Deep Neural Model for Automated Sleep Staging System using Single Channel EEG Signal

Under the Supervision of

Dr. Santosh Kumar Satapathy
Assistant Professor, ICT Department

Presented By

Tanmay Rathod – 23MAI007

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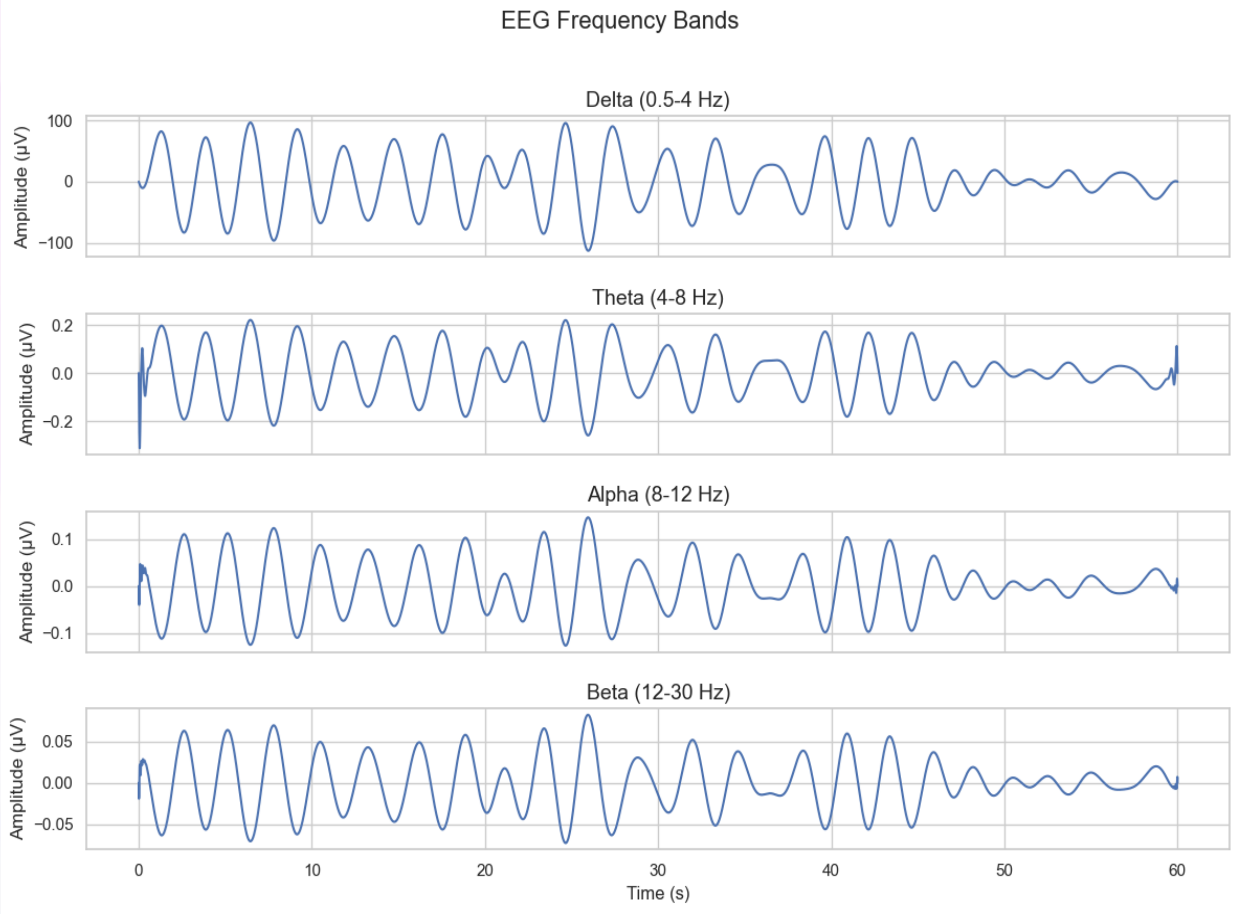
Abstract

- Sleep stage classification has been traditionally manual and labor-intensive.
- Recent advancements in deep learning provide promising pathways to enhance automation.
- Utilizing EEG data from the Sleep Physionet dataset, we explore machine learning models and propose a transition to deep learning techniques.
- Focus on model evaluation: current machine learning models vs. potential deep learning architectures like CNN-Transformer-ConvLSTM.

