Sleep Stage Classification from Wearable Sensor Data: Toward Transparent and Accessible Health AI

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Introduction

Context & Motivation:

- **Essential Role of Sleep:** Supports cognitive function, physical health, and overall well-being
- **Clinical Limitations:** Polysomnography is accurate but expensive and inconvenient (labor-intensive, clinical setting)
- **Wearable Potential:** Smartwatches and non-invasive sensors offer continuous, real-world data

Goals & Objectives:

- **Develop Explainable Machine Learning Models:** Classify sleep stages from wearable signals with known algorithm and transparent data use
- **Improvable Accessibility:** Provide a cost-effective, user-friendly approach to personalized health insights through an open-source platform

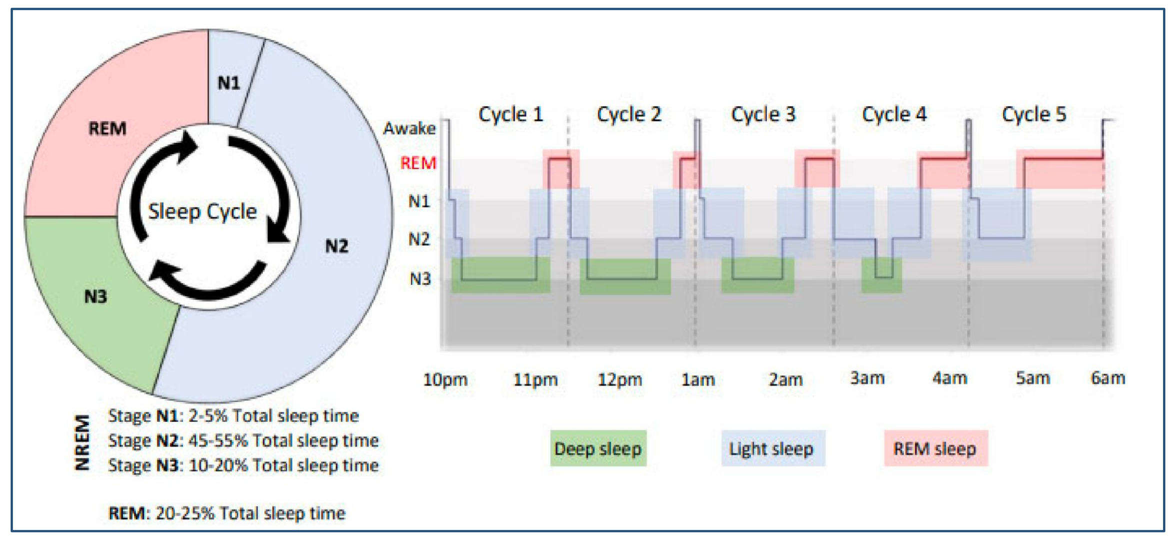
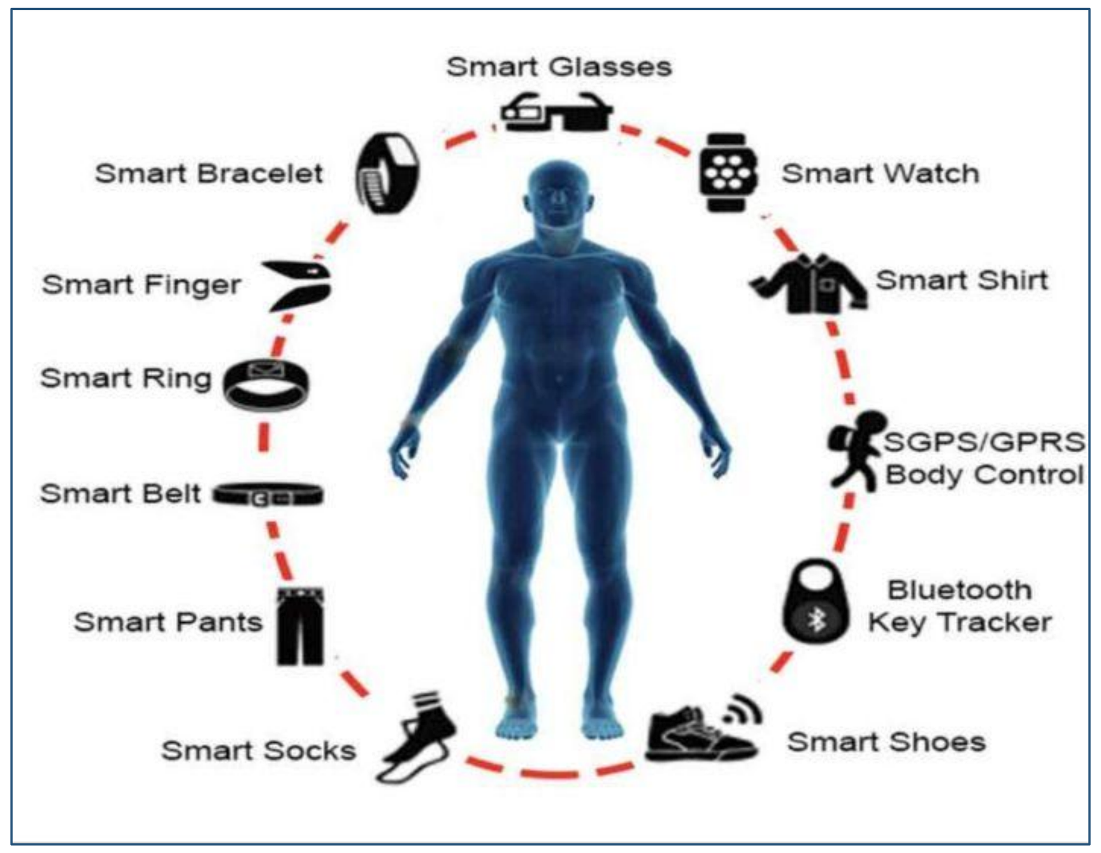


