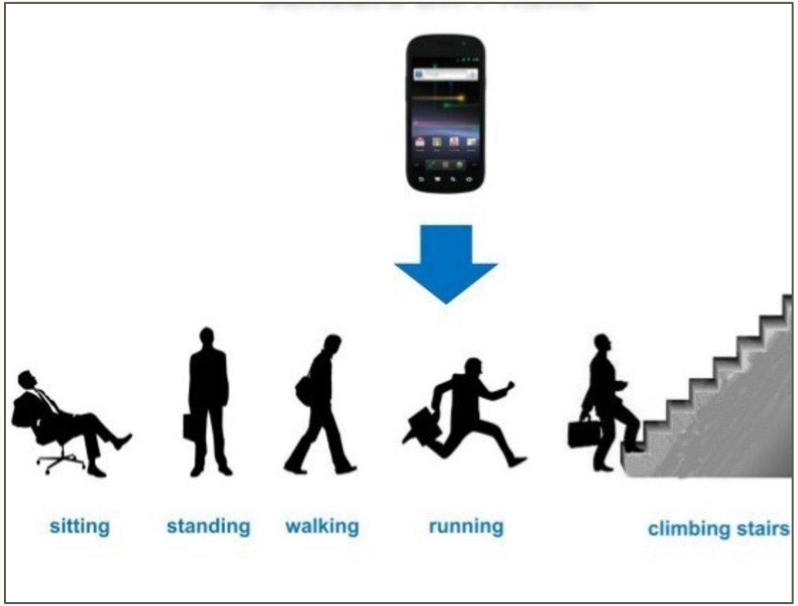
Human Activity Recognition using Smartphone Sensor Data



PROJECT-I

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Contents

↗ Background

Human Activity Recognition (HAR) is the process of identifying **human movements**, like walking or standing, through data gathered from sensors such as **accelerometers** and **gyroscopes**. These sensors are usually **embedded** in **wearables** and **smartphones** and collect real-time information that is **analyzed to classify** different physical activities.

HAR is very common in fields such as **healthcare, fitness, security,** and **smart homes**, where activities like **patient monitoring, fall detection, exercise tracking,** and **behavior analysis for security purposes** can be enabled.

Objective

1. Primary Objective

To develop an efficient **Human Activity Recognition (HAR)** system using smartphone sensor data **(accelerometer and gyroscope)** to accurately classify and **predict human activities in real time** for applications in healthcare, fitness, smart homes, and security.

2. Sub-Objectives

(A) **Data Collection and Preprocessing**

- Collect sensor data from smartphone accelerometers and gyroscopes sampled at **50Hz**.

- Preprocess the raw data by applying techniques such as **Standardization, Sliding Window Segmentation** and **Label Encoding.**

↗ Objective

(B) **Feature Extraction:**

Derive meaningful features from the time-series sensor data, such as **statistical measures** (mean,variance), frequency domain features using **Fast Fourier Transform**(FFT) and **temporal patterns** for better activity classification.

(C) **Real-time Processing:**

The sensory data logger is designed to support **real-time activity recognition** through **edge computing**, minimizing **cloud dependency** and ensuring **low latency**. This approach **enhances system responsiveness** while protecting user data.

Objective

(D) **Machine Learning Architectures**:

Multiple **deep learning models** are to be employed for activity classification, including:

- **LSTM (Long Short-Term Memory)**: Captures temporal dependencies in sensor data.
- **BiLSTM (Bidirectional LSTM)**: Enhances feature learning by processing data in both forward and backward directions.
- **GRU (Gated Recurrent Unit)**: Provides faster training with reduced complexity.
- **Transformer Networks**: Explored for their self-attention mechanisms, though less suited for sequential time-series data.
- **CNN-LSTM**: Leverages CNNs for spatial feature extraction and LSTMs for temporal information, often achieving high accuracy in activity recognition.

