Respiratory Events Screening Using Consumer Smartwatches

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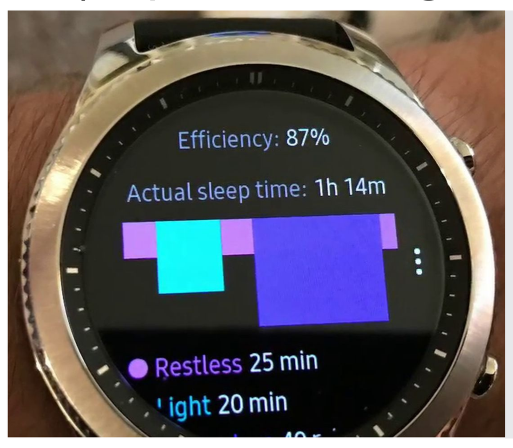
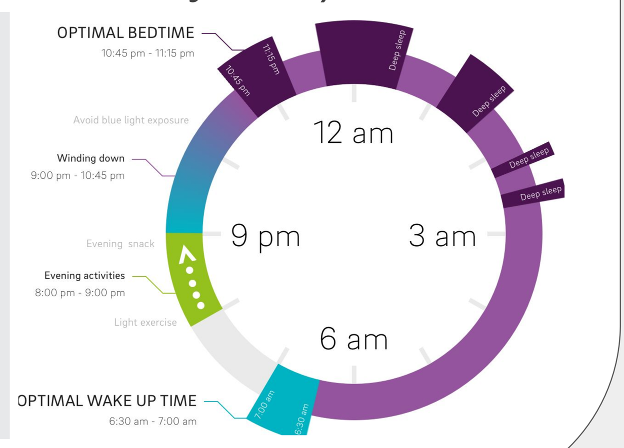
Respiratory related events (RE) during nocturnal sleep disturb the natural physiological pattern of sleep. This events may include all types of apnea and hypopnea, respiratory-event-related arousals and snoring. The particular importance of breath analysis is currently associated with the COVID-19 pandemic. This paper proposes a new accessible and convenient approach to RE detection, apnea-hypopnea index (AHI) estimation and screening of respiratory threat severity using photoplethysmography and accelerometer sensors data taken from consumer Samsung smartwatches. The proposed algorithm is a NN with long short-term memory cells for RE detection for each 1 minute epoch. Our approach provides the basis for a smartwatch based respiratory-related sleep pattern analysis (accuracy of epoch-by-epoch classification is greater than 80 %), can be applied for a potential risk of respiratory-related diseases screening (mean absolute error of AHI estimation is about 6.5 events/h on the test set, which includes participants with all types of apnea severity; two class screening accuracy (AHI threshold is 15 events/h) is greater than 90%). Our experimental results demonstrate that proposed model constitutes a noninvasive and inexpensive screening system for the RE detection and analysis.

