Human Activity Recognition (HAR) Project

1. Project Overview

1.1 Objective

Develop an advanced deep learning model to recognize and classify human activities using sensor data from the UCI Human Activity Recognition (HAR) Dataset.

1.2 Problem Statement

Accurately identify and classify different human activities based on smartphone sensor measurements, leveraging deep learning techniques.

2. Dataset Description

2.1 UCI HAR Dataset

- Source: University of California, Irvine
- Data Collection: Smartphone sensors (accelerometer, gyroscope)
- Activities Recorded:
  1. Walking
  2. Walking Upstairs
  3. Walking Downstairs
  4. Sitting
  5. Standing
  6. Laying

2.2 Dataset Characteristics

- Total Samples: 10,299

- Training Samples: 7,352

- Testing Samples: 2,947

- Features: 561 time and frequency domain variables

- Sampling Rate: 50 Hz

3. Methodology

3.1 Data Preprocessing

1. Standardization

   - Use StandardScaler to normalize features

   - Ensure zero mean and unit variance

2. Reshaping

   - Reshape data into 3D tensor

   - Time steps: 51

   - Features per step: 11

3.2 Model Architecture: CNN-LSTM

Convolutional Layers

- First Conv1D Layer

  - Filters: 128

  - Kernel Size: 3

  - Activation: ReLU

- Batch Normalization

- Max Pooling

LSTM Layers

- First LSTM Layer: 128 units
- Second LSTM Layer: 64 units
- Sequence processing for temporal features

Fully Connected Layers

- Dense Layer: 100 units
- Dropout: 0.5 for regularization
- Output Layer: Softmax activation

3.3 Training Strategy

- Optimizer: Adam (learning rate: 0.0005)
- Loss Function: Categorical Crossentropy
- Callbacks:
  - Early Stopping
  - Learning Rate Reduction
- Epochs: 100
- Batch Size: 32

4. Experimental Results

4.1 Performance Metrics

- Test Accuracy: 93.25%
- Precision: 0.92
- Recall: 0.93
- F1-Score: 0.92

4.2 Confusion Matrix Analysis

- Highest accuracy: Laying, Standing
- Moderate accuracy: Walking, Sitting
- Slight confusion: Walking Upstairs/Downstairs

5. Technical Implementation

5.1 Key Libraries

- TensorFlow/Keras
- NumPy
- Scikit-learn
- Matplotlib
- Seaborn

5.2 Code Structure

- Data Loading
- Preprocessing
- Model Building
- Training
- Evaluation
- Visualization

6. Challenges and Solutions

6.1 Data Challenges

- High-dimensional sensor data

- Temporal dependencies
- Class imbalance

6.2 Model Challenges

- Overfitting
- Feature extraction
- Sequence modeling

6.3 Implemented Solutions

- Standardization
- Batch Normalization
- Dropout
- Early Stopping
- Learning Rate Reduction

7. Future Work

7.1 Potential Improvements

- Experiment with attention mechanisms
- Try transfer learning
- Incorporate more advanced architectures
- Collect more diverse activity data

7.2 Potential Applications

- Healthcare monitoring
- Fitness tracking
- Elderly care

- Sports performance analysis
- Human-computer interaction

8. Conclusion

The CNN-LSTM model demonstrates high effectiveness in recognizing human activities, achieving 93.25% accuracy. The approach combines convolutional feature extraction with LSTM sequence processing, showcasing the power of deep learning in sensor-based activity recognition.