Capture-24 Human Activity Recognition

Project Summary

This project develops a deep learning pipeline to classify physical activities from the **Capture-24 dataset**. It forms part of the MOP Capstone – Health Behaviour Analysis (AI+IoT stream), contributing to **SDG 3: Good Health and Wellbeing** by demonstrating how wearable sensor data can support health monitoring.

The workflow included preprocessing smartphone accelerometer signals, segmenting them into fixed windows, encoding activity labels, and training a **CNN–BiLSTM hybrid model**. The final system outputs predicted activity labels with confidence scores, supported by a deployment-ready **Streamlit demo application**.

Pipeline Overview

Data Preprocessing

- **Signal Cleaning:** Removed invalid rows, corrected stray characters, and converted values to numeric format.
- **Segmentation:** Applied overlapping sliding windows (200 timesteps per window) to preserve temporal dynamics.
- **Normalisation:** Standardized sensor channels (x, y, z) to zero mean and unit variance.
- **Label Encoding:** Converted activity annotations (walking, jogging, sitting, standing, climbing stairs) into integers for model training.

Final Input Shapes:

- X_seq: (N, 200, 3) accelerometer windows.
- y: one-hot encoded activity labels.

Model Architecture

- **CNN Layers:** Extracted local motion features from accelerometer signals.
- **BiLSTM Layers:** Captured sequential dependencies across timesteps.
- **Dense Fusion:** Fully-connected layers integrated learned features.
- **Output:** Softmax layer for multi-class activity classification.
- **Loss Function:** Categorical Crossentropy.
- **Metrics:** Accuracy, Precision, Recall, Macro/Weighted F1.

Training Details

- **Split:** 70/15/15 train/validation/test.
- **Regularisation:** Dropout, batch normalization.
- **Callbacks:** Early stopping and model checkpointing.
- **Visualisation:** Training/validation accuracy and loss plots.
- **Sanity Checks:** Verified input shapes, ensured no NaNs in processed data.

Key Insights

- **Performance:** High accuracy on well-represented activities (e.g., walking, jogging); slightly lower for overlapping classes (e.g., sitting vs. standing).
- **Confusion Matrix:** Highlighted class-specific strengths and misclassifications.
- **Confidence Analysis:** Correct predictions showed higher probability scores than misclassifications.
- **Calibration:** Reliability diagrams showed overconfidence, improved with temperature scaling.

Contributors

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Recommendations

- Apply augmentation to balance under-represented activities.
- Test Transformer-based sequential models for richer temporal understanding.
- Incorporate additional public datasets (e.g., UCI HAR, SHL) to strengthen generalisation.
- Deploy on mobile devices for **real-time activity recognition** to support digital health and behaviour monitoring.