HUMAN ACTIVITY RECOGNITION USING MMASH

A Project Report Presented to

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In Partial Fulfillment for the Class

Spring 2025: CS 256

May, 2025

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I. Project Objective

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.

II. Dataset Overview

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

Multilevel Monitoring of Activity and Sleep in Healthy people (MMASH) dataset provides 24 hours of continuous beat-to-beat heart data, triaxial accelerometer data, sleep quality, physical activity and psychological characteristics (i.e., anxiety status, stress events and emotions) for 22 healthy participants. Moreover, saliva bio-markers (i.e.cortisol and melatonin) and activity log were also provided in this dataset. The MMASH dataset will enable researchers to test the correlations between physical activity, sleep quality, and psychological characteristics.

For this implementation the primary focus was on triaxial accelerometer data (Axis1, Axis2, Axis3), Steps, HR, and posture data for activity recognition.

III. Technical Approach/Methodology

Code Repository: MMash-data-exploration

- Dataset Preprocessing:
    a. Handled missing values using linear interpolation.
    b. The time format was different in two of the primary data sources. So they were synchronized in a standard format.
    c. Applied noise reduction using a Butterworth low-pass filter.
    d. Normalized sensor values using z-score normalization.
    e. Segmented time-series into fixed-size 1-second overlapping windows for modeling (50, 3).

- 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.

c. Features selected:

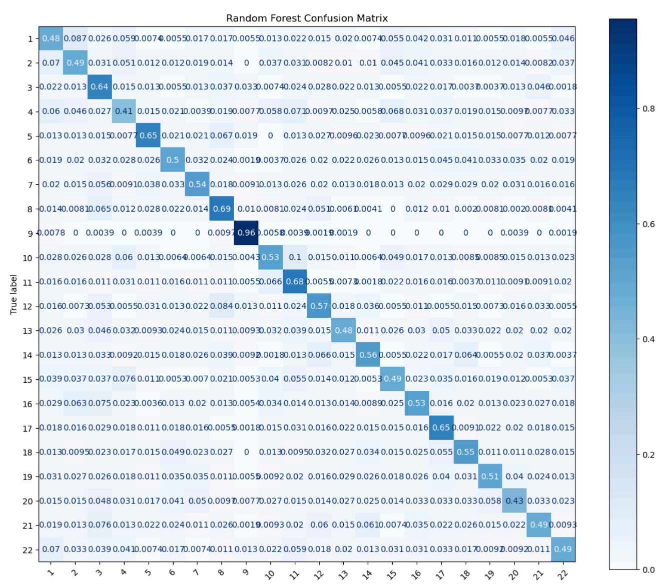
```
Original shape: (58475, 33)
Selected shape: (58475, 17)
Selected feature indices: [ 0  2  3  7  8  9 10 11 15 16 18 19 26 28 29 31 32]
Number of features selected: 17
```

- 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.
    e.

- 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.

```
📊 Final Results (averaged over folds):
Accuracy:  0.5679
F1 Score:  0.5720
Precision: 0.6170
Recall:    0.5679
```

    c. Confusion matrices were plotted to visualize class-wise performance.



- 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)

IV. CONCLUSION

This project successfully demonstrated how time-series deep learning models can be applied to sensor data for activity recognition. Using both engineered features and raw data inputs, it was demonstrated that CNNs and LSTMs generalize well across subjects. Through LOSO and transfer learning via architectural reuse, the project built a strong foundation for personalized activity models.

V. FUTURE SCOPE

- Multimodal Integration: Incorporate other MMASH modalities such as heart rate variability, stress levels, and questionnaire data to improve context-aware classification.

- Sequence Models: Explore advanced temporal architectures like Bi-LSTMs, Temporal Convolutional Networks (TCNs), or Transformer-based models for richer time dependencies.

VI. LEARNING OUTCOME

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.