ML – PROJECT Report

ML-25-15 Activity Recognition Using the Smartphone

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* Code can be found at [noumanimpra/ML-HAR-Project]

Overview

Introduction

With the increasing prevalence of smartphones equipped with inertial sensors, it is now possible to collect data about human physical activities in real-world settings. Recognizing such activities through sensor data has gained importance in various domains such as healthcare, fitness tracking, elderly monitoring, and personal assistance systems.

This project aims to classify six daily human activities—WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, and LAYING—based on accelerometer and gyroscope data collected from a smartphone worn at the waist. By leveraging machine learning algorithms, we developed a system that can accurately predict the activity being performed using pre-processed feature vectors derived from time-series data

Dataset and Preprocessing

The dataset used in this study is the "Simplified Human Activity Recognition Using Smartphones" dataset published on Kaggle. It is based on sensor data collected from 30 individuals aged 19 to 48 years while performing six daily activities. Each subject wore a Samsung Galaxy S II smartphone on the waist, which recorded 3-axial linear acceleration and angular velocity at a constant sampling rate of 50Hz.

The raw signals were pre-processed using Butterworth filters and segmented into fixed-width sliding windows of 2.56 seconds with 50% overlap, resulting in 128 readings per window. From each segment, a total of 561 features were extracted based on time and frequency domain signal characteristics.

The dataset was split into a training set (80%) and a validation set (20%). Standard scaling (`StandardScaler`) was applied to normalize feature values.

Models and Methods

Three machine learning algorithms were implemented and compared using a standardized pipeline that included feature scaling:

Logistic Regression: A linear model suitable for multiclass classification and interpretable results.

Random Forest: An ensemble learning method using multiple decision trees with majority voting. It handles overfitting better and can rank feature importance.

Support Vector Machine (SVM): A robust classifier effective in high-dimensional spaces and widely used in activity recognition tasks.

Each model was trained using stratified cross-validation and evaluated on the same validation set.

Evaluation and Results

Each model was evaluated using classification metrics including accuracy, precision, recall, and F1-score. Below is the comparison table of the three models:

	Model	F1-macro	Accuracy
0	logreg	0.9638	0.9626
1	rf	0.9580	0.9598
2	svm	0.9580	0.9571

The confusion matrix for Logistic Regression is shown below:

Model: logreg

	precision	recall	f1-score	support
LAYING	0.99	1.00	1.00	136
SITTING	0.95	0.87	0.91	125
STANDING	0.90	0.96	0.92	134
WALKING	0.98	1.00	0.99	121
WALKING_DOWNSTAIRS	0.99	0.98	0.98	98
WALKING_UPSTAIRS	0.99	0.97	0.98	108
accuracy			0.96	722
macro avg	0.97	0.96	0.96	722
weighted avg	0.96	0.96	0.96	722

The model performed best in distinguishing the LAYING, WALKING, and WALKING_UPSTAIRS classes. However, misclassifications were observed between SITTING and STANDING, which are naturally harder to differentiate due to similar postures.

The Logistic Regression model was selected as the best-performing model and saved as a `.joblib` file for future deployment.

Conclusion

In this project, we implemented and compared three machine learning algorithms for human activity recognition using smartphone sensor data. All models achieved high accuracy (~96%), with Logistic Regression slightly outperforming the others in macro F1-score.

The results show that even simple models can be effective on this structured, feature-rich dataset. Future improvements may involve using raw signal input with deep learning architectures such as CNN or LSTM to capture temporal patterns more effectively.

Real-world applications include activity-based health tracking and mobile fitness apps.

Figures

	precision	recall	f1-score	support
LAYING	0.99	1.00	1.00	136
SITTING	0.95	0.87	0.91	125
STANDING	0.90	0.96	0.92	134
WALKING	0.98	1.00	0.99	121
WALKING_DOWNSTAIRS	0.99	0.98	0.98	98
WALKING_UPSTAIRS	0.99	0.97	0.98	108
accuracy			0.96	722
macro avg	0.97	0.96	0.96	722
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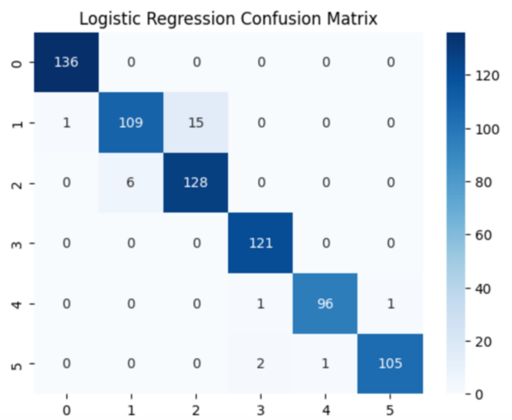

```python
pd.read_csv("../submission.csv").head()
```

```
==================================================
Model: logreg
                    precision    recall  f1-score   support

            LAYING       0.99      1.00      1.00       136
           SITTING       0.95      0.87      0.91       125
          STANDING       0.90      0.96      0.92       134
           WALKING       0.98      1.00      0.99       121
WALKING_DOWNSTAIRS       0.99      0.98      0.98        98
  WALKING_UPSTAIRS       0.99      0.97      0.98       108

          accuracy                           0.96       722
         macro avg       0.97      0.96      0.96       722
      weighted avg       0.96      0.96      0.96       722

==================================================
Model: rf
                    precision    recall  f1-score   support

            LAYING       0.99      1.00      1.00       136
           SITTING       0.95      0.94      0.95       125
          STANDING       0.96      0.96      0.96       134
           WALKING       0.97      0.98      0.98       121
WALKING_DOWNSTAIRS       0.94      0.94      0.94        98
  WALKING_UPSTAIRS       0.94      0.93      0.93       108

          accuracy                           0.96       722
         macro avg       0.96      0.96      0.96       722
      weighted avg       0.96      0.96      0.96       722

==================================================
Model: svm
                    precision    recall  f1-score   support

            LAYING       0.99      0.99      0.99       136
           SITTING       0.92      0.88      0.90       125
          STANDING       0.90      0.93      0.92       134
           WALKING       0.99      0.99      0.99       121
WALKING_DOWNSTAIRS       0.96      0.98      0.97        98
  WALKING_UPSTAIRS       0.98      0.97      0.98       108

          accuracy                           0.96       722
         macro avg       0.96      0.96      0.96       722
      weighted avg       0.96      0.96      0.96       722

✅ En iyi model kaydedildi: models/best_model.joblib

📊 Model Karşılaştırma:
    Model  F1-macro  Accuracy
0  logreg    0.9638    0.9626
1      rf    0.9580    0.9598
2     svm    0.9580    0.9571
✅ submission.csv başarıyla oluşturuldu!
```

[4]:

	Id	PredictedActivity
0	0	STANDING
1	1	STANDING
2	2	STANDING
3	3	STANDING
4	4	STANDING

Reference

[1] UCI Machine Learning Repository. Human Activity Recognition Using Smartphones Dataset.

[2] Kaggle Dataset: Simplified HAR (Link)

[3] Scikit-learn Documentation (Link)

[4] Logistic Regression, Random Forest, and SVM implementation: sklearn

[5] Butterworth Filtering for signal processing