Figure 1: Hypnogram Depicting Sleep Stage Distribution Across Cycles [1]



BORACLE:

- **Boracle Platform** [4]**:** This project contributes to Boracle, an open-source cyber-physical system for collecting, standardizing, and analyzing health data from wearables.
- **Transparent Health AI:** Aligned with Boracle's mission to make ML-driven health insights more accessible and understandable by enabling algorithm transparency and user control.

Methodology

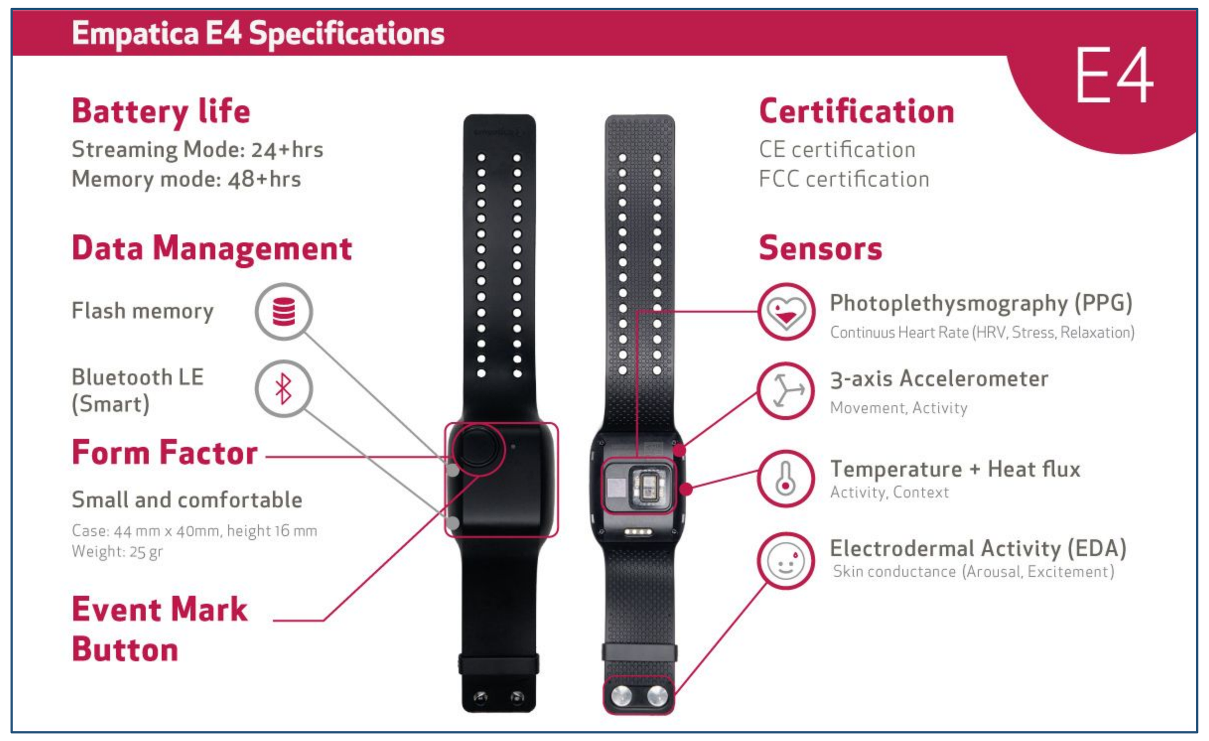


Figure 2: Empatica E4 Wristband with Core Specifications [2]

Dataset Overview:

- **DREAMT:** Dataset for Real-time sleep stage EstimAtion using Multisensor wearable Technology [3]
  - **100 individuals** recruited from Duke University Health System Sleep Disorder Lab
