Deep Learning-based EEG Analysis for Sleep Apnea Detection

MSDS Capstone Day 2024

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Our Team

Matthew Bonner

Addison Gambhir

Quinn Glovier

August Lamb

Ben Nikolai

Jack Van Horn
Advisor

Jianxin Xie
Sponsor

Project Premise

- Sleep apnea is a prevalent disorder that can be dangerous if left undiagnosed

- Analysis of electroencephalogram (EEG) data could provide a promising avenue for detection of sleep apnea events

- Can we use neural networks to analyze EEG data to enhance accuracy and reliability of sleep apnea detection?

What is sleep apnea?

About Sleep Apnea

- Disruption of normal breathing patterns during sleep

- Two primary variants:
  - **Obstructive Sleep Apnea (OSA):** Physical blockage of the airway
  - **Central Sleep Apnea (CSA):** Disruption of the brain's respiratory rhythm generator

- Affects ~7% of the population

- Related health complications
  - Cognitive dysfunction
  - Cardio/cerebrovascular disorders
  - Much more…

Diagnosis Process

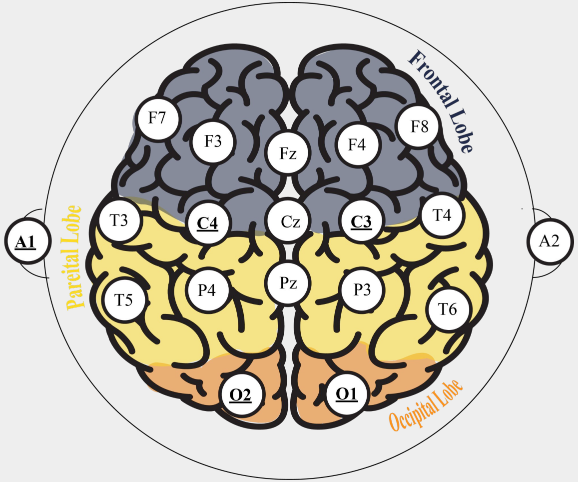
- **Polysomnography:** data collection methods used in sleep studies to illustrate the body's sleep behavior and identify abnormalities
- **Apnea event threshold:** Blood oxygen levels drop below 94% (may vary by patient baseline)
- Diagnosis severity determined by apnea event frequency
  - **Mild:** >5 desaturation events per hour
  - **Moderate:** 15-30 desaturation events per hour
  - **Severe:** >30 desaturation events per hour

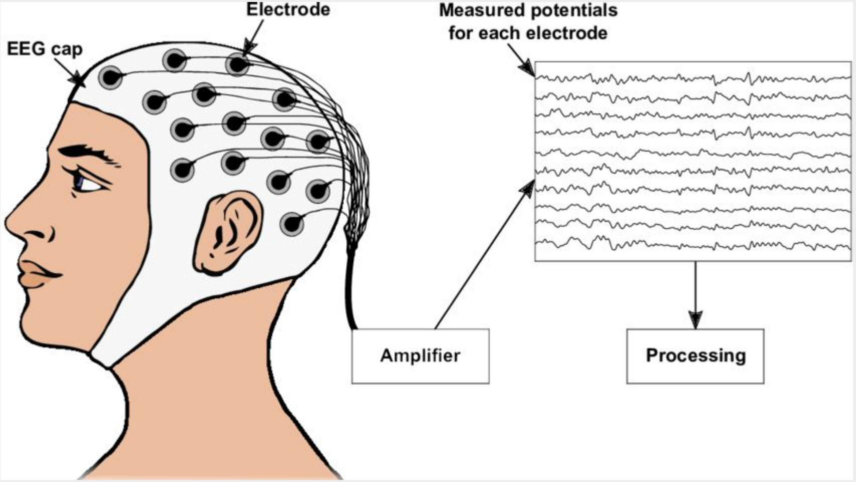
Polysomnography Data Channels:

- EEG
- ECG
- EMG
- Respiration
- Pulse Oximetry
- Blood Pressure
- and many more!

Electroencephalography (EEG)

- Non-invasive technique to record electrical activity in the brain
- Utilizes a mesh of electrodes placed along the scalp





Top: Diagram of electrode placement based on the 10-20 system. Bolded and underlined nodes correspond to the locations used in the MIT dataset.

Bottom: Example of the EEG recording process.
Credit: Nagel, Sebastian. (2019). Towards a home-use BCI: fast asynchronous control and robust non-control state detection. 10.15496/publikation-37739.

