MotionSense AI Competition

Project name: Rehab Tracker

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Abstract

This project presents an AI-powered rehabilitation motion tracker that leverages smartphone inertial sensors and machine learning to monitor patient movement. Using the **UCI Human Activity Recognition (UCI-HAR) dataset** and implementing methods inspired by *Susi et al., 2013*, we developed a **Support Vector Machine (SVM)** classifier capable of identifying physical activities with an **accuracy of up to 96%.** Our solution extracts relevant **time** and **frequency** domain features from **accelerometer** and **gyroscope** data, processes them through a custom model, and outputs predicted activity modes such as **walking**, **sitting**, or **standing**. The system is integrated into a user-friendly web interface, enabling patients or physical therapists to upload motion data and receive instant insights into rehabilitation progress. This work aims to bridge AI and healthcare by offering an accessible tool for tracking recovery patterns and fostering remote, data-driven physiotherapy.

RehabTracker

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1. Project Overview

RehabTracker introduces a smart rehabilitation tracking system based on human activity recognition **(HAR)** using **smartphone sensor data**. By leveraging the **UCI HAR dataset**, which captures time-series readings from embedded **accelerometers** and **gyroscopes** during various physical movements, we trained a machine learning model—specifically a **Support Vector Machine (SVM)**—to classify six types of human activities with up to **96% accuracy**.

To bridge the gap between technical implementation and user accessibility, we developed a web-based interface where users can interact with the model. Patients undergoing physical rehabilitation can record and upload their motion data (e.g., using **Phyphox or mobile sensors**), and receive real-time feedback on their movement patterns. The platform is designed to aid physiotherapists and caregivers in monitoring progress remotely, offering a data-driven supplement to in-person sessions.

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2. Motivation & Problem Statement

Traditional physical rehabilitation often relies on in-clinic supervision, where therapists guide and assess patient progress through repeated sessions. However, this model faces several challenges: inconsistent adherence to prescribed exercises at home, lack of real-time monitoring, and limited access for individuals in remote or underserved areas.

The absence of affordable, intelligent, and non-intrusive tools for continuous rehabilitation tracking has created a gap in patient care. Many individuals recovering from surgeries, injuries, or mobility impairments lack the motivation or feedback necessary to sustain consistent recovery efforts outside clinical settings.

Traditional physical therapy relies heavily on in-person sessions, manual reporting, and subjective progress tracking. Patients often lack real-time feedback and continuity between sessions. This creates challenges in:

- Monitoring home-based rehabilitation
- Ensuring proper technique during exercises
- Tracking real progress accurately

Our motivation stems from the need to empower these individuals by giving them actionable insights into their recovery process using devices they already own; **smartphones**. By *applying machine learning to motion sensor data, we aim to automate activity recognition and progress tracking, making rehabilitation more measurable, interactive, and accessible.*

This project seeks to transform passive recovery into an engaging, AI-assisted journey—one where patients are informed and supported throughout their rehabilitation.

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3. UCI-HAR Dataset

Dataset used: UCI Machine Learning Repository
Dataset information:
The experiments have been carried out with a group of **30 volunteers** within an age bracket of **19-48 years**. Each person performed six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a **smartphone** (Samsung Galaxy S II) **on the waist**. Using its embedded **accelerometer** and **gyroscope**, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of **50Hz**. The experiments have been video-recorded to label the data manually. The obtained dataset has been randomly partitioned into two sets, where 70% of the volunteers were selected for generating the training data and 30% the test data.

The **sensor signals** (accelerometer and gyroscope) were **pre-processed** by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (**128 readings/window**). The sensor acceleration signal, which has **gravitational** and **body motion components**, was separated using a **Butterworth low-pass filter** into body acceleration and gravity. The gravitational force is assumed to have only low frequency components, therefore **a filter with 0.3 Hz cutoff frequency was used**. From each window, a vector of features was obtained by calculating variables from the time and frequency domain.

Reference: Human Activity Recognition Using Smartphones - UCI Machine Learning Repository

4. Machine Learning model pipeline

This pipeline takes segmented **IMU windows** (accelerometer + gyroscope, 128 samples at 50 Hz = 2.56 s per window) and c**onverts them into a feature vector for classification**.

Our activity recognition system processes windows of **raw IMU data** (3-axis accelerometer and gyroscope). The raw signals are first refined through a custom signal processing pipeline to extract discriminative features. A model is subsequently trained on this processed feature set derived from the fundamental acceleration and gyroscopic measurements.

5. Signal processing

The pipeline begins by **processing raw accelerometer and gyroscope signals to extract meaningful features while mitigating orientation dependence**. First, a Butterworth low-pass filter **separates** the low-frequency gravity component (**tGravityAcc**) from the **total acceleration**, **leaving** the higher-frequency body motion component (**tBodyAcc**). To highlight **dynamic movements**, **jerk signals** are computed as the **first derivative** of both the body acceleration and gyroscope data. Finally, the **Euclidean magnitude** of each signal type is calculated, creating **orientation-invariant features** by combining the **three axes into a single value**. This multi-stage approach effectively isolates distinct motion characteristics—gravity, body acceleration, and their dynamic derivatives—while ensuring the resulting features are **robust to device orientation**.

