Sleep Stage Classification Using Non-Invasive Bed Sensing and Deep Learning

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MOTIVATION

- Polysomnography (PSG) is a comprehensive study of biological data consisting of numerous signals that capture changes in the body while sleeping. It is the gold standard used in sleep studies to monitor sleep.
- However, extracting PSG data requires the usage of various bed sensors while sleeping. A technician must also continuously score the data gathered. This makes the extraction process not as accessible to public and very tedious.

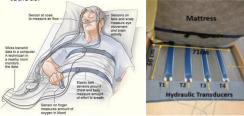


Figure 1: An illustration of a wearable sensor used in traditional PSG studies. Figure 2: The hydraulic bed sensor used to capture BCG movements.

Our motivation is to provide an **automatic**, **non-invasive** and more accessible method of classifying sleep stages by gathering data from the hydraulic bed sensor and analyzing the data via a deep learning approach.

DATA COLLECTION

- The data gathered from bed sensors and de-identified and synchronized PSG data were collected from the Boone Hospital Center (BHC) sleep center at Columbia. MO.
- The subjects monitored consisted mainly of elderly and people with sleep disorders and has a skew towards the NREM stage.

Subject	Gender / Age	WAKE(%)	REM(%)	NREM(%)
1	F / 69	21.57%	14.13%	64.3%
2	M / 66	14.95%	16.61%	68.44%
3	M / 68	33.76%	12.30%	53.94%
4	F / 66	46.98%	7.32%	45.7%
5	F / 62	29.85%	19.53%	50.63%

Table 1: Data distribution of elderly subjects with low-apnea-hypopnea index (API).

DATA PREPROCESSING

The data was preprocessed in order to consolidate four different signals (from four transducers) into one signal:

- First, a 30 second sliding window (3000 data points) calculated average amplitudes for each of the four raw signals.
- Then for each window, the 3000 filtered data points from the transducer with the maximum average amplitude was used in the consolidated single channel signal.
- Finally, a sixth order

Butterworth filter with a cutoff frequency of 0.7 and 10 Hz was implemented

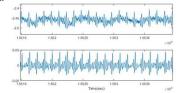


Figure 3: Plot showing the signal before filtering and after the Butterworth filter was applied

ARCHITECTURE

- Our architecture consists of 2 Convolutional Neural Network (CNN) Models attached to a Long-Short Term Memory (LSTM) Model.
- The 2 CNNs have different filter sizes to make sure that features on both the large and small scale are captured.
- The CNNs are trained on class balanced data before being connected to the LSTM. The CNN is also frozen to make sure it extracts features based on the class balanced data
- The LSTM is trained on sequential data to learn the transition rules that sleep experts use to identify the next possible sleep stages from a sequence of PSG epochs

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CONV: 50, 64, 6	CONV: 400, 64, 6
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Maxpool: 8, 8	Maxpool: 4, 4
Ļ	+
Dropout: 0.5	Dropout: 0.5
CONV: 8, 128, 1	CONV: 6, 128, 1
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CONV: 8, 128, 1	CONV: 6, 128, 1
+	+
CONV: 8, 128, 1	CONV: 6, 128, 1
Ļ	+
Maxpool: 8, 8	Maxpool: 2, 2
+	+
Dropout: 0.5	Dropout: 0.5

20- 000

Concatenate
Bi-LSTM:128/128

Sleep Stage

Figure 4: Diagram of the Architecture

RESULTS

- In this model, the CNN was pretrained on balanced data and then frozen, the LSTM was trained on sequential data, and the model was tested on sequential data
- We achieved an average test accuracy of 75%.

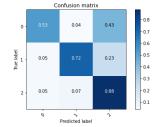


Figure 5: Confusion matrix of the results. 0 is Wake, 1 is REM, and 2 is NREM

 We also used a Leave One Subject Out (LOSO) method to evaluate our model more comprehensively. In this method, we did 5 combinations in which 4 subjects were used for training and 1 subject was used for testing.
 We achieved an average accuracy of 75.5%

Subject	Acc(%)	Wake(%)	REM(%)	NREM(%)
1	78.3	84	65	79
2	77.5	58	66	85
3	74.9	60	42	92
4	76.8	74	58	82
5	70.3	58	85	72

Table 2: Shows the Average Accuracy and Accuracy per class for each of the 5 combinations in the LOSO method

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