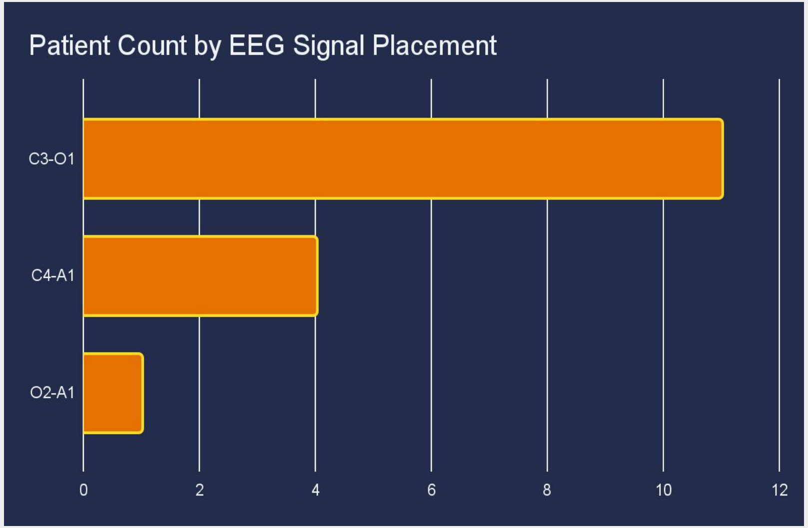
Dataset

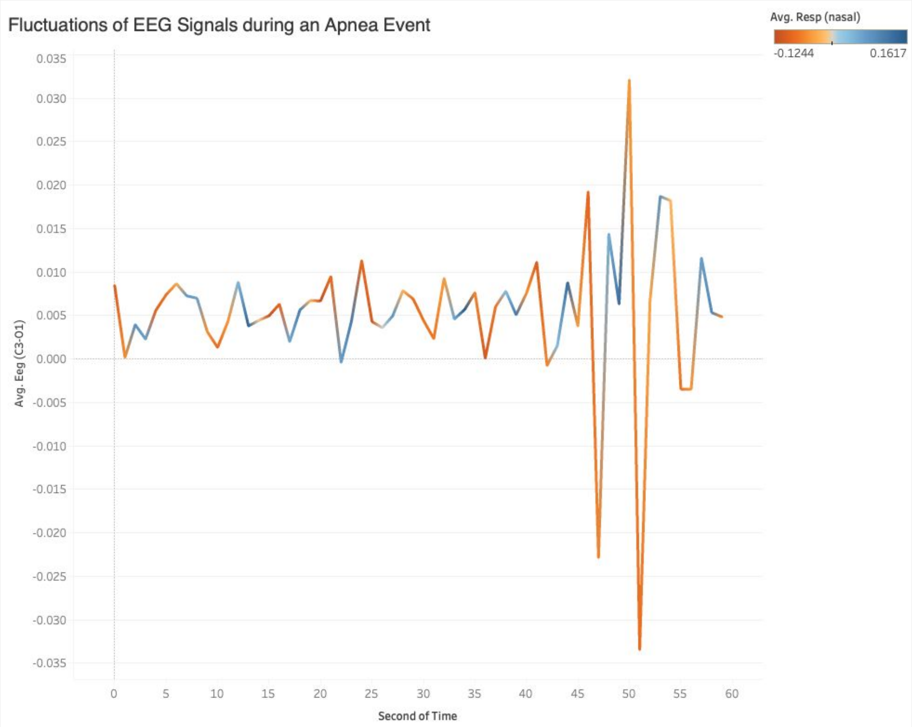
- **Source:** Massachusetts Institute of Technology/Beth Israel Hospital Sleep Laboratory Polysomnographic Dataset (1999)

- **Patient Info:** 16 subjects, male, aged 32-56

- **Database Content:** 18 recordings totaling 80 hours worth of data
  - Recordings include single-channel EEG, EKG, BP, Sp02, EOG, EMG, and a few additional respiratory signals
  - EEG probe locations used: C3-O1, C4-A1, O2-A1 (10-20 system)

Exploratory Data Analysis





Top: Bar chart indicating the number of patients with readings from each type of EEG signal used in our data
Right: Line graph displaying the trend in EEG signals during an apnea event. Data used in this graph was sampled from one minute of eeg readings from patient four during an apnea event (as labeled in the data). Color changes in the line reflect changes in the average nasal respiration by second.

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Can we identify what EEG patterns correspond to a sleep apnea event?

Methodology

- **Our Data:** 30-Second EEG time sequences labeled *Apnea* or *No Apnea*
- **Challenge:** build a model to *accurately* predict if new time sequences contain apnea events or not
- **Previous Work:** Models built with CNN-Transforms, SVMs, or LDA
    - Fails to utilize temporal information found within EEG recordings
    - While CNN's do capture temporal relationships to some extent it is difficult in tasks requiring extensive temporal understanding across longer time periods.

