**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.