↗ Objective

(E) **Performance Evaluation*:***

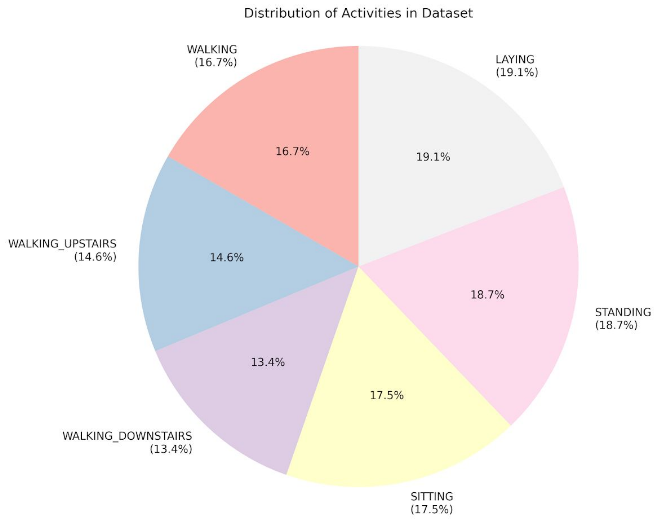
Evaluate the model using metrics like **accuracy, recall, precision** and **f1-score, confusion matrix** for activity-wise performance.

3. **Broader Goals*:***
   - *Healthcare Applications*: Monitor patients for real-time detection of falls, irregular movements, and recovery progress.
   - *Fitness Monitoring*: Track user activities such as steps, calories burned, and exercise patterns.
   - *Smart Homes and Automation*: Improve energy efficiency through activity-aware smart systems.

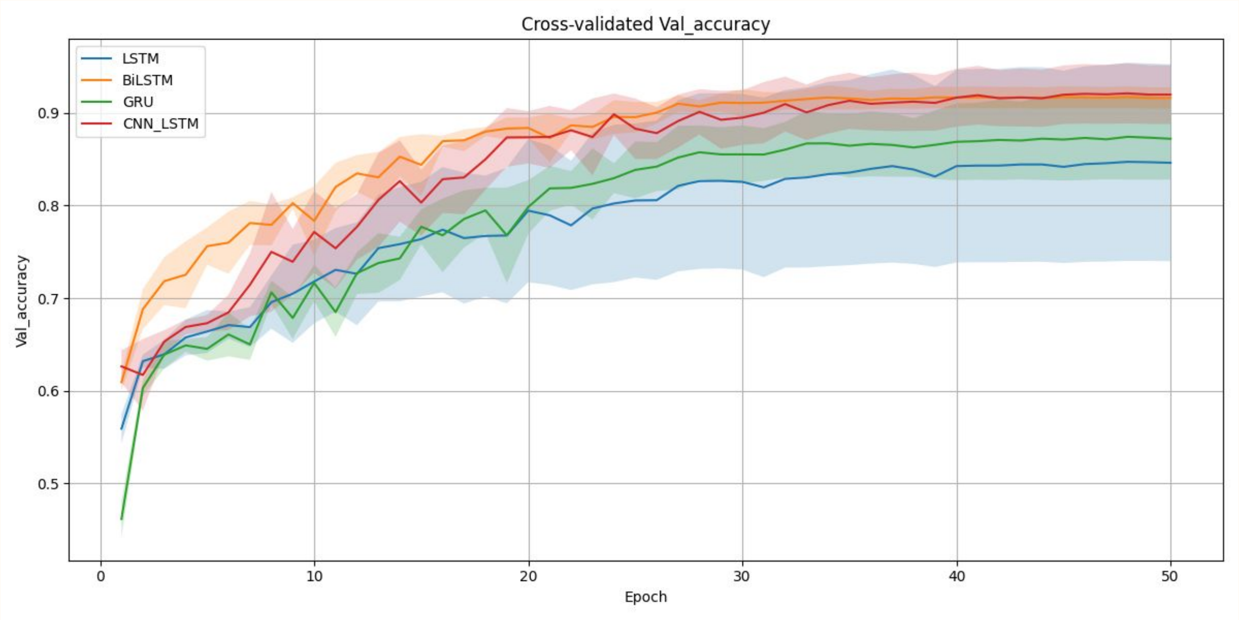
Methodology

Data Acquisition and Preprocessing:

- Sensor data (accelerometer and gyroscope) collection at 50Hz.
- Preprocessing techniques: Standardization and sliding window segmentation (window size: 128 samples, ~2.56 seconds).
- Target activity classes: Walking, walking upstairs, walking downstairs, sitting, standing, and laying.