A closer look at Temporal Convolutional Networks (TCN)

- **Temporal Convolutional Network:** a type of deep learning model designed for capturing long-range relationships in temporal data

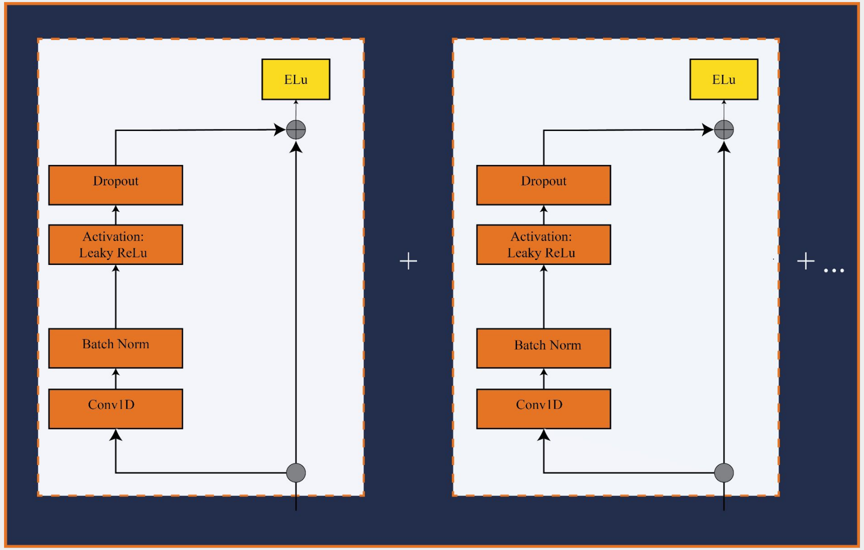
- **2 components:**
  - **Dilated Convolutions:** expands the receptive field of a convolution by skipping input values with a specified dilation rate.
    - allows the network to capture information from distant time steps
  - **Causal Convolutions:** ensures each output in a convolution only depends on past inputs
    - *not* allowing future information to influence present predictions

Related Work

Model Architecture

How our TCN works:

1. 3 convolutional layers → reduces signals to frequency-specific feature maps
2. Maps imputed into TCN
3. Softmax activation to generate probabilities



- **Temporal Convolutional Neural Network (TCN):** a chain of "Residual Blocks" with Dilated Convolutions followed by Batch Normalization, Activation and Dropout layers

Block	Layer	# Filters	Kernel Size	# Params	Output	Notes
1	Input				(T, C)	
	Conv1D	$F_1 = 50$	$k_1 = 300$	$(F_1 * k_1) + F_1$	$(T - k_1, F_1)$	Activation = ELU
	BatchNorm			$4 * F_1$		
	MaxPool1D				(T_2, F_1)	$Pool_1 = 12$ $T_2 = T - k_1 // Pool_1$
	Dropout					$p = 0.3$
2	Conv1D	$F_2 = 80$	$k_2 = 50$	$(F_2 * k_2) + F_2$	$(T_2 - k_2, F_2)$	Activation = ELU
	BatchNorm			$4 * F_2$		
	MaxPool1D				(T_3, F_2)	$Pool_2 = 4$ $T_3 = T_2 - k_2 // Pool_2$
	Dropout					$p = 0.3$
3	Conv1D	$F_3 = 50$	$k_3 = 20$	$(F_3 * k_3) + F_3$	$(T_3 - k_3, F_3)$	Activation = ELU
	BatchNorm			$4 * F_3$		
	MaxPool				(T_4, F_3)	$Pool_3 = 4$ $T_4 = T_3 - k_2 // Pool_3$
	Dropout					
	Flatten				$(T_4 * k_3, 1)$	
TCN					$(T_4 * k_3, 10)$	
4	Dense			$(10 * 2) + 2$	(2)	Activation = $softmax$

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The results...