  - **Wearable (Empatica E4) signals:**
    - Raw: Blood Volume Pulse (BVP), Accelerometry (ACC_X,Y,Z), Electrodermal Activity (EDA), Skin Temperature (TEMP)
    - Derived: Heart Rate (HR), Inter-Beat Interval (IBI)
    - Sleep Stage Labels: Technician-annotated (PSG) every 30 seconds (W, N1, N2, N3, R)
- Chosen for its high-accuracy, sensor availability and signal collection capability

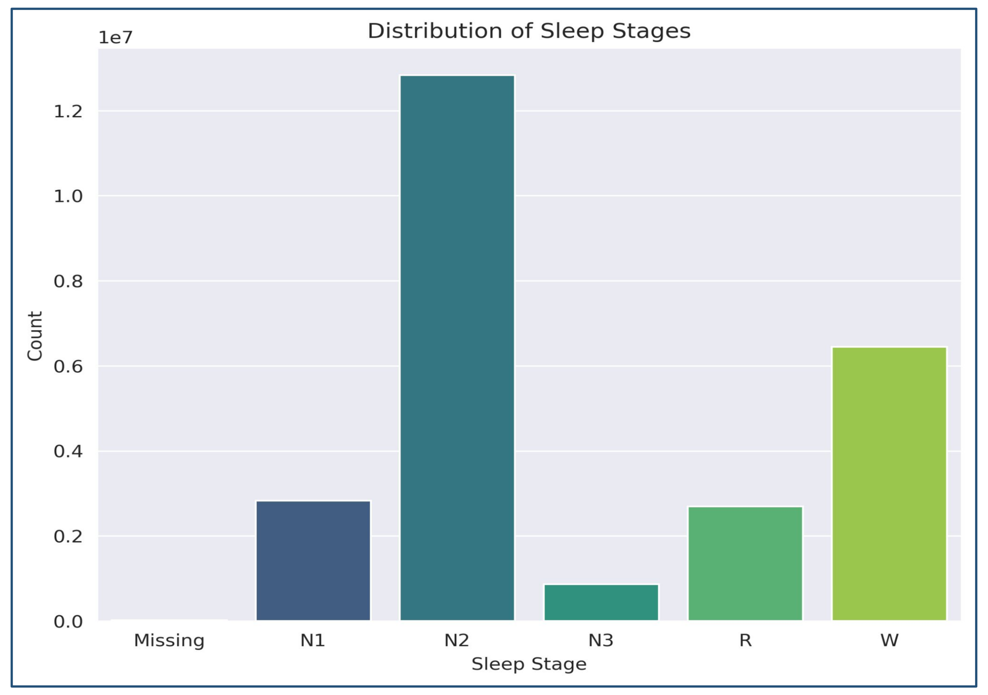


Figure 3: Distribution of Sleep Stage Frequency

Exploratory Data Analysis (EDA) Insights:

- Sufficient Data Per Participant: ~7 hours of data/participant
- Natural Class Imbalance: N2 is the most frequent stage, N3 is underrepresented, potentially impacting model performance