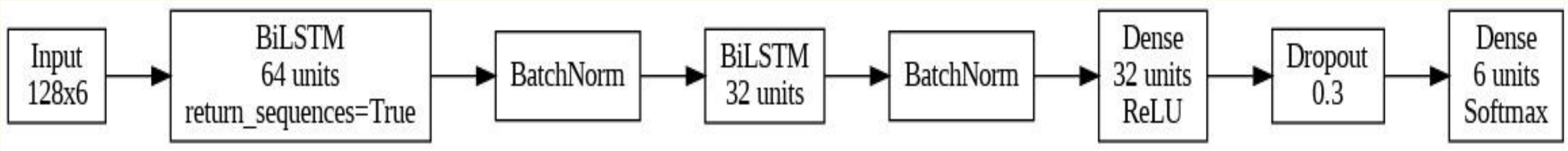


↗ Methodology



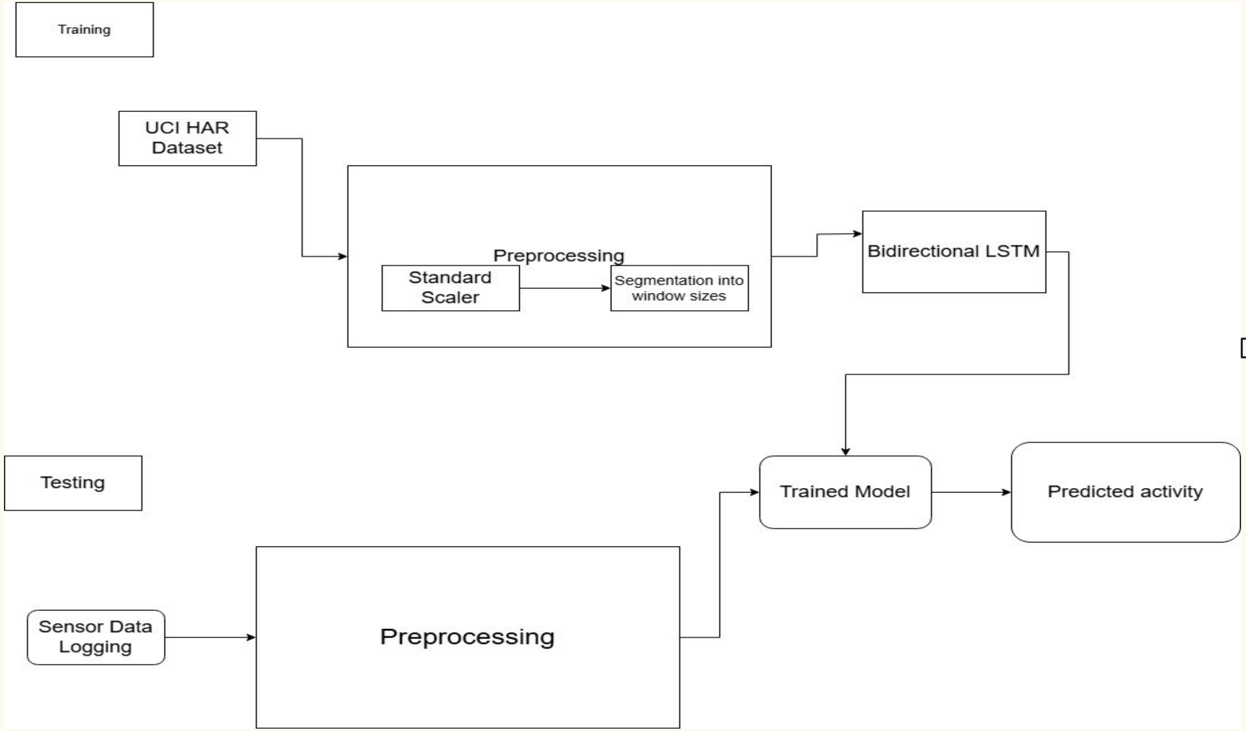
The BiLSTM model was chosen due to consistently better performance over epochs compared to other models (LSTM, GRU, Transformer, CNN-LSTM).

↗ Methodology



NEURAL NETWORK ARCHITECTURE

↗ Methodology



FLOW DIAGRAM OF PROTOTYPE

↗ Algorithm

Based on the aforementioned neural network architecture,
we can definitively state the algorithms as:

1. LSTM (Long Short Term Memory)

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \quad i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i),$$
$$\tilde{C}_t = \tanh(W_C x_t + U_C h_{t-1} + b_C), \quad C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t,$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \quad h_t = o_t \odot \tanh(C_t),$$

where f_t, i_t, o_t are the forget, input, and output gate activations, C_t is the cell state, and h_t is the hidden state.

