

**Topic:** Human Activity Recognition Using Deep Learning

**Domain:** Sensor-Based Time-Series Classification

**Dataset:** UCI HAR Dataset

**Course:** Machine Learning

**Assignment:** 5.3

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## 1. Introduction

Human Activity Recognition (HAR) is a key application of machine learning in healthcare monitoring, fitness tracking, and smart wearable systems. While classical machine learning models can perform reasonably well on engineered features, they often struggle to capture complex non-linear patterns present in time-series sensor data.

In Assignment 5.1, we explored the dataset and problem formulation. In Assignment 5.2, we applied classical machine learning models using engineered features. In this assignment (5.3), we extend the work by applying a **deep learning approach** using a **Fully Connected Neural Network (FCNN)** and compare its performance with classical models.

## 2. Dataset Description

**Dataset Name:** UCI Human Activity Recognition Using Smartphones

**Source:**

<https://archive.ics.uci.edu/dataset/240/human+activity+recognition+using+smartphones>

**Activities (6 classes):**

1. Walking
2. Walking Upstair
3. Walking Downstairs
4. Sitting
5. Standing
6. Lying

**Sensors Used:**

- 3-axis Accelerometer

- 3-axis Gyroscope

#### **Dataset Size:**

- Training samples: 7352
- Testing samples: 2947
- Total samples: 10,299

Each sample contains **561 time- and frequency-domain features**, extracted from fixed-length sliding windows.

### **3. Deep Learning Model (FCNN)**

#### **3.1 Model Architecture**

A **Fully Connected Neural Network (FCNN)** was implemented to classify activities directly from the 561-dimensional feature vectors.

##### **Architecture Overview:**

- Input Layer: 561 neurons
- Hidden Layers: Fully connected layers with ReLU activation
- Output Layer: 6 neurons with Softmax activation

This architecture enables the model to learn complex non-linear relationships between sensor features.

#### **3.2 Training Configuration**

- **Loss Function:** Categorical Cross-Entropy
- **Optimizer:** Adam
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-score
- **Train/Test Split:** Official UCI HAR split

### **4. Evaluation Metrics**

The following evaluation metrics were used:

- Accuracy

- Precision
- Recall
- F1-score
- Confusion Matrix
- Classification Report

These metrics provide a comprehensive assessment of model performance across all activity classes.

## 5. Results

### 5.1 FCNN Test Performance

- **Accuracy:** 0.9437
- **Weighted F1-score:** 0.9436

### 5.2 Confusion Matrix Analysis

- Dynamic activities (Walking, Upstairs, Downstairs) are classified with high accuracy
- Minor confusion exists between **Sitting and Standing**, which is expected due to similar motion patterns
- **Lying** activity is classified almost perfectly

### 5.3 Classification Report Summary

- Precision and recall for most classes exceed **0.90**
- The model demonstrates strong generalization on unseen data

## 6. Comparison with Assignment 5.2 (Classical ML)

Model	Accuracy
Logistic Regression	0.5541
SVM (RBF Kernel)	0.5507
Random Forest	0.5467
XGBoost (Best Classical)	0.5632
<b>FCNN (5.3)</b>	<b>0.9437</b>

## Interpretation:

- Classical models rely on compressed engineered features
- FCNN learns hierarchical representations directly from full feature vectors
- Deep learning significantly outperforms classical ML for HAR tasks

## 7. Discussion

The FCNN achieved a substantial improvement over classical models due to its ability to model non-linear patterns and interactions among features. Unlike classical methods, deep learning does not require aggressive feature compression and can exploit the full representational power of the dataset.

The results confirm that neural networks are better suited for complex time-series classification problems.

## 8. Conclusion

In this assignment, a Fully Connected Neural Network was successfully implemented for Human Activity Recognition. The model achieved **94.37% accuracy**, significantly outperforming classical machine learning models from Assignment 5.2.

This demonstrates the effectiveness of deep learning approaches for sensor-based time-series classification tasks.