Automated Sleep Stage Classification: A Comparative Analysis of Machine Learning and Deep Learning on EEG Signals

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Background

- Sleep stage classification is crucial for diagnosis of sleep disorders (insomnia, sleep apnea).
- Polysomnography (PSG) records EEG, EOG, EMG; EEG is critical for brain activity.
- Manual sleep scoring by experts is time-consuming, expensive, and prone to human error.
- Automation using EEG can improve efficiency and reliability.

Significance in BCI

- BCIs leverage EEG signals to enable brain-signal-driven control and diagnostics.
- Automated sleep scoring fits in BCI pipeline for objective, scalable assessment.
- Reduces reliance on expert intervention and speeds up clinical workflows.

Overview of Base Research

Santaji & Desai (2020) [1]

- Proposed manual feature extraction from single-channel EEG for sleep stage classification.
- Used band decomposition (Delta, Theta, etc.) and feature extraction (mean, entropy, PSD, energy).
- Compared Decision Tree, SVM, Random Forest; RF achieved 97.8% on their dataset.

Project Objectives

- Replicate the manual feature pipeline from the base paper [1] using a public dataset (60 patients).
- Extend methodology by implementing XGBoost, MLP, and 1D-CNN on the same dataset.
- Compare performance of manual feature-based ML versus end-to-end deep learning.

Preprocessing

- Dataset: PhysioNet Sleep-EDF Expanded [2, 3], 60 subjects, EEG, expert sleep stage labels.
- Selected single EEG channel (Fpz-Cz or Pz-Oz), segmented into 10-second epochs.
- Filtering (0.1–15 Hz), standardization, mapped epochs to five classes.
- Dropped unscored/movement epochs.

Analytical Approach

Path A: Manual Feature Engineering

- Decomposed each epoch into 4 frequency bands.
- Extracted 4 features/band, 16 total features/epoch.
- Models: Decision Tree, SVM, Random Forest, XGBoost, MLP.

Path B: End-to-End Deep Learning

- Used standardized, raw filtered signals as direct input (1000 points/epoch).
- Model: 1D-CNN (2 conv blocks, pooling, dropout, dense layers).
- Model learns discriminative patterns without manual features.

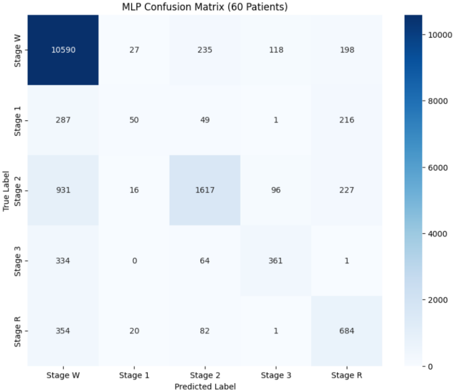
Comparative Results

Table: Model performance on the 60-patient test set.

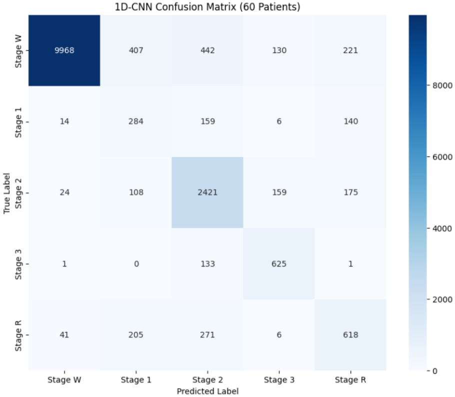
Model	Feature Type	Accuracy	Macro F1
Decision Tree	Manual (16 Features)	69.00%	0.44
SVM (Balanced)	Manual (16 Features)	62.00%	0.48
Random Forest	Manual (16 Features)	64.00%	0.50
XGBoost	Manual (16 Features)	77.00%	0.56
MLP	Manual (16 Features)	80.00%	0.56
1D-CNN	**End-to-End (Raw Signal)**	**84.00%**	**0.67**

Visual Comparison: MLP vs. CNN

MLP (Features)



1D-CNN (Raw Signal)



- MLP ignored rare classes (Stage 1 recall only 8%); CNN was more balanced (Stage 1 recall 51%, Stage 3 recall 88%).

Key Findings

- Deep learning (1D-CNN) clearly surpasses best manual models (MLP/XGBoost) in both accuracy and balance.
- Fully automatic feature learning is more flexible than selecting fixed statistical features.
- Accuracy alone can be misleading for imbalanced datasets.

Challenges and Limitations

- Severe class imbalance: most epochs are Wake or N2, rare stages underrepresented.
- Only single EEG channel used; would be more powerful with EOG/EMG.
- Risk of overfitting deep models on small datasets.
- Manual annotation still required for ground truth training labels.

Conclusion Future Work

- Project confirmed: End-to-end deep learning is superior for EEG sleep-stage classification (on this dataset/task).
- Next steps: use larger/multimodal datasets, introduce hybrid CNN-LSTM models, tune hyperparameters, and test on real-time BCI applications.

References I

- S. Santaji and V. Desai, "Analysis of EEG Signal to Classify Sleep Stages Using Machine Learning," *Sleep and Vigilance*, vol. 4, pp. 145–152, 2020.
- B. Kemp et al., "Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG," *IEEE TBE*, vol. 47, no. 9, pp. 1185–1194, 2000.
- A. L. Goldberger et al., "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

Thank You

Questions?