Algorithm

2. BiLSTM (Bi-Directional Long Short Term Memory)

The BiLSTM processes input sequences in both forward and backward directions:

$$\overrightarrow{h_t} = \mathrm{LSTM}(x_t, \overrightarrow{h_{t-1}})$$

$$\overleftarrow{h_t} = \mathrm{LSTM}(x_t, \overleftarrow{h_{t+1}})$$

Output of the BiLSTM:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

where h_t is the concatenated hidden state at time t, x_t is the input at time t, and $\overrightarrow{h_t}, \overleftarrow{h_t}$ are the hidden states from forward and backward LSTMs.

↗ Algorithm

3. Batch Normalization

Batch normalization normalizes activations to stabilize training:

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}$$

$$y = \gamma\hat{x} + \beta$$

where x is the input, μ and σ^2 are the batch mean and variance, ϵ is a small constant for numerical stability, and γ, β are learnable parameters.

Algorithm

4. Dense Layer

The output of the dense layer is computed as:

$$y = \phi(Wx + b)$$

where W is the weight matrix, x is the input, b is the bias, and ϕ is the activation function (ReLU in the first dense layer).

Algorithm

5. Dropout

Dropout randomly sets a fraction p of the input units to zero during training:

$$y_i = \begin{cases} 0 & \text{with probability } p \\ \frac{x_i}{1-p} & \text{with probability } 1-p \end{cases}$$

where x_i is the input to the dropout layer.

Algorithm

6. Softmax Activation

The softmax layer converts logics into probabilities for classification:

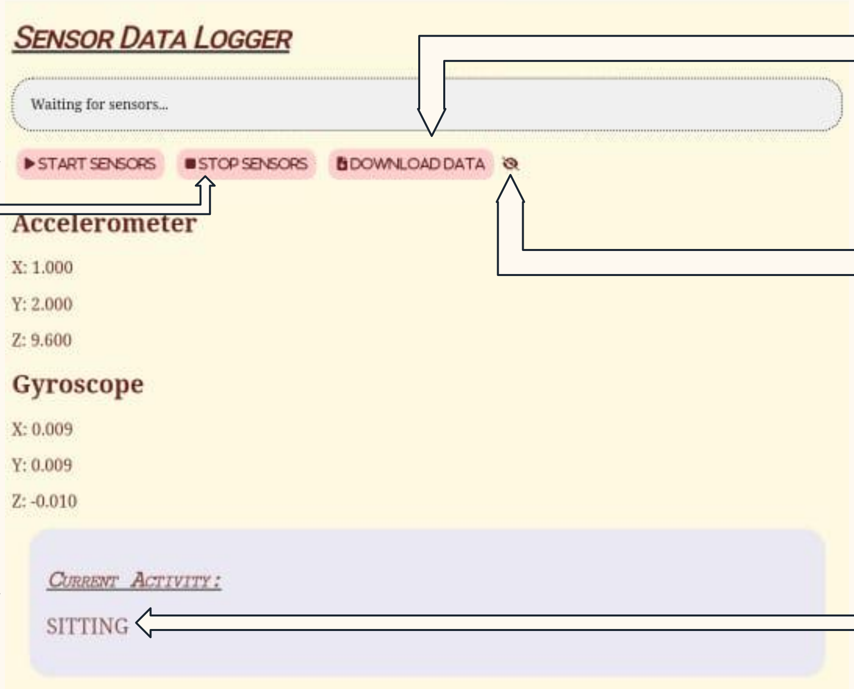
$$p_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

where z_i is the i-th output logit, and p_i is the corresponding probability.

