CS256 - Topics in AI - Spring 2025
Final Project Report

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Objective: To develop, evaluate, and enhance machine learning models for human activity recognition using the MMASH dataset, focusing on sensor-based time-series classification and user-level generalization.

Dataset: [Multilevel Monitoring of Activity and Sleep in Healthy People (MMASH)]

Code Repository: [MMash-data-exploration]

Process steps involved:

1. Dataset Preprocessing:
   a. Handled missing values using linear interpolation.
   b. Applied noise reduction using a Butterworth low-pass filter.
   c. Normalized sensor values using z-score normalization.
   d. Segmented time-series into fixed-size 1-second overlapping windows for modeling.

2. Feature Engineering:
   a. Time-domain features: mean, std, min, max, peak-to-peak, skewness, kurtosis, and signal magnitude area (SMA).
   b. Frequency-domain features: FFT-based dominant frequency, energy, and spectral.

3. Model Development:
   a. Baseline models: Decision Tree, K-NN, Naive Bayes.
   b. Advanced models: Random Forest, SVM, CNN, and LSTM.
   c. CNN/LSTM models trained on raw sensor segments (shape (50, 3)), using one-hot encoded labels.
   d. Performed transfer learning by loading a public HAR CNN model (model.h5) from GitHub.

4. Evaluation:
   a. Used both k-fold cross-validation (k=5) and Leave-One-Subject-Out (LOSO).
   b. Reported metrics: accuracy, precision, recall, and F1-score.
   c. Confusion matrices were plotted to visualize class-wise performance.

5. Outcomes:
    a. Best accuracy (~56%) achieved using Random Forest and CNNs.
    b. LSTM and CNN models showed strong generalization when combined with LOSO.
    c. Demonstrated architecture-based transfer learning using the HAR CNN design on a different dataset (MMASH)

6. Future Scope:
    a. Multimodal Integration: Incorporate other MMASH modalities such as heart rate variability, stress levels, and questionnaire data to improve context-aware classification.
    b. Sequence Models: Explore advanced temporal architectures like Bi-LSTMs, Temporal Convolutional Networks (TCNs), or Transformer-based models for richer time dependencies.

Learning outcomes:

This project gave me hands-on experience in working with real-world time-series sensor data, from preprocessing to deploying deep learning models. I learned how to handle missing values, apply signal filtering, and extract both time- and frequency-domain features for meaningful classification.

I particularly enjoyed exploring deep learning models like CNNs and LSTMs, and understanding how their architectures affect performance on sequential data. Implementing LOSO cross-validation taught me how to evaluate models for personalized scenarios, and experimenting with transfer learning using an existing HAR model helped me appreciate the challenges and benefits of reusing model architectures.

Overall, I gained practical skills in signal processing, model evaluation, and the end-to-end machine learning pipeline — all grounded in a real human activity recognition problem.