Data Preprocessing:

- **Filter** out preparation (P) stages
- **Raw signals** collected at 64 HZ:
  - Downsample to 10 Hz for full model
  - Downsample to 1 Hz for reduced model
- 4th-order **Butterworth low-pass filter** to BVP, ACC, EDA, and TEMP **to remove high-frequency noise**
- **Majority voting** with smoothing over downsampled windows to **maintain sleep stage transitions**

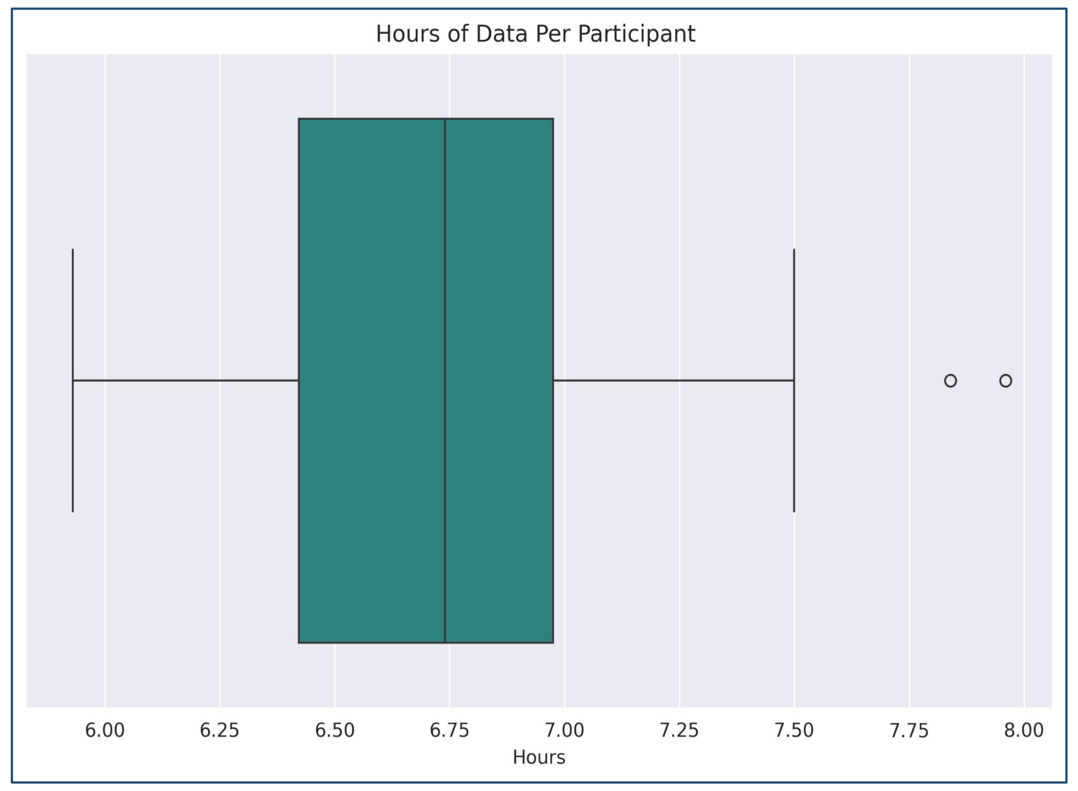


Figure 4: Hours of Data Per Participant

Neural Network Development & Training:

- **Neural Network Architectures**
  - Long-Short Term Memory (LSTM)
  - Convolutional Neural Network (CNN)
- **Training Setup:**
  - Train-Test Split of Data: 70% train, 15% validation, 15% test
  - Class Imbalance Mitigation
    - Focal Loss
    - Class weighting
  - **Full-Feature Models:**
    - BVP, ACC_X,Y,Z, EDA, TEMP, HR, IBI
  - **Reduced-Feature Models:**
    - HR, IBI, ACC_X,Y,Z

Results

Full-Feature Model:

- LSTM: Sequences of 10 seconds at 10 Hz
- CNN:Sequences of 10 seconds at 10 Hz

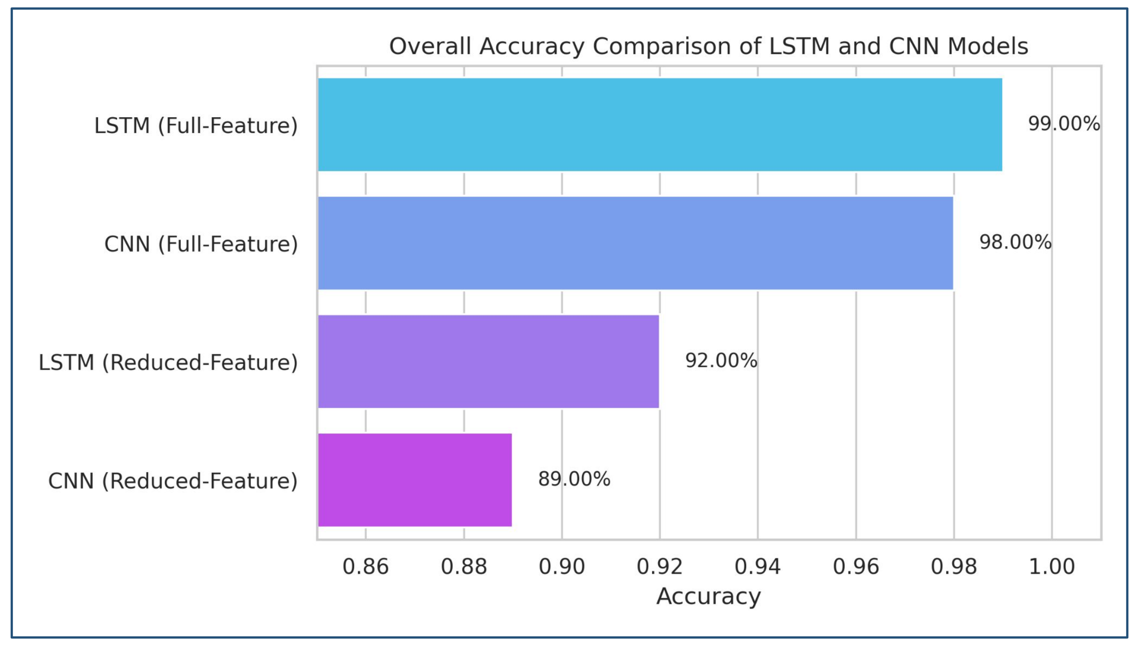


Figure 4: Overall Accuracy Comparison of LSTM & CNN

Reduced-Feature Model:

- LSTM: Sequences of 30 seconds at 1 Hz
- CNN: Sequences of 30 seconds at 1 Hz

	Precision	Recall	F1-Score
Wake	0.99	0.99	0.99
N1	0.98	0.99	0.98
N2	1.00	1.00	1.00
N3	0.90	0.96	0.93
REM	1.00	1.00	1.00

	Precision	Recall	F1-Score
Wake	0.99	0.93	0.96
N1	0.88	0.89	0.88
N2	0.93	0.93	0.93
N3	0.59	0.84	0.70
REM	0.95	0.91	0.93

Table 1, 2: Classification Report of LSTM; Full-Feature (left), Reduced Feature (right)

	Precision	Recall	F1-Score
Wake	0.99	0.98	0.98
N1	0.91	0.93	0.92
N2	0.97	0.98	0.98
N3	0.72	0.83	0.77
REM	0.96	0.96	0.96

	Precision	Recall	F1-Score
Wake	0.96	0.91	0.94
N1	0.83	0.87	0.85
N2	0.91	0.93	0.92
N3	0.75	0.81	0.78
REM	0.94	0.92	0.93

Table 3, 4: Classification Report of CNN; Full-Feature (left), Reduced Feature (right)

Conclusion & Future Work

- Our methodology effectively classifies sleep stages using smartwatch sensor data, achieving high classification performance with few, accessible features

Future Work:

- Explore domain adaptation techniques to improve robustness across different wearable devices
- Deployment of this model to the Boracle Platform for use with user wearable devices

References

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[3] K. Wang, J. Yang, A. Shetty, and J. Dunn, "DREAMT: Dataset for Real-time sleep stage EstimAtion using Multisensor wearable Technology," Physionet.org, Feb. 05, 2025. https://physionet.org/content/dreamt/2.0.0/ (accessed Mar. 26, 2025).
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