1. Relevance and usecases

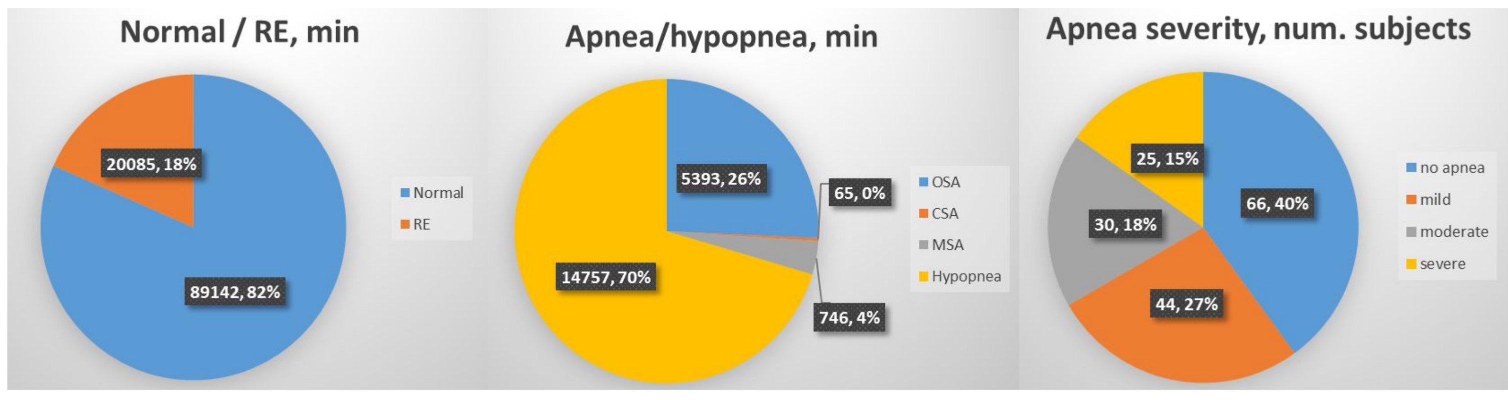
1. *Sleep disorders potential risk detection* (apnea, hypopnea, snoring, etc., https://sleepsherpa.com/sleep-apnea/)
2. *Sleep data analysis and sleep quality improvement* (https://www.youtube.com/watch?v=DOpkW5rqL2g)
3. *Full day activity monitoring (circadian rhythms)* (https://ouraring.com/find-your-own-circadian-rhythm/)