Introduction

Band	Frequency (Hz)
Delta	0.5 – 4
Theta	4 – 8
Alpha	8 - 12
Beta	12 - 30



Introduction

Sleep Stage	Frequency Range (Hz)	Description
Wake	12 - 30 (Beta)	Active, alert state; engaged in cognitive activities.
N1 (Light Sleep)	4 - 8 (Theta)	Transition stage between wakefulness and sleep; easy to wake up.
N2 (Moderate Sleep)	4 - 6 (Theta)	Sleep spindles and K-complexes; more difficult to awaken.
N3 (Deep Sleep)	0.5 - 4 (Delta)	Slow-wave sleep; very difficult to wake; restorative processes occur.
REM (Rapid Eye Movement)	4 - 6 (Theta)	Associated with dreaming; brain activity resembles wakefulness.

Problem Statement

- Manual sleep studies (e.g., PSG) are time-consuming and costly.
- Need for an automated, accurate method for real-time sleep stage classification.

- How can we leverage both traditional machine learning and emerging deep learning methodologies to enhance classification accuracy?

Motivation

- Enhanced efficiency and scalability for sleep disorder diagnosis.
- Integration potential with consumer-grade devices like wearables for sleep monitoring.
- Opportunities to improve sleep quality analysis using advanced deep learning techniques and personalized health recommendations & disease Classification .

Literature Review

Sl. No	Author/Title/Journal	Technique(s) used	Database Used	Advantages	Limitations
1.	Yan, R., Zhang, C., Spruyt, K., Wei, L., Wang, Z., Tian, L., … Cong, F. (2019). Multi-modality of polysomnography signals' fusion for automatic sleep scoring. Biomedical Signal Processing and Control, 49, 14–23. doi:10.1016/j.bspc.2018.10.001	Multi-modality PSG signals+ Automated sleep staging	Cyclic Alternating Pattern(CAP) PhysioNet Database	An automatic sleep scoring me thods by fusing four modalities of PSG signals	Stage S1 is often misclassified as wakefull ness and REM BY autom atic sleep scoring
2.	Zhou, J., Tian, Y., Wang, G., Liu, J., Wu, D., Xu, W., … Hu, Y. (2020). Automatic Sleep Stage Classification with Single Channel EEG Signal Based on Two-layer Stacked Ensemble Model. IEEE Access, 1–1. doi:10.1109/access.2020.2982434	Single-channel EEG signal+Stacked ensemble Model	Sleep-EDF Sleep-EDF Expanded	Class balancing Strategy	Only considered healthy controlled subjects Not analyze the EEG signals in detail

Literature Review

Sl. No	Author/Title/Journal	Technique(s) used	Database Used	Advantages	Limitations
3.	Shen, H., Ran, F., Xu, M., Guez, A., Li, A., & Guo, A. (2020). An Automatic Sleep Stage Classification Algorithm Using Improved Model Based Essence Features. Sensors, 20(17), 4677.doi:10.3390/s20174677	Improved model based essence fea tures + Single-channel EEG signals	ISRUC-Sleep dataset	Grid-search strategy	Misclassified Ratio was more for S2 stage
4.	Huang, W., Guo, B., Shen, Y., Tang, X., Zhang, T., Li, D., & Jiang, Z. (2019). Sleep staging algorithm based on multichannel data adding and multi feature screening. Computer Metho ds and Programs in Bio medicine,105253.doi:10.10 16 /j.cmpb.2019.105253	Multi-channel adding+ Multi-channel screening	Sleep-EDF dataset	Multi-channel sig nal superposition method use d to reduce the noise and improve the effective informa tion contained in original signals	Ineffective perfo rmance with the heterogeneous combinations of the signals.