↗ User Interface

OPTIONS TO START/STOP SENSORS

RESULT



OPTION TO DOWNLOAD SENSOR DATA LOGS FOR TRAINING/ANALYSIS

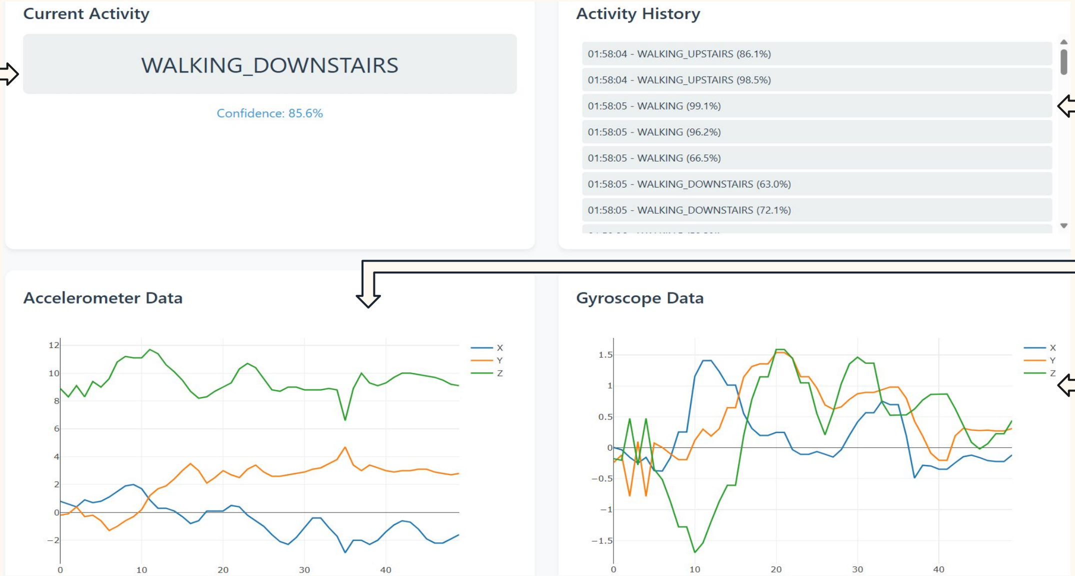
OPTION TO TOGGLE VISIBILITY OF SENSOR METRICS

WALKING (NORMAL/DOWNSTAIRS/UPSTAIRS)/SITTING/ STANDING/ LYING

FIG: SMARTPHONE USER INTERFACE

↗ User Interface

CURRENT ACTIVITY DISPLAY (with confidence parameter)



HISTORY OF ACTIVITY LOGS

GRAPHICAL REPRESENTATION OF DATA FROM SMARTPHONE SENSORS

FIG: DASHBOARD INTERFACE

↗ Challenges

1. ***Variability in Human Activities***
- Human activities differ significantly from one person to another, and thus it is hard to develop models that generalize well across different users.

2. ***Sensor Noise and Data Quality***
- Sensor data can be noisy or incomplete, which affects the accuracy of activity recognition models.

3. ***Real-time Processing***
- Accurate real-time recognition is challenging due to the computational demands of processing large volumes of data quickly.

↗ Challenges

4. ***Context Awareness***

- Human Activity Recognition systems generally fail to account for the context within which activities take place, such as changes in environmental conditions or similar activities.

5. ***Data Privacy and Security***

- Collecting personal activity data and processing it gives rise to privacy issues, mandating strong protection and security of such data.

↗ Challenges

6. ***Energy Efficiency***

- Continuous data collection and processing may put a drain on the battery life in wearable devices, so methods have to be energy-efficient.

7. ***Poor Training Data***

- Building reliable HAR models requires extensive training data, which can be difficult and time-consuming to collect for diverse activities and environments.

↗ Future Scope

1. ***Advanced Machine Learning Techniques***

- Integration of methods like **Multi-Instance Multi-Label Learning (MIML)** for accurate classification of complex human activities, including overlapping or concurrent tasks.

2. ***Applications in Old-Aged Homes***

- **Activity Monitoring:** Tracks residents' daily routines for healthy living.
- **Anomaly Detection:** Identifies emergencies like falls or inactivity and alerts caregivers.
- **Independence Promotion:** Ensures safety while spreading awareness regarding individual independence.

↗ Future Scope

3. ***Improved Sensor Technology***
- Advanced wearable, environmental sensors, and cameras enable **precise human activity recognition** and **holistic data collection**.

4. ***Personalization and Adaptability***
- Tailored to individual routines, **reducing false alarms** and **increasing authenticity in sensitive environments**

5. ***Real-time Data Processing with Edge Computing***
- Ensures **faster decision-making**, minimizes **cloud dependency**, and **enhances privacy/security** in **healthcare** settings.

↗ Future Scope

6. ***IoT and Smart Home Integration***

- Enables **responsive** environments, e.g., **notifying caregivers** during prolonged inactivity or **triggering reminders**.

7. ***AI Research and Development***

- Advances in **deep learning, transfer learning,** and **reinforcement learning** to create robust, generalizable **algorithms for dynamic environments**.

Thank You!