0.81	0.81	496
WALKING_DOWNSTAIRS	0.67	0.74	0.71	420
WALKING_UPSTAIRS	0.80	0.73	0.76	471
Accuracy			0.67	**2947**
Macro Avg	**0.68**	**0.68**	**0.67**	**2947**
Weighted Avg	**0.68**	**0.67**	**0.67**	**2947**

Naive Bayes Performance

Accuracy: 0.4662

Macro Precision: 0.5268

Macro Recall: 0.4781

Classification Report:

Class	Precision	Recall	F1-Score	Support
STANDING	0.51	0.07	0.13	537
SITTING	0.35	0.92	0.50	491
LAYING	0.55	0.15	0.24	532
WALKING	0.60	0.43	0.50	496
WALKING_DOWNSTAIRS	0.63	0.40	0.49	420
WALKING_UPSTAIRS	0.53	0.90	0.67	471
Accuracy			0.47	**2947**
Macro Avg	**0.53**	**0.48**	**0.40**	**2947**
Weighted Avg	**0.52**	**0.47**	**0.40**	**2947**

In the context of accelerometer data, both the KNN and Decision Tree models exhibit a remarkable enhancement in accuracy, achieving rates of 82% and 78%, respectively (this is significant). These models perform exceptionally well when classifying the "Standing" activity, highlighting a high precision rate. Furthermore, the Naive Bayes model also shows a considerable improvement in accuracy, increasing to nearly 82% (which is almost double its prior performance) after the application of entropy. This particular model demonstrates proficiency in identifying stationary activities, including "Standing," "Sitting," and "Laying.

However, regarding gyroscope data, the advancements in performance are considerably more modest. Although there is a slight uptick in accuracy, approximately 1-2%, it is not as pronounced as that observed with the accelerometer data.

Nevertheless, the application of entropy indicates a positive enhancement in performance. Given that the sensor data exhibit low variability, especially with movements with similar patterns, the use of entropy helps identify the most informative features. As a result, this approach improves the accuracy of classification for the models, leading to better results, particularly for accelerometer data. By focusing on the most relevant features, entropy aids in refining the models' ability to distinguish between different activities, enhancing overall classification performance.

Discussion

In this study, we aimed to classify human activity using accelerometer and gyroscope data with different machine learning models, including KNN, Decision Trees, and Naive Bayes. We wanted to determine how well these models could identify common activities like sitting, standing, walking, and lying down. Overall, KNN performed the best, achieving the highest accuracy across both accelerometer and gyroscope data. For the accelerometer, KNN reached an accuracy of 63.49% with k=19, and for the gyroscope, it was slightly better at 64.10%. On the other hand, Naive Bayes performed the worst, especially with accelerometer data, where its accuracy was just 46.69%. This low performance can be explained by Naive Bayes' assumption of feature independence, which doesn't hold in human activity recognition tasks, where the sensor features are often correlated.

When we added entropy-based feature selection, both KNN and Decision Trees showed a notable improvement. Entropy helped identify the most informative features, which boosted the accuracy of all models. With accelerometer data, KNN's accuracy improved to 82.46%, while Decision Trees and Naive Bayes also saw gains, reaching 77.88% and 82.22%, respectively. However, improvements with gyroscope data were more modest, with KNN's accuracy only rising to 66.03%. This difference suggests that accelerometer data might have more distinct movement patterns, making it easier for the models to classify activities effectively compared to the gyroscope data.

A major challenge we encountered was distinguishing between walking upstairs and walking downstairs, as both activities produce similar motion patterns. Despite using techniques like SMOTE to balance the dataset, this issue persisted. In future work, it may be beneficial to explore more advanced models or additional feature engineering to better handle such overlapping activities.

Beyond the machine learning models, we also considered external factors that could influence the activity patterns in the data. One possible explanation for the observed similarities in activity patterns is geographic location. For example, individuals living in urban areas may show more walking or standing, as they often commute or wait for public transportation. In contrast, people in rural areas might engage in more outdoor activities, which could result in different patterns. Climate could also play a role—colder weather generally leads to less outdoor activity, so people might sit or lie down more. On the other hand, in hotter climates, people are more likely to walk or run, which would reduce sitting patterns.

Other factors, such as lifestyle and occupation, also seem to influence activity patterns. People with active lifestyles, like athletes or those with physically demanding jobs, are likely to be more active throughout the day, which would be reflected in the data. In contrast, individuals with sedentary jobs, such as office workers, may show more sitting or lying down in their data. Age is another important factor. Younger people, such as students, may display patterns of sitting mixed with walking due to their study and school routines. Older adults, however, may show more stationary behavior due to reduced mobility.

In conclusion, while the machine learning models provided useful insights into classifying human activity based on sensor data, our findings also highlight the importance of considering external factors like location, climate, lifestyle, and age. These factors can greatly impact activity patterns, and understanding them can help improve future activity recognition models.

