Human Activity Recognition
LSTM Deep Learning Model

Project Objective

The primary goal of this project is to classify human activities using time-series data collected from motion sensors embedded in an iPhone 6s. The activities include walking, jogging, sitting, standing, going upstairs, and going downstairs using a machine learning approach based on Long Short-Term Memory (LSTM) networks.

Dataset Summary

- **Device**: iPhone 6s (50Hz sampling rate)
- **Collected using**: SensingKit, Core Motion framework
- **Participants**: 24 (varied in gender, age, height, weight)
- **Activities**: 6 (upstairs, downstairs, walking, jogging, sitting, standing)
- **Data Types**:
  - attitude (roll, pitch, yaw)
  - gravity
  - rotationRate
  - userAcceleration

Data Preparation

- Merged CSVs into a single DataFrame.
- Dropped unnecessary metadata: Unnamed: 0, subject_id, session_id, age, gender, height, weight.
- Encoded the categorical activity labels using LabelEncoder.
- Visualized class distribution.
- Split dataset into training and test sets (80/20 split).
- Created time-sequenced windows of length 150 (stride 10) for LSTM.

🔄 *LSTM-based Deep Learning Model:*

- **Architecture**:
  - 1 LSTM Layer (6 units, return_sequences=True)
  - 1 Flatten Layer
  - 1 Dense Layer (128 units, ReLU)
  - Output Layer (Softmax)
- **Compilation**:
  - Loss: Categorical Crossentropy
  - Optimizer: Adam

Conclusion

- 📈 **Maximum Accuracy**: 99.36%
- 📉 **Minimum Accuracy**: 95.98%
- 📊 **Mean Accuracy**: **98.17%**
- 📐 **Standard Deviation**: 1.25%

The LSTM model performs exceptionally well on time-series data and demonstrates excellent generalization with low variance across folds. **LSTM networks** are well-suited for time-series sensor data, providing excellent performance in recognizing human activities with sequence modeling.

To **accurately recognize and classify human activities**—such as walking, jogging, sitting, etc.—from **raw time-series motion sensor data** using a deep learning approach that can capture **temporal dependencies** and patterns over time.

Unlike traditional machine learning models that treat each sample independently, this project aims to:

- **Leverage the sequential nature** of sensor readings (e.g., acceleration, rotation) using **LSTM**, which is designed for time-series data.
- **Developed a model capable of learning from historical context** (i.e., previous timesteps) to improve activity recognition accuracy.
- **Build a scalable, real-time recognition system** that could be used in practical applications like:
    - Fitness tracking
    - Elderly fall detection
    - Smart healthcare monitoring
    - Activity-aware mobile apps

✅ **In essence**: The goal is to build a **deep learning-based system that understands how people move over time**—not just based on isolated data points, but on patterns across sequences of sensor measurements.