Results

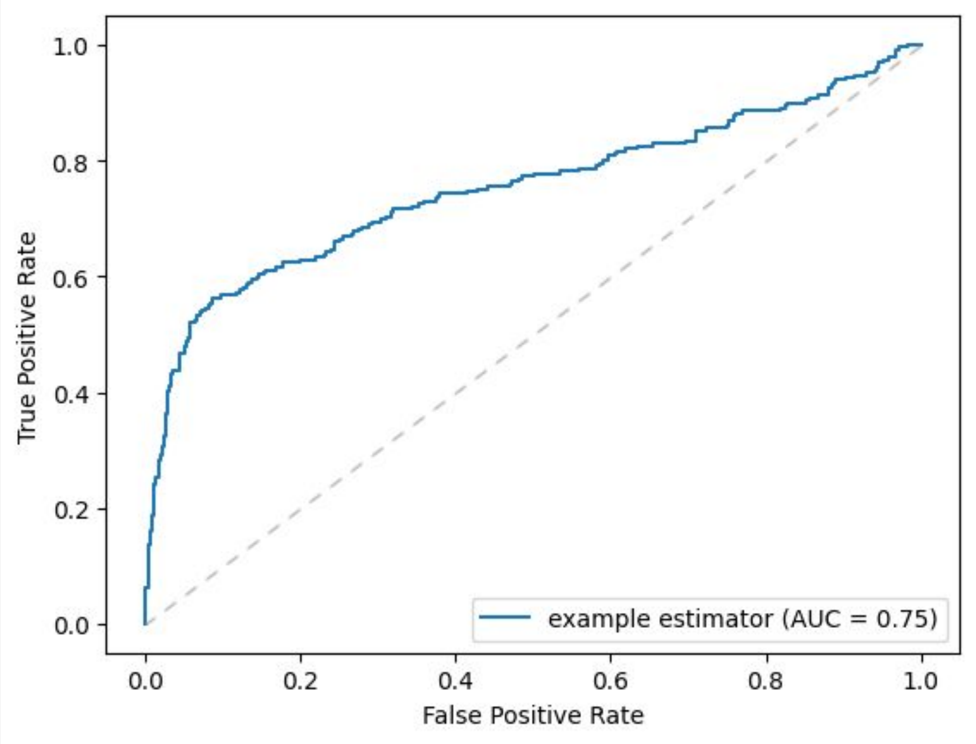
0.75

AUC

84%

Accuracy

Results



		Predicted	
		Non-Apnea	Apnea
True	Non-Apnea	903	97
	Apnea	102	127

Results Comparison

	AUC	Accuracy	Precision	Recall	F1
TCNN	0.75	0.84	0.59	0.55	0.57
LDA		0.82	0.66	0.90	0.77
SVM		0.94	0.64	0.94	0.76
k-NN		0.92	0.65	0.92	0.76
ANN		0.94	0.64	0.94	0.76
CNN	0.80	0.70	0.34	0.82	0.48

*SVM, LDA, k-NN and ANN results come from: Indrawati et al. 2022
*CNN results come from: Barnes et al. 2016

So what?

Implications

- More progress needed to transition neural networks from a research to a diagnostic tool
- Best for analyzing nuances in readings with recognizable EEG patterns
  - Struggles to identify sleep apnea patterns when presented with new data and different manifestations of sleep apnea in EEG readings
  - differences in EEG patterns include frequency of events, length of events, severity of change in EEG reading during apnea event, etc.
- Model must learn to recognize variances in apnea EEG readings before use in a diagnostic setting

Limitations

Data Challenges

- Data Age and Quality: single channel data from 1999
  - Modern, high resolution scans→ 32 to 256 channels
    - Trade-Off between resolution and simplicity, accessibility, and affordability
- Size and Variety of Information:
  - Limited patient representation → all subjects are middle-aged men
  - Sparse apneic events
  - Small sample size (especially compared to other available data)
- Binary Classification of a Time Period:
  - Apnea classifications do not indicate *where* in the time-slice the event occurs
  - Limited information on locating apnea within each time chunk

Counter Arguments

- SpO2 readings may be more practical?
  - Potential to gain greater insights with EEG
- Is this useful?
  - Cheap and accessible diagnosis tools are in high demand
- Identification vs. prediction?
  - Prediction provides an interesting potential for next steps

Future Work

- Next steps
  - Use of higher-quality, multi-channel EEG data
  - Incorporate predictive capabilities into the model
- A predictive model could alert the patient or caregiver of an upcoming apneic event
- TCN's could have greater effectiveness on non pre-segmented data, if used within the correct context

Questions

References

A. N. Indrawati, N. Nuryani, A. S. Nugroho, and T. P. Utomo, “Obstructive Sleep Apnea Detection using Frequency Analysis of Electrocardiographic RR Interval and Machine Learning Algorithms,” J Biomed Phys Eng, vol. 12, no. 6, pp. 627–636, Dec 2022

L. Barnes, K. Lee, A. Kempa-Liehr, and L. Hallum, “Detection of sleep apnea from single-channel electroencephalogram (EEG) using an explainable convolutional neural network (CNN),” PLoS ONE, vol. 17, no. 9, 2022. [Online]. Available: https://doi.org/10.1371/journal.pone.0272167