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Title of Thesis

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AG Machine Learning

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Contents

Abstract

Abstract text

Chapter 1

Introduction

A recent study estimated that over 900 million adults globally are affected by the common group of respiratory sleep disorders called Sleep-disordered breathing (SDB) [1], or in particular, Sleep Apnea, which clinical manifestations include sleepiness, fatigue, cardiovascular disease, and hypertension. SDB is even linked to higher cases of diabetes, stroke occurrences and increased morbidity [2, 3, 4]. Diagnosis of the disorder relies on detecting repeated respiratory events in which airflow is either reduced (hypopnea) or entirely paused (apnea) during sleep [2, 5]. These events can further be categorized into obstructive or central origin, depending on if the apnea happens due to a physical blockage of the upper airway or if caused by the brain failing to signal breathing resulting in missing breathing effort. In case the event shows features of both, it is classified as a mixed.Dividing the number of events by the total sleep time (TST) gives the Apnea-Hypopnea-Index (AHI), which indicates the severity of the disorder.

Gold standard for detecting SDB in Polysomnography (PSG) which captures physical and biological signals like heart (electrocardiogram, ECG) and brain (electroencephalogram, EGG) activity, airflow, peripheral oxygen saturation (SpO2), chest and abdominal movements, sleeping position, and blood volume changes (photoplethysmographie, PPG). This approach comes with a few downsides: Firstly, due to the vast amount of sensors and specialized equipment, setup and analysis of the full PSG is costly, requires human experts and might impact sleep quality. Secondly, looking only at a single night might have low diagnostic meaningfulness [6] and the analysis of multiple nights is needed. All this contributes to the fact that an estimated 93% of women and 82% of men with at least moderate SDB are undiagnosed [7].

In 2000, PhysioNet started interest in the topic of less complex apnea detection by holding a competition on their Apnea-ECG Dataset that only consists of labeled ECG recordings split into one-minute epochs. Although presented

models reached high performances, later studies showed poor generalizability for these models and indicated that the dataset doesn't fully cover the broad spectrum of apneic events [8]. Therefore, in the last decades, a wide range of sleep disorder datasets and apnea detection architectures were published that focused on generalizability. For instance, Olsen et al. [9] used bidirectional GRUs on ECG data to achieve a sensitivity (Se) of 68.7%, a precision (Pr) of 69.1%, and an F1-score of 66.6% on their self-defined event-level metric and an AHI-correlation of $R^2 = 0.829$. Xie et al. [10] later validated Olsens model on the SOMNIA dataset and achieved an F1-score of 70.8% using the PSG-computed hypnogram and an F1-score of 0.631 with their Multi-Task model that computed sleep stages based on ECG and respiratory effort (RE) only [11]. Also using ECG and RE, Fonseca et al. [12] achieved intraclass correlation coefficient of 0.91 across different datasets.

Using the signal on which sleep apnea is mainly defined on, Airflow, also helps to increase performance greatly. Li et al. [13] achieved an F1-score of 85.7% on classifying one-minute segments of Airflow and ECG. Later, Yook et al. [14] used Airflow and SpO2 together to achieve an F1-score of 93% on classifying 10-second segments converted into scalograms. Downsides to this approach includes that the nasal cannula, a thin tube placed under the nostrils, might be uncomfortable during sleep and hard to set up properly.

One of the more simple signals to set up and record while sleep is PPG, which can be obtained through the use of a pulse oximeter that illuminates the skin to measure changes in light absorption. These devices come in a range of forms such as wrist-worn, like most modern smart-watch already have, or finger-worn, mounted typically on the index finger, which can also calculate SpO2. Lazazzera et al. [15] used PPG and SpO2 signals to achieve a Sensitivity of 76.9% and Specificity of 73.2%, although their dataset only consisted of 96 patients without any kind of co-morbidity.With the same input signals, Wu et al. [16] trained a trasnformer-based model on a dataset containing patients with co-morbidities and were able to validate their performance on PPG and SpO2 signals measured by a Smart Ring resulting in an F1-score of 64.9%.

In this work, we present an event-level apnea detection model that relies solely on signals obtained by easy to use recording hardware, namely PPG and SpO2, and show the importance of correct sleep stage identification.

Chapter 2

Methods

2.1 Dataset

The data we used in this work came from the Multi-Ethnic Study of Atherosclerosis (MESA) [17], a large-scale sleep study aimed to investigate correlations between sleep quality, cardiovescular health, SDB, and other factors across different ethnic groups. Over 6,800 men and women from six different US communities were approached in the initial examination. For the final sleep exam ten years later, 288 participants were ineligible[1], roughly 2,700 were not contacted, and roughly 1,500 refused to participate. From the 2,261 participants undergoing the sleep exam, 2,060 had full-night PSG recordings, 2,156 had actigraphy data, and 2,240 completed a sleep questionnaire.

For the sleep event scoring, we used the automatic Somnolyzer system TODO: cite, which scored events based on the recommended criteria from the American Academy of Sleep Medicine (AASM) TODO: cite: apnea events were defined as a 90% or greater reduction in airflow for at least 10 seconds, while hypopnea events were defined as a 30% or greater reduction in airflow for at least 10 seconds, with either a $\geq 3\%$ oxygen desaturation or an associated arousal. TODO: obstructive vs central vs mixed?