Methodology

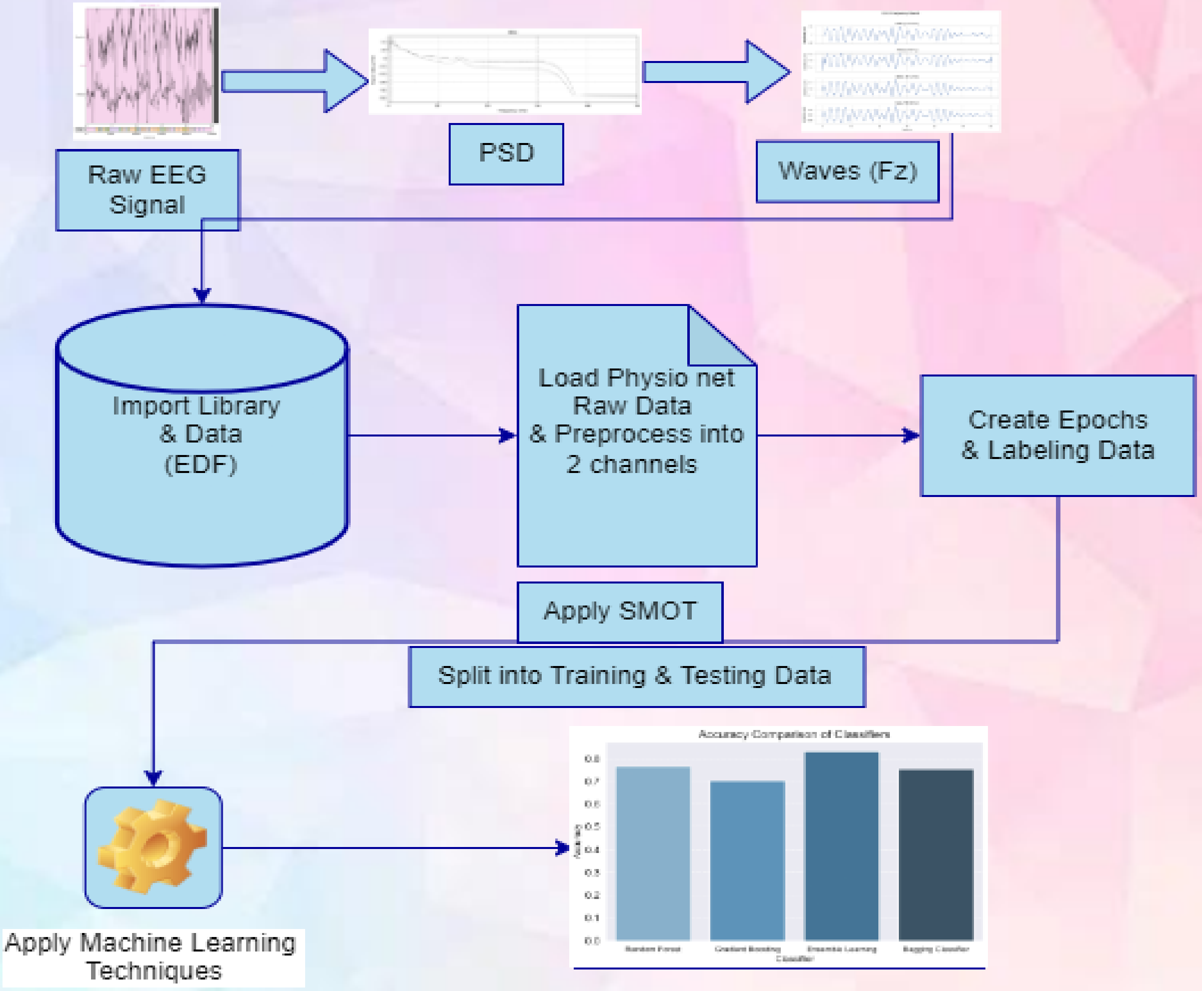


Fig. 1 : Proposed Architecture of M.L. Model

Methodology

- Data Collection
  - Dataset Source
  - Recording Format
- Data Preparation
  - File Loading
- Data Processing
  - Filtering
  - Epoch Creation
- Data Reshaping
  - Reshaping Data
  - Label Distribution
- Handling Class Imbalance
  - SMOTE (Synthetic Minority Over-sampling Technique)
- Model Training and Evaluation
  - Train-Test Split
  - Model Selection & Tuning
  - Performance Metrics & Plotting

