FINAL REPORT: Comprehensive Comparative Analysis of Classification Approaches

Title:

Comparative Study of Classical Machine Learning, Fully Connected Neural Networks, and Sequence-Based Deep Learning Models for Elderly Fall Detection

Abstract

This report presents a comprehensive comparison of three classification approaches applied to the **MobiFall Dataset v2.0** : feature-engineering-based classical machine learning models, fully connected deep neural networks (FC-DNN) using raw data, and sequence-based deep learning models (LSTM). Performance is evaluated using accuracy and F1-score to analyze the strengths and limitations of each approach in classifying human activities and fall events. Results indicate that while feature engineering provides high accuracy on limited samples, sequence models like LSTM offer robust performance by capturing temporal dependencies in raw data.

1. Introduction / Problem Statement

Human activity recognition (HAR) and fall detection are critical applications in healthcare, particularly for monitoring elderly individuals. Wearable sensor data such as accelerometer readings produce time-series signals that contain rich temporal information.Classification of human activities using sensor data can be addressed through various paradigms. Traditional machine learning relies heavily on manual feature engineering, while deep learning models learn representations directly from raw signals. However, standard fully connected networks often fail to model the temporal relationships inherent in sequential sensor data. This project aims to compare these approaches to determine the most effective method for detecting falls and standard activities.

2. Methodology

Three different classification approaches were implemented and evaluated using the same dataset and evaluation metrics.

Approach 1: Feature Engineering + Classical Machine Learning

Statistical features such as mean, standard deviation, minimum, and maximum were extracted from fixed-length windows of sensor data. These features were used to train classical classifiers including Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, and XGBoost.

Approach 2: Fully Connected Deep Neural Network

A multilayer perceptron (MLP) was trained directly on normalized raw sensor data without explicit feature engineering. This approach treats each data sample independently and does not model temporal relationships.

Approach 3: Sequence-Based Deep Learning

Raw accelerometer signals were segmented into fixed-length sequences and fed into a Long Short-Term Memory (LSTM) network. This approach preserves temporal ordering and learns motion dynamics directly from the data.

3. Experiments and Results

3.1 Dataset Description

- **Dataset Name:** MobiFall Dataset v2.0.
- **Source:** Downloaded from Kaggle.
- Link: **https://www.kaggle.com/datasets/kmknation/mobifall-dataset-v20**
- **Data Type:** Time-series sensor data (Tri-axial Accelerometer: accX, accY, accZ).
- **Number of Samples:** 355,313 rows.
- **Class Labels:** 6 classes including Walking, Sitting, Standing, and three types of falls (Back Sitting Chair, Fall Forward Lying, Sideward Lying).

3.2 Data Settings

- **Train-Test Split:** Typically 80%–20%.
- **Preprocessing:** Included parsing timestamps, chronological sorting, handling missing values via forward filling, and standardizing features .

- **Label Encoding:** Categorical labels were converted to numeric forms for compatibility with neural networks.
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-score

3.3 Results (Comparison of All Approaches)

The following table summarizes the best results achieved under each approach:

Approach	Model Type	Accuracy	F1-Score (Macro)
Feature Engineering + ML	Random Forest	98.31%	0.9626
Fully Connected DNN	FC-DNN (Raw Data)	90.05%	0.73
Sequence Model	**LSTM (Sequential Data)**	**96.48%**	**0.9165**

3.4 Discussion

- **Approach-1** achieved the highest accuracy on the test set, benefiting from high-quality manual statistical features (Mean, Std Dev, Min, Max) . However, this required significant manual effort and domain knowledge.

- **Approach-2** served as a baseline but struggled significantly with fall detection (lower macro F1), as it could not relate sequential readings to each other.This approach treats each data sample independently and does not model temporal relationships.

- **Approach-3 (LSTM)** provided a more robust deep learning solution than the FC-DNN. By processing data in 50-step windows, it successfully learned the temporal "signature" of a fall, achieving an F1-score of 0.9165 without requiring manual feature extraction.

4. Conclusion and Future Work

This project demonstrated that while classical machine learning with feature engineering is highly effective for smaller, well-defined windows, **sequence-based models (LSTM)** are the most suitable for raw sequential data as they automatically learn temporal context. The LSTM significantly outperformed the standard fully connected network by capturing the dynamic nature of movements.

Future Work: May include exploring hybrid architectures (CNN-LSTM) to capture both spatial and temporal features simultaneously,transformer-based architectures, or utilizing Attention mechanisms to focus on critical moments within a fall sequence.