As SDB events manifest differently accross sleep stages, we used a modified version of the hypnogram prediction model from Bakker et al. [18], that used only PPG signals, ensuring that our model works doesn't depend on signals outside of the finger-worn PPG sensor setup. Comparing the predicted hypnogram[2] with the Somnolyzer hypnogram, we achieved a Cohen's Kappa of 0.55,

[1] due to undergoing apnea treatment, living to far away, or other reasons

[2] Bakker's model combined N1 and N2 stages into one, resulting in four stages: Wake, N1/N2, N3, and REM. For calculating the Kappa, Somnolyzer scorings were adjusted to the same format

Fold	N	Age (years)	BMI (kg/m^2)	Sex (N male)	TST (h)
1	470	70 ± 9 **[55, 90]**	29 ± 5 **[19, 48]**	228 (48.5%)	6.2 ± 1.36 **[1.7, 10]**
2	470	70 ± 9 **[54, 90]**	29 ± 6 **[17, 56]**	208 (44.3%)	6.2 ± 1.36 **[1.6, 10]**
3	470	69 ± 9 **[55, 90]**	29 ± 5 **[16, 50]**	229 (48.7%)	6.2 ± 1.47 **[0.7, 10]**
4	470	69 ± 9 **[55, 90]**	28 ± 5 **[17, 50]**	210 (44.7%)	6.2 ± 1.32 **[0.9, 10]**
Full	1880	69 ± 9 **[54, 90]**	29 ± 6 **[16, 56]**	875 (46.5%)	6.2 ± 1.38 **[0.7, 10]**

Table 2.1: Demographic distribution and sleep times of the MESA dataset subset. Format for Age, BMI, and TST is mean ± std [min, max].

showing moderate agreement.

Filtering the MESA participants for those with PPG and SpO2 data, Somnolyzer scorings, and available predicted hypnograms, we ended up with a dataset size of 1,880 participants. Table 2.1 shows the demographic distribution and sleep times of our dataset subset together with the generated folds. To assess SDB severity, the AHI is often categorized into four classes. These so called severity classes are defined as follows: Normal (AHI < 5), Mild ($5 \leq$ AHI < 15), Moderate ($15 \leq$ AHI < 30), and Severe (AHI ≥ 30). Table 2.2 shows their distribution. The amount of different apnea classes is shown in table 2.3.

2.2 Preprocessing

- PPG [256Hz], SpO2 [1Hz], Hypnogram [1Hz]
- For PPG: Statistical Analysis, Denoising, VAE?, Conv-Block

2.3 Model Architecture

- U-Net (with PPG Conv-Block), Batch-Norm, Attention, ...
- Output: Detection at 1Hz - Event vs No Event
- TODO Next model then classifies into SDB classes

		Severity Class			
Fold	AHI	normal	mild	moderate	severe
1	22.2 ± 18.3 **[0.4, 100]**	61	153	136	120
2	22.0 ± 18.3 **[0.3, 93]**	61	151	134	124
3	21.3 ± 17.1 **[0.4, 95]**	61	151	138	120
4	22.0 ± 18.3 **[0.4, 107]**	61	150	140	119
Full	21.9 ± 18.0 **[0.3, 107]**	244	605	548	483

Table 2.2: AHI and severity class distribution accross folds and full dataset subset.TODO: better use [25%,75%] interval instead of [min, max]? Format for the AHI is mean ± std [min, max].

Fold	obstructive apnea	central apnea	mixed apnea	hypopnea
1	15k (24%)	4k (7%)	1k (2%)	42k (67%)
2	16k (26%)	4k (6%)	1k (2%)	42k (66%)
3	15k (24%)	3k (6%)	1k (2%)	41k (67%)
4	17k (26%)	4k (6%)	1k (2%)	42k (66%)
Full	63k (25%)	16k (6%)	5k (2%)	167k (67%)

Table 2.3: Total number of apnea events.

2.4 Training and Evaluation

- Training Parameters (Optimizer, LR, BS, ...) and Setup (Machines, ...)
- Seed and Cross-Validation (mainly balanced for AHI severity, but with seed 42 we got a good distribution fo demographic data in the folds)
- Train on 30min (?) segments. For Testing: Concat 30min Windows with Overlap for full night result.
- Correct results (like Olsen, 10sec minimum event and distance between events)
- Event-based metrics (Se, Pr, F1) and when to count TP, TN, FP, FN
- AHI-based metric (Linear Correlation, Severity Classes, Near-Boundary Double-Classification)

Chapter 3

Results

- Baseline Model vs PPG Preprocessing vs Attention Model Results
- Significance of SpO2 and the Hypnogram (No SpO2/Hypnogram, Only PPG Baseline Model)
- AHI correlations and Severity class results

Chapter 4

Discussion

- Discussion and Implications (Is this way applicable in the real world)
- Limitations
- Further work

Chapter 5

Conclusion

- Summerization of paper
- Significance of work
- Outlook

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