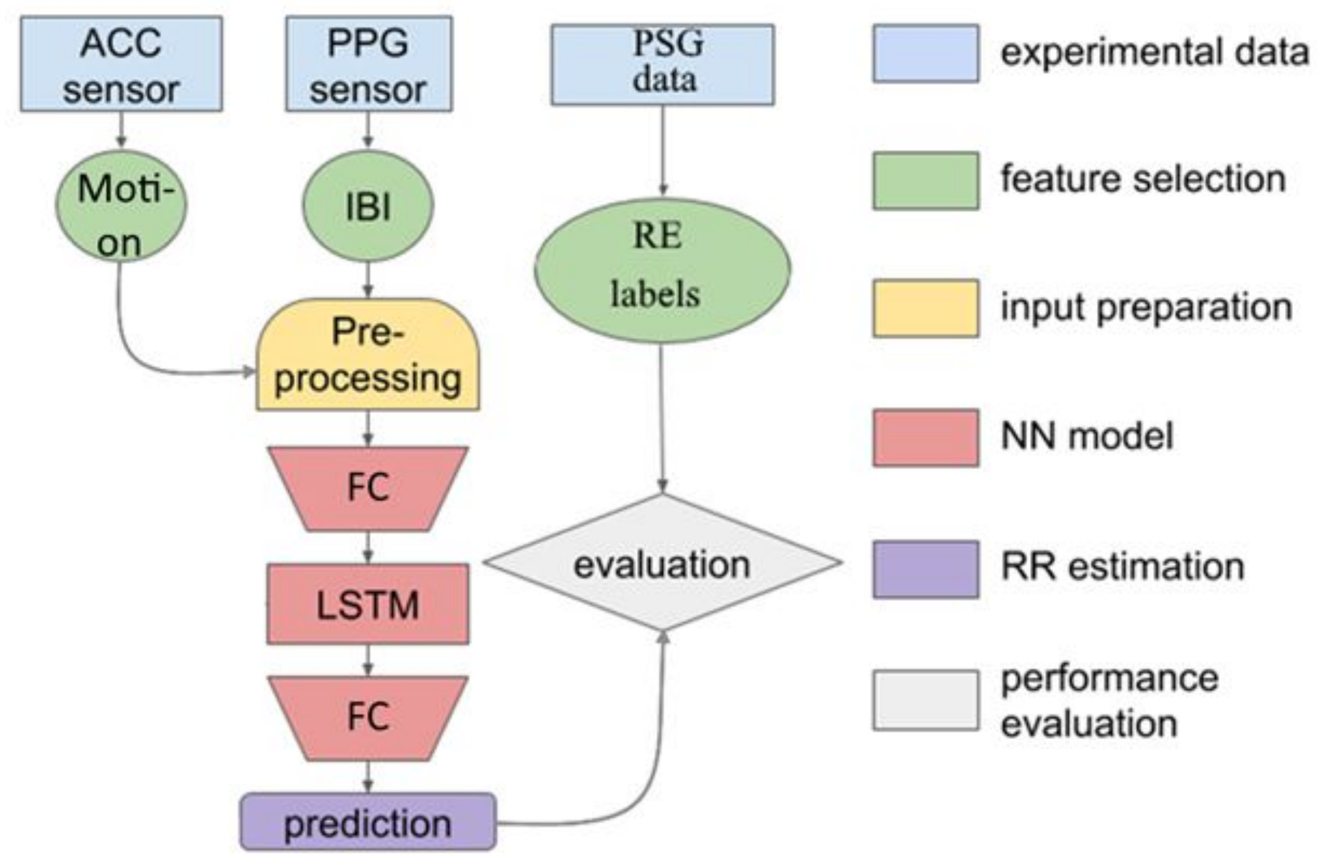


2. Dataset analysis

1. *253 nights belonging to 165 different subjects (altogether this amounts to 109,227 minutes of sleep).*
2. *The subjects had an average age of 39.60 (11.52) years, BMI index of 23.99 (3.43) and AHI of 12.69 (15.92) events/h at the time of the recording.*
3. *Full nocturnal PSG.*
4. *Band-type wearable devices (Samsung) collected 3D-accelerometer and PPG signals at a sampling frequency of 20 Hz.*



3. Study Procedure



***Respiration event** (RE) represents any of apnea or hypopnea events.*
***The epoch** was considered as containing a RE if at least 5 seconds of this event is contained in a given epoch.*

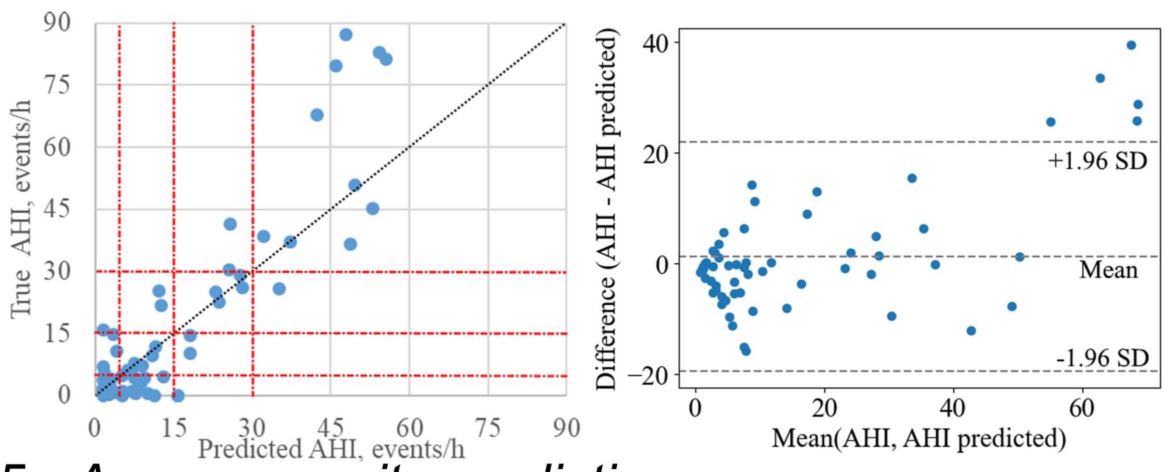
4. ML Model, Procedure and Results

1. ***Features types:*** *HRV, PPG shape, respiration rate (based on the inter-beat intervals (IBI) extracted from the PPG signal), activity and posture (based on the ACC signal).*
2. ***Two datasets*** *(containing 181 night recordings of 94 different subjects) are used for model training and hyperparameters tuning (validation). The cross-validation is performed at the subject's level using the leave-one-subject-out approach (LOSO). The final model performance is then evaluated by the* ***third dataset****, containing 64 night recordings of 64 different subjects.*
3. *General RE detection performance metrics*

