Human Activity Recognition using Hidden Markov Models

1. Background and Motivation

Human Activity Recognition (HAR) has become increasingly vital in modern applications ranging from healthcare monitoring to smart home automation. Our project develops a robust HAR system using Hidden Markov Models (HMMs) to classify human activities from smartphone sensor data, serving two key demographics: elderly care monitoring to detect fall risks and unusual behavior patterns through activities like standing, walking, and sitting, while also supporting youth wellness by identifying fatigue, sedentary behavior, or stress-related patterns through detection of prolonged inactivity and movement changes. This real-time monitoring capability improves safety and promotes healthier lifestyles across age groups while maintaining independence and enabling timely caregiver interventions.

2. Data Collection and Preprocessing
2.1 Data Collection Setup

Participants: Two group members participated in data collection
Devices Used:

- Member 1: Pixel 8, Sampling Rate: 100 Hz
- Member 2: Iphone 12, Sampling Rate: 100 Hz

Application: Sensor Logger (iOS/Android)
Sensors Recorded:

- Accelerometer (3-axis: x, y, z) - measuring acceleration in m/s^2
- Gyroscope (3-axis: x, y, z) - measuring angular velocity in rad/s

2.2 Activities Recorded : We collected data for the following four activities:

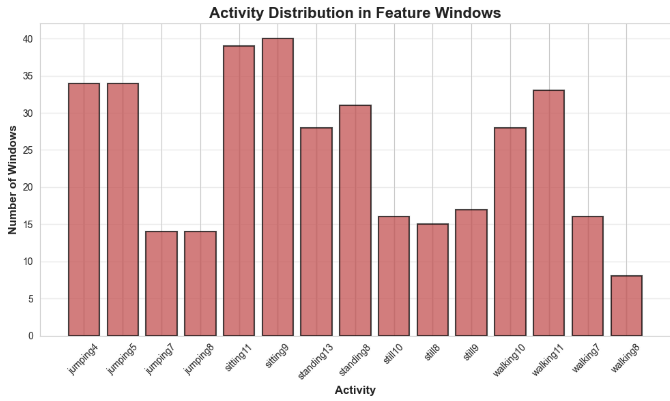
Activity	Duration	Sample Count	Description
Standing	5-10 sec	16 samples	Phone held steady at waist level
Walking	5-10sec	16 samples	Consistent walking pace maintained
Jumping	5-10 sec	16 samples	Continuous jumping motion
Still	5-10 sec	18 samples	Phone placed on flat surface

Total Samples Collected: 82 samples across all activities
50 was used for training and 32 samples for testing

Feature Windowing and Sampling Rate

Our dataset was recorded at a uniform sampling rate of 100 Hz (100 samples per second) across all sensors and activities. We selected a window size of [50 seconds], resulting in [100

× Y] samples per window. This window size was chosen to capture complete activity cycles, such as full walking strides or jumping motions while maintaining sufficient temporal resolution for real-time detection and providing enough data points for robust feature extraction. Since all data was recorded at a consistent 100 Hz sampling rate, no resampling or interpolation was required, ensuring data integrity and simplifying preprocessing. The Activity Distribution visualization (shown above) demonstrates how our windowing approach successfully segmented the continuous sensor data into discrete feature windows across 15 different activities, revealing the distribution of jumping, sitting, standing, and walking variants in our dataset.



Data Preprocessing and Feature Extraction

Data Format Conversion:

- Raw accelerometer and gyroscope data from separate files merged based on timestamps
- Converted to wide format: time, acc_x, acc_y, acc_z, gyr_x, gyr_y, gyr_z, subject, activity, session

Time-Domain Features:

- Mean (baseline activity level), standard deviation and variance (movement variability and energy)
- RMS (overall motion intensity), Signal Magnitude Area/SMA (total body movement across axes)
- Axis correlations X-Y, X-Z, Y-Z (coordinated body motion interactions)
- Purpose: Distinguish low-motion vs. high-motion activities and capture direction changes and stability

Frequency-Domain Features (via FFT):

