Deliverable 5.3: Neural Network–Based Activity Classification

1. Objective

The objective of this deliverable is to design, implement, and evaluate a deep learning–based classifier for elderly activity recognition using wearable sensor data. A fully connected deep neural network (FC-DNN) is employed as a baseline neural model to classify multiple daily activities and fall events using raw accelerometer signals from the MobiFall dataset.

2- Dataset Description

Dataset Name

MobiFall Dataset v2.0

Dataset Source

- Downloaded from Kaggle
  Link: **https://www.kaggle.com/datasets/kmknation/mobifall-dataset-v20**

Domain

Human Activity Recognition using Motion Sensor Data

Data Characteristics

- **Type:** Time-series sensor data
- **Sampling:** Continuous sensor readings during activities
- **Selected Subject:** sub10

Type of Sensors

This dataset uses **smartphone sensors**:

- **Accelerometer**
- **Gyroscope**

Both record motion in **x, y, z axes**.

Collected Variables (Columns)

Typical file format contains:

Column	Description
timestamp	Time of recorded event
x	Acceleration along x-axis
y	Acceleration along y-axis
z	Acceleration along z-axis

Each `.txt` file contains thousands of rows → one time-series sample.

Activities (Classes Used)

6 classes are selected:

Normal Activities (ADL):

1. **Walking**
2. **Sitting**
3. **Standing**

Fall Activities:

4. **Fall Forward**
5. **Fall Backward**

6. **Fall Sideways**

This makes a **multiclass classification problem**.

Dataset Size

- **Total Samples:** 355,313 rows
- **Features (raw):** accX, accY, accZ + timestamp
- **Target Variable:** Activity label (6 classes)

3- Preprocessing Steps

Removal of Metadata:

Header information and comments were ignored, and only numerical sensor readings were retained.

Timestamp Handling:

Sensor timestamps were converted into datetime format and used to maintain chronological order.

Sorting:

Data samples were sorted based on timestamps to preserve temporal consistency.

Missing Value Handling:

Missing values were handled using forward filling to maintain continuity in time-series data.

Duplicate Removal:

Duplicate rows were removed to avoid redundancy and bias in training.

Label Encoding:

Activity labels were converted from categorical text format to numeric form using label encoding for compatibility with neural networks.

Feature Scaling:

Standardization was applied to accelerometer features to improve neural network convergence and stability.

4. Feature Engineering

Raw accelerometer signals along the X, Y, and Z axes were directly used as input features. No handcrafted statistical features were extracted. This approach allows the neural network to learn representations directly from sensor data, serving as a baseline deep learning model.

5. Neural Network Architecture

A **fully connected deep neural network (FC-DNN)** was implemented with the following structure:

- Input layer with 3 features (accelerometer X, Y, Z)
- Three hidden dense layers with ReLU activation
- Dropout layers for regularization
- Output layer with Softmax activation for multi-class classification

The model was trained using:

- **Optimizer:** Adam
- **Loss function:** Categorical Cross-Entropy
- **Training epochs:** 30
- **Batch size:** 32

6. Results and Performance Analysis

Overall Performance

- **Accuracy:** 90.05%
- **Macro F1-score:** 0.73

The high accuracy indicates strong overall performance, while the lower macro F1-score reflects class imbalance and varying difficulty across activities.

Class-Wise Performance

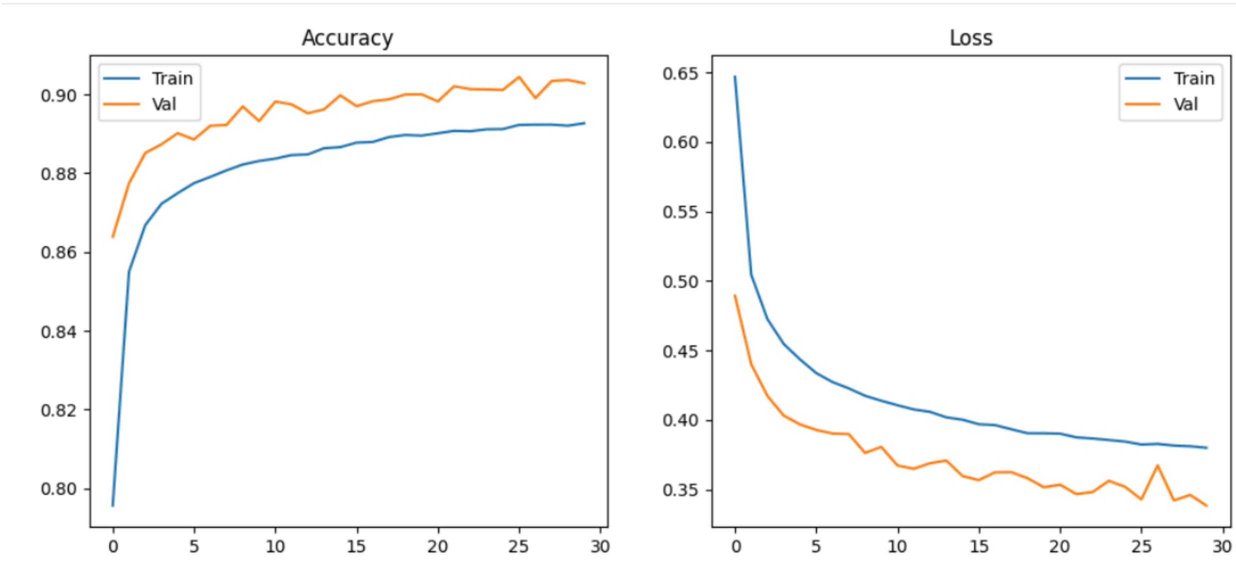
- **Standing and Walking** achieved very high recall due to consistent and repetitive motion patterns.

- **Sitting** showed moderate confusion with Standing due to similar low-movement characteristics.

- **Fall activities** exhibited lower recall as different fall postures share similar sensor patterns and occur less frequently in the dataset

```
Accuracy: 0.9005108143478322
Macro F1: 0.7259105407206049

Classification Report:

                    precision    recall  f1-score   support

Back_Sitting_Chair       0.97      0.53      0.69      2904
Fall_Forward_Lying       0.75      0.46      0.57      2889
    Sideward_Lying       0.93      0.42      0.58      2908
           Sitting       0.90      0.49      0.63      3493
          Standing       0.89      1.00      0.94     29187
           Walking       0.92      0.98      0.95     29682

          accuracy                           0.90     71063
         macro avg       0.89      0.65      0.73     71063
      weighted avg       0.90      0.90      0.89     71063
```

Graphical Representation



Conclusion

This deliverable demonstrates the application of a fully connected deep neural network for multi-class activity recognition using wearable sensor data. The model achieves high overall accuracy and effectively separates fall and non-fall activities. However, performance on fall classification can be further improved using sequence-based models that capture temporal dependencies.