Epoch-by-epoch			AHI, events/h		Accuracy of apnea severity prediction, %	
Accuracy, %	Cohen's kappa	F1 score	MAE	MSE	4 cl.	2 cl.
82	0.44	0.82	6.6	10.6	70	95

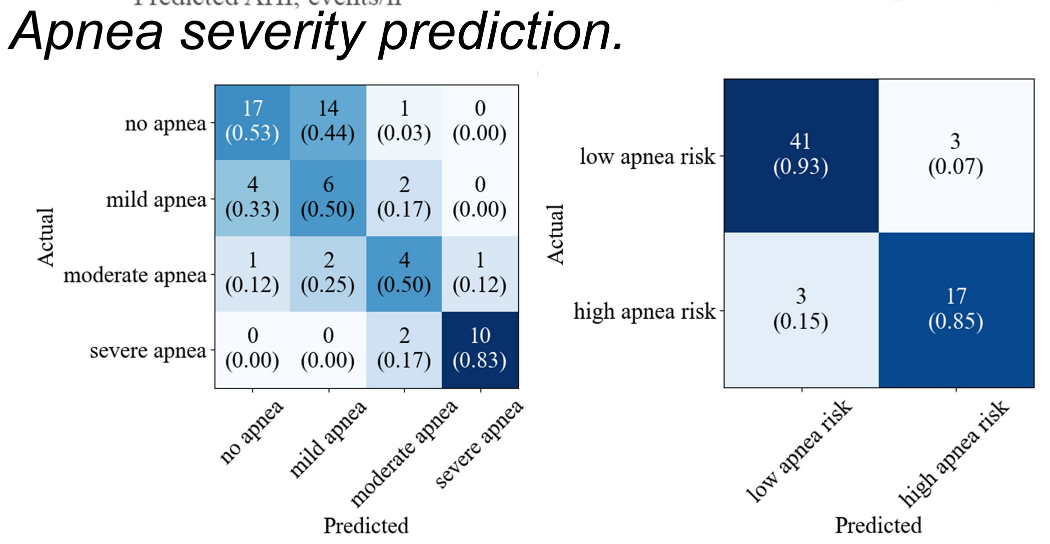
AHI predicted, events/h	MAE, events/h	MSE, events/h
<5.0	2.7	4.5
5.0-15.0	5.2	6.6
15.0-30.0	6.0	8.1
>30.0	17.0	21.0