Signal Domain	**Time**	**Frequency**
tBodyAcc	**1**	**1**
tGravityAcc	**1**	**0**
tBodyAccJerk	**1**	**1**
tBodyGyro(Angular Speed)	**1**	**1**
tBodyGyroJerk(Angular Acc)	**1**	**1**
tBodyAccMag	**1**	**1**
tGravityAccMag	**1**	**0**
tBodyAccJerkMag	**1**	**1**
tBodyGyroMag	**1**	**1**
tBodyGyroJerkMag	**1**	**1**

For each **derived signal**, we calculated a set of time-domain statistics (e.g., **mean, max, correlation**). The Freq column indicates whether we also transformed the signal into the frequency domain using a Fast Fourier Transform (**FFT**) to calculate **spectral features**. A value of **'1'** means frequency features were extracted, which is valuable for analyzing **periodic motions like walking**. A value of **'0'** means only time-domain features were used, as this is appropriate for **non-periodic**, **quasi-static** signals like the **estimated gravity component**.

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6. Feature Extraction

Our feature extraction pipeline is designed to capture both the **statistical properties** and **spectral characteristics** of each motion signal. For every tri-axial signal (X, Y, Z axes), we calculate a comprehensive suite of **15 time-domain features** and **12 frequency-domain features** for each individual axis. This provides a detailed, axis-wise profile of the motion. For the magnitude signals (**the combined Euclidean norm of the axes**), we calculate **the same set of 15 time-domain and 12 frequency-domain features**, treating the magnitude as a single, **unified signal**. This two-pronged approach ensures our model receives information about the intensity, variability, smoothness, and periodicity of movements, making it highly effective at distinguishing between different physical activities.

Feature	**Description**
Mean	**Mean Value**
Std	**Standard Deviation**
MAD	**Median Absolute Deviation**
Maxi	**Maximum**
Mini	**Minimum**
SMA	**Signal Magnitude Area**
Energy	**Energy**
iqr	**Inquartile Range**
Ent	**Entropy**
AR Coefficient 1	**First Autorregresion coefficients**
AR Coefficient 2	**Second Autorregresion coefficients**
AR Coefficient 3	**Third Autorregresion coefficients**
AR Coefficient 4	**Fourth Autorregresion coefficients**
Sk	**Skewness**
kt	**Kurtosis**

7. Model Selection and Training

We conducted a comparative analysis of multiple classifiers for the activity recognition task. A Support Vector Machine (**SVM**) with a **linear kernel** was identified as the **optimal mode**l, achieving superior test **accuracy** and **efficient training time**. **This indicates our feature engineering pipeline successfully created a space where the activities are highly separable by a linear model**.

Model Performance Overview

Model	Kernel	Train Accuracy	Test Accuracy	Training Time
SVM	Linear	99.6%	96.0%	2.5 s
SVM	RBF	94.8%	94.8%	12.9s
SVM	Polynomial	91.9%	91.9%	9.7s
Random Forest		100%	90%	

Linear SVM- Detailed Performance

Activity	Precision	Recall	F1-Score
Walking	0.97	0.98	0.98
Walking Upstairs	0.97	0.97	0.97
Walking Downstairs	0.98	0.97	0.97
Sitting	0.93	0.89	0.91
Standing	0.91	0.94	0.92
Laying	1.00	1.00	1.00
Overall Accuracy			96%

8. Website

To translate the machine learning model into a user-facing solution, we developed a responsive and intuitive web application that serves as the interface between patients and the AI-based rehabilitation monitoring system. The application allows users—primarily patients or physiotherapists—to upload motion data collected from smartphone sensors using tools like **Phyphox**, which captures raw accelerometer and gyroscope readings. Once uploaded, this data is processed by the trained **SVM classifier**, which identifies the performed activity (e.g., walking, sitting, standing) and provides immediate feedback on the accuracy and frequency of the movements.

The platform features a simple dashboard displaying recent activity predictions, session statistics, and progress over time. It includes modular sections for patients to initiate new tracking sessions, review historical performance, and optionally share results with their physiotherapists. This connection between the ML model and the frontend enables a low-friction, accessible tool for continuous rehabilitation engagement. The site is designed with accessibility and motivation in mind—supporting patients in following through with their routines and offering data-driven insight into their recovery journey.

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9. Future Work

As we continue to enhance the functionality and impact of our rehabilitation support system, we have outlined the following directions for future development:

- **Real-time Sensor Streaming:**
  We aim to integrate real-time data streaming from mobile phone sensors and other connected devices (e.g., via Bluetooth or WebSockets). This will eliminate the need for manual uploads and enable continuous monitoring of users' physical activity.

- **AI Assistant Chatbot (GPT-based):**
  An interactive AI-powered assistant will be embedded into the web platform to provide guidance during rehab sessions, answer user queries, give reminders, and deliver motivational feedback in order to enhance the overall user experience and adherence to therapy plans.

- **Rehabilitation Dashboard with Long-term Analytics:**
  We plan to build a dedicated dashboard where users and clinicians can track long-term trends, progress over time, step counts, and recovery milestones. This will support personalized treatment adjustments and increase user engagement.

- **Integration of Wearable Sensors (e.g., Smartwatches):**
  Expanding beyond smartphone sensors, we intend to incorporate data from smartwatches and other wearable IoT devices for more granular and accurate motion tracking; especially useful in clinical settings.

These future upgrades will help transform the platform into a comprehensive, scalable, and intelligent rehabilitation companion tailored to the evolving needs of patients and healthcare professionals.

Thank you.