Self Assessment

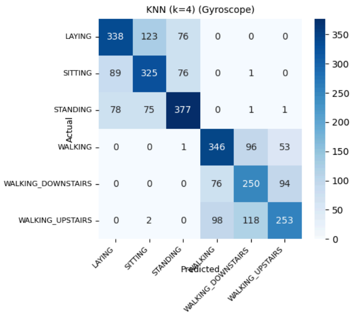
Johnson Dang - Suggested ideas to add to the EDA, added to discussion, helped analysis for EDA, created a group chat for easier communication, gave feedback, helped edit the final report to make it look professional, created a slideshow to present the data, suggested the concept of SMOTE to answer the question.

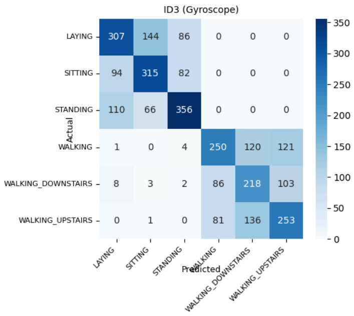
Quayna Busacay - Introduction, data description, added to appendix and exploratory data, added to discussion, suggested Q1, techniques to answering Q1, analysis and code to Q1

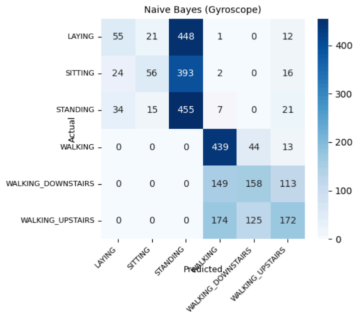
Khiem Nguyen - Exploratory data analysis with insights to the data, added to the appendix, techniques to answering Q1, analysis and code for Q1(Entropy parts)

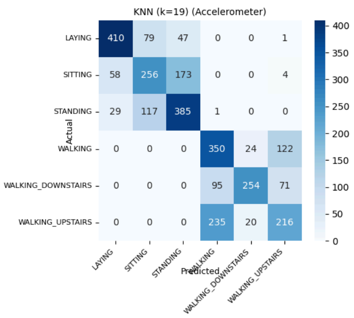
Ryan Straughan - assisted with slideshow creation and EDA

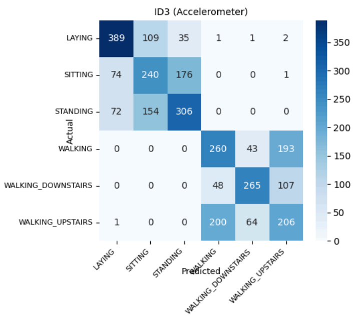
Appendix

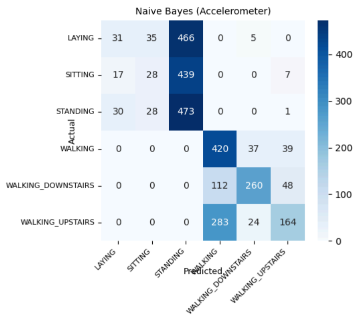

KNN (k=4) (Gyroscope)
LAYING 338 123 76 0 0 0
SITTING 89 325 76 0 1 0
STANDING 78 75 377 0 1 1
WALKING 0 0 1 346 96 53
WALKING_DOWNSTAIRS 0 0 0 76 250 94
WALKING_UPSTAIRS 0 2 0 98 118 253
Actual
Predicted
LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS WALKING_UPSTAIRS
350 300 250 200 150 100 50 0