Initial results

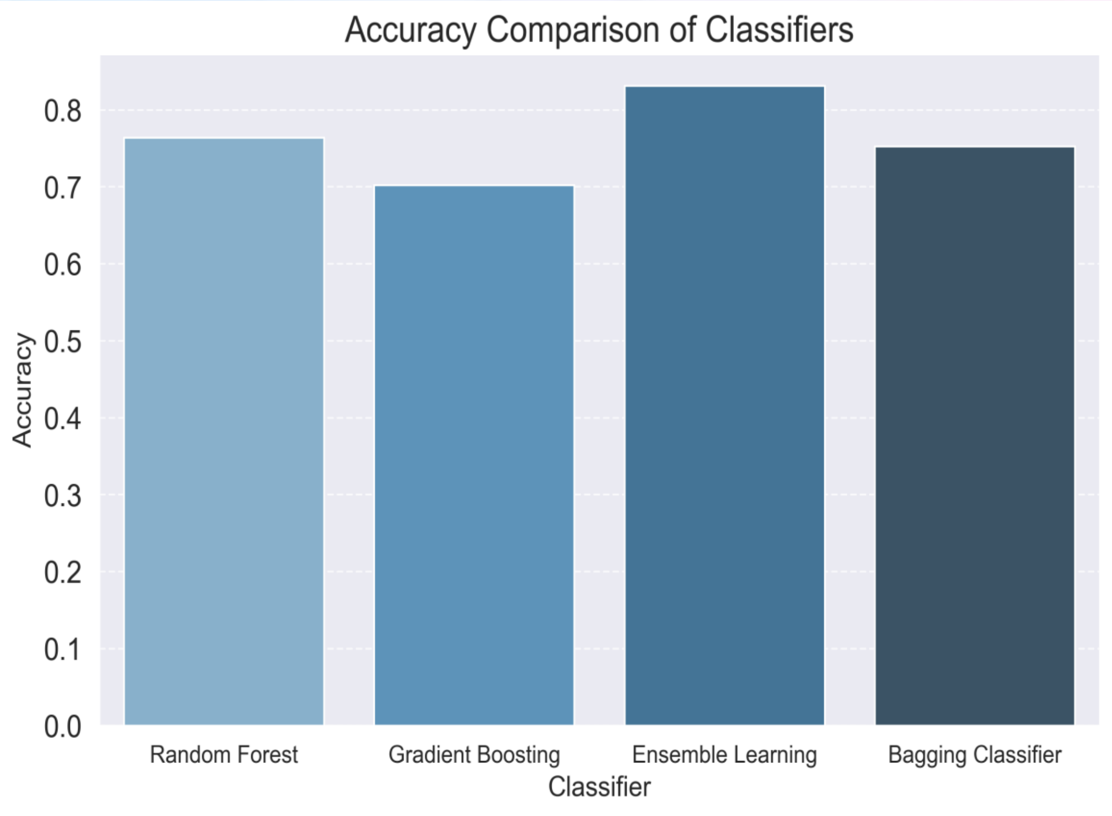


Fig. 2 : Comparison Plot 1

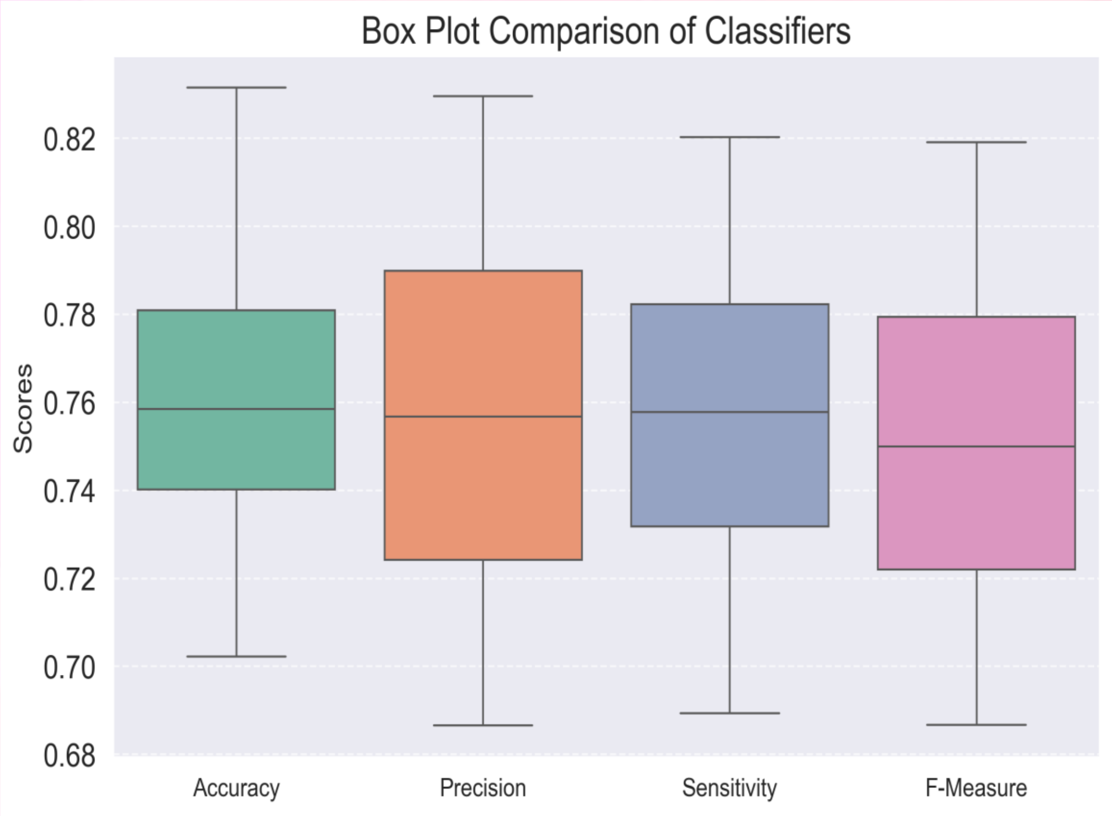


Fig. 3 : Comparison Plot 2

Future Plan

- **Deep Learning Exploration**
  - Investigate **CNN**, **LSTM**, and hybrid models to capture temporal dependencies and improve accuracy beyond existing benchmarks.
- **Scalability**
  - Test deep learning models on **larger datasets** and **real-time systems**.
- **Dataset Expansion**
  - Increase dataset to **20 additional patients** to improve model robustness and generalizability.
- **Accuracy Improvement**
  - Aim to **increase classification accuracy** by leveraging larger datasets and advanced models.

Future Plan


Research Project Timeline
October - November
Result analysis
Model training
December
Paper write-up

Conclusion

- We have faced challenges in sleep stage classification with traditional machine learning, especially in capturing EEG data complexities. To overcome these, we are transitioning to deep learning techniques, planning to develop **hybrid models that combine CNNs**, **Transformers**, and **ConvLSTM**.

Reference

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6. Ghimatgar, H., Kazemi, K., Helfroush, M. S., Pillay, K., Dereymaeker, A., Jansen, K., … Aarabi, A. (2020). Neonatal EEG sleep stage classification based on deep learning and HMM. Journal of Neural Engineering. doi:10.1088/1741-2552/ab965a

Thank You