4. *AHI estimation*



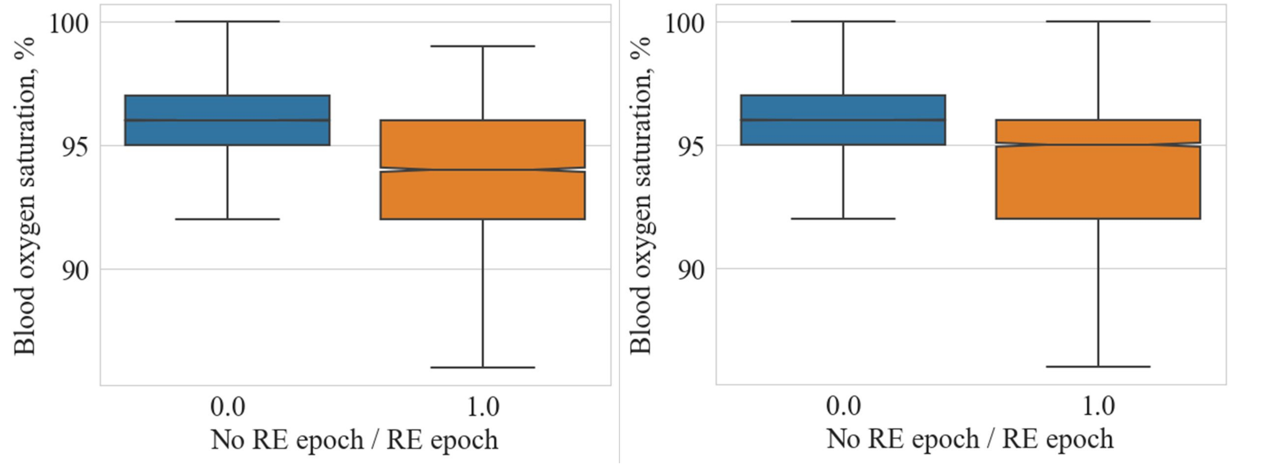
(a) Actual AHI (y-axis) versus predicted AHI (x-axis) (b) Bland-Altman plot of the actual AHI and predicted AHI.

5. *Apnea severity prediction.*

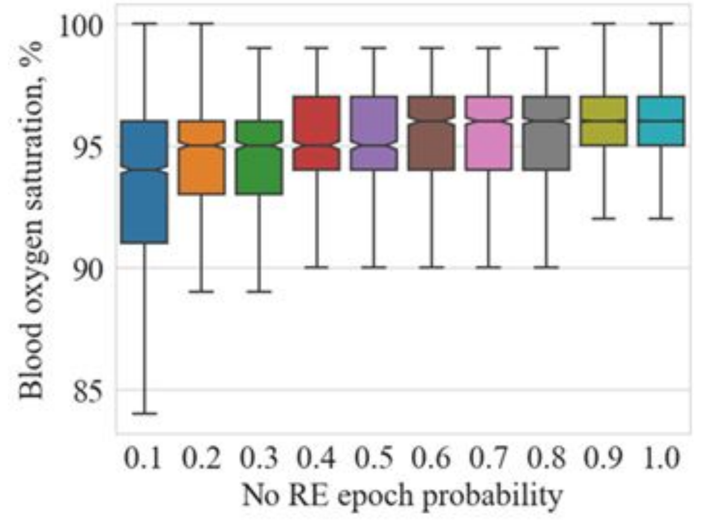


Confusion matrix of the apnea severity prediction. (a) Four apnea severity levels with thresholds of 5, 15 and 30 events/h. (b) Two severity levels with a threshold of 15 events/h.

5. Respiration events vs blood oxygen saturation



Blood oxygen saturation distribution for "no RE epoch" - 0 and "RE epoch" - 1 for a) true PSG data and b) predicted by the proposed algorithm.



Blood oxygen saturation at different values of the predicted probability of belonging to the class "RE epoch" / "no RE epoch". Probabilities exceeding 0.5 refer to the "No RE epoch", and less than 0.5 – "RE epoch".

Here, we proposed the deep learning LSTM based model for sleep-related RE detection during nocturnal sleep based on data from Samsung smartwatch sensors. High accuracy of epoch-by-epoch RE classification along with the sufficient correspondence with AHI values were achieved. To increase the model robustness and performance the sleep stages classifier was combined with the RE classification model. A good correlation was obtained between the level of blood oxygen saturation and the probability that the classifier would classify each particular epoch as a normal or RE class. Results showed that such model can be effectively used as the RE screening tool, RE severity estimation and respiratory pattern reconstruction during sleep. The further studies may be useful to improve RE screening and prevent negative health consequences.

References

[1] Matt T. Bianchi. 2018. Sleep devices: wearables and nearables, informational and interventional, consumer and clinical. Metabolism 84 (2018), 99 – 108. https //doi.org/10.1016/