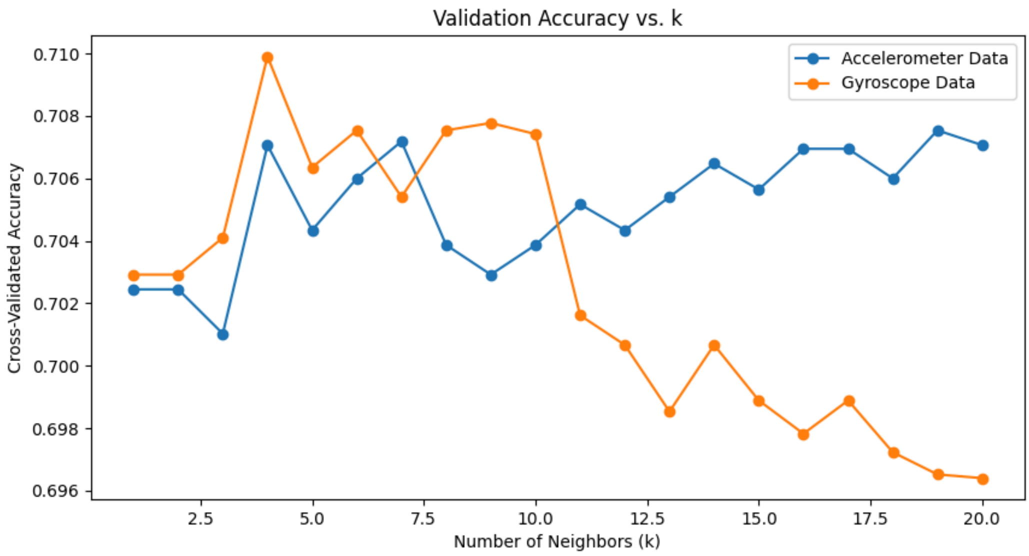

ID3 (Gyroscope)
LAYING 307 144 86 0 0 0
SITTING 94 315 82 0 0 0
STANDING 110 66 356 0 0 0
WALKING 1 0 4 250 120 121
WALKING_DOWNSTAIRS 8 3 2 86 218 103
WALKING_UPSTAIRS 0 1 0 81 136 253
Actual
Predicted
LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS WALKING_UPSTAIRS
350 300 250 200 150 100 50 0


Naive Bayes (Gyroscope)
LAYING 55 21 448 1 0 12
SITTING 24 56 393 2 0 16
STANDING 34 15 455 7 0 21
WALKING 0 0 0 439 44 13
WALKING_DOWNSTAIRS 0 0 0 149 158 113
WALKING_UPSTAIRS 0 0 0 174 125 172
Actual
Predicted
LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS WALKING_UPSTAIRS
400 300 200 100 0

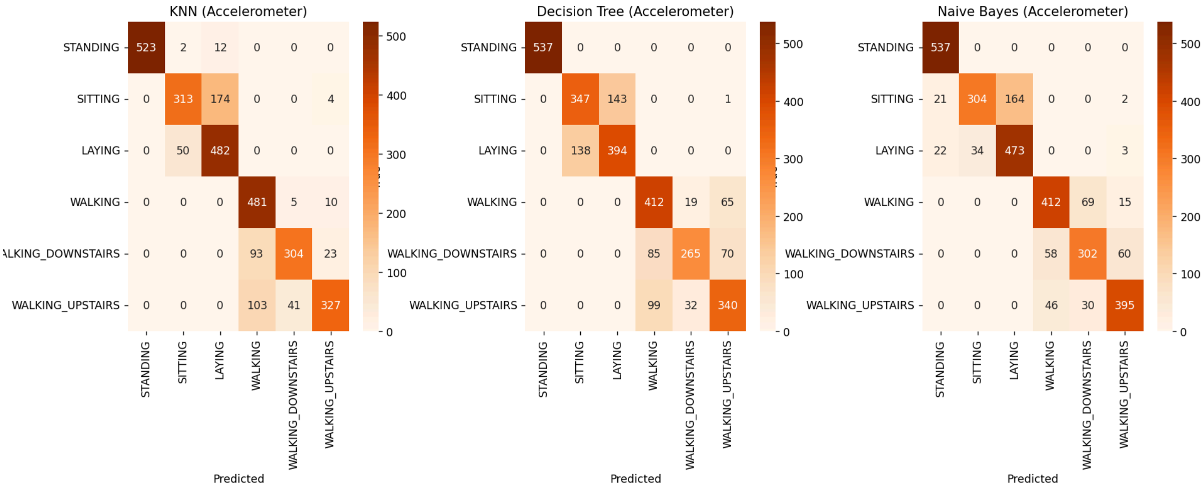

KNN (k=19) (Accelerometer)
LAYING 410 79 47 0 0 1
SITTING 58 256 173 0 0 4
STANDING 29 117 385 1 0 0
WALKING 0 0 0 350 24 122
WALKING_DOWNSTAIRS 0 0 0 95 254 71
WALKING_UPSTAIRS 0 0 0 235 20 216
Actual
Predicted
LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS WALKING_UPSTAIRS
400 350 300 250 200 150 100 50 0


ID3 (Accelerometer)
LAYING 389 109 35 1 1 2
SITTING 74 240 176 0 0 1
STANDING 72 154 306 0 0 0
WALKING 0 0 0 260 43 193
WALKING_DOWNSTAIRS 0 0 0 48 265 107
WALKING_UPSTAIRS 1 0 0 200 64 206
Actual
Predicted
LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS WALKING_UPSTAIRS
350 300 250 200 150 100 50 0


Naive Bayes (Accelerometer)
LAYING 31 35 466 0 5 0
SITTING 17 28 439 0 0 7
STANDING 30 28 473 0 0 1
WALKING 0 0 0 420 37 39
WALKING_DOWNSTAIRS 0 0 0 112 260 48
WALKING_UPSTAIRS 0 0 0 283 24 164
Actual
Predicted
LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS WALKING_UPSTAIRS
400 300 200 100 0


Validation Accuracy vs. k
Accelerometer Data
Gyroscope Data
Cross-Validated Accuracy
0.710
0.708
0.706
0.704
0.702
0.700
0.698
0.696
2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0
Number of Neighbors (k)

Confusion Matrices for Accelerometer Data (with entropy)



Confusion Matrices for Gyroscope Data (with entropy)