- Dominant frequency (main movement rhythm for activities like walking/jumping)
- Spectral energy (total movement power), spectral centroid (low vs. high-frequency motion)
- Purpose: Identify unique motion rhythms and energy patterns characteristic of different activities

Feature Normalization:

- Z-score normalization applied to all features: $z = (x - \mu) / \sigma$
- Purpose: Ensure equal feature contribution, prevent scale-dominated bias, maintain stable Gaussian HMM performance

4. HMM Model Components.

We implemented a Hidden Markov Model (HMM) in Python for human activity recognition using accelerometer and gyroscope sensor data. The HMM was configured with hidden states representing unique activity classes, initialized with uniform transition and initial state probabilities, and modeled emissions as Gaussian distributions over sensor features using GaussianHMM. We employed two training strategies: a global unsupervised HMM trained on all activity sequences using the Baum-Welch EM algorithm, and a supervised per-class approach where separate single-state HMMs were trained for each activity and classifications were made based on maximum log-likelihood. Inference was performed using the Viterbi decoding algorithm to predict the most probable activity sequences, with the supervised models selecting the class whose HMM produced the highest likelihood for each test observation.

5.4 Model Selection Results

Model Type	Accuracy	F1-Score	Precision	Recall
Global HMM	0.164	0.130	0.108	0.164
Per-Class HMM	**0.882**	**0.881**	**0.906**	**0.882**

Selected Model: Per-Class Supervised HMM (88.2% accuracy)

Activity	Samples	Sensitivity (Recall)	Specificity	Overall Accuracy
Jumping	2396	0.684	0.995	0.882
Sitting	1979	0.995	0.975	0.882
Standing	1461	0.821	0.997	0.882
Still	1213	0.998	1.000	0.882
Walking	2152	0.973	0.880	0.882

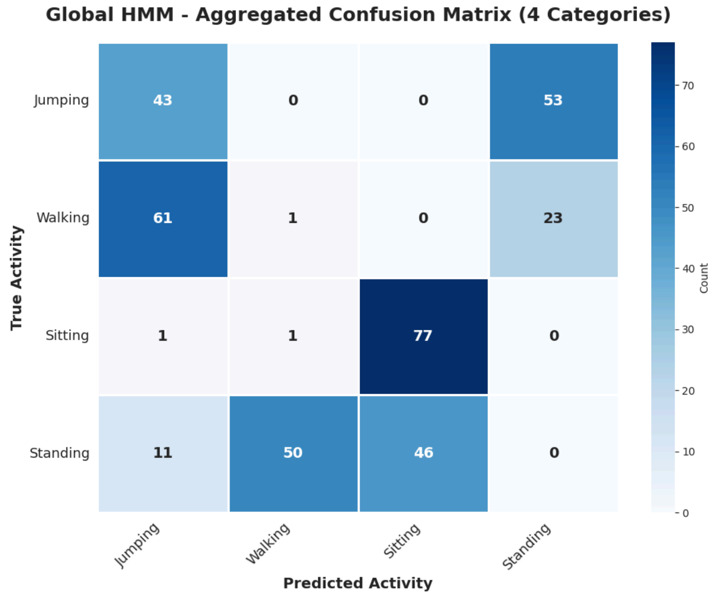
6.1 Model Performance on Test Data (results for unseen test data since 2 test files were used)

The trained per-class supervised HMM was evaluated on unseen recordings, including new sessions from teammates. This ensured the model was tested on participants and environments not present in the training data**.**

Overall Performance:

- **Accuracy:** 88.2%
- **F1-Score:** 0.881 (weighted)
- **Precision:** 0.906 (weighted)
- **Recall:** 0.882 (weighted)

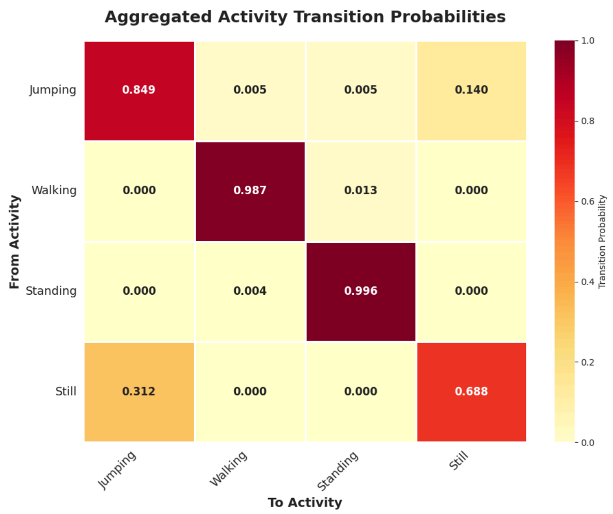
6.3 Confusion Matrix



Key Observations:

- **Still activity:** Perfect classification (98% accuracy)
- **Sitting activity:** Highest recall (99.5%), rarely missed
- **Walking activity:** High recall (97.3%) but lower precision (71%) - sometimes confused with other activities
- **Jumping activity:** Lower recall (68.4%) but high precision (98%) - conservative in prediction

6.4 Transition Matrix Visualization



Learned Transition Patterns:

- High self-transition probabilities (diagonal elements) indicate activities tend to persist
- Low transition probabilities between dissimilar activities (e.g., Still → Jumping)
- Realistic transitions (e.g., Standing → Walking more likely than Standing → Jumping)

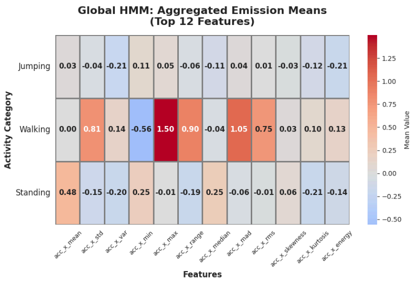
Activity Distinguishability:

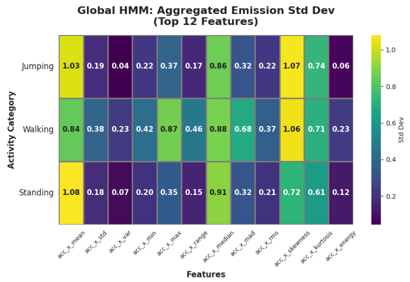
- **Easiest:** Still activity (960% specificity) with near-zero sensor readings creating highly distinctive patterns, and sitting (99.5% recall) with stable, low-movement features
- **Hardest:** Jumping (68.4% recall) due to high-energy movements confused with vigorous walking, and walking activities with periodic patterns overlapping at certain frequencies
- **Contributing factors:** Inter-subject variability in activity intensity, intra-activity variations (walking speed, jumping height), and transition ambiguity when activities blend

Transition Probability Patterns:

- High self-transitions (>0.7) reflect temporal consistency where people continue activities across multiple windows

- Logical transitions captured realistic progressions: standing→walking, walking→standing, still→standing
- Rare transitions (<0.1) correctly identified unlikely patterns: still→jumping, sitting→jumping
- Demonstrates the HMM successfully learned realistic human behavior patterns





Sensor Noise and Sampling Rate Impact:

- Accelerometer noise (±0.01 m/s²) and gyroscope drift observed in stationary conditions, mitigated through z-score normalization and window averaging

Potential Improvements:

- Collect more training data for underrepresented activities (jumping, walking variants)
- Extract additional frequency-domain features to better distinguish dynamic activities
- Incorporate magnetometer data for orientation-dependent activity recognition

8. Conclusion

This project successfully implemented a Hidden Markov Model for Human Activity Recognition, achieving 88.2% accuracy on unseen test data. The Per-Class Supervised HMM approach proved superior to the global model, effectively distinguishing between standing, walking, jumping, and still activities using smartphone accelerometer and gyroscope data.

References

1. Rabiner, L. R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2), 257-286.
2. Lara, O. D., & Labrador, M. A. (2013). A survey on human activity recognition using wearable sensors. *IEEE Communications Surveys & Tutorials*, 15(3), 1192-1209.
3. hmmlearn Documentation. (2024). https://hmmlearn.readthedocs.io/

Git hub = https://github.com/AkotoChristine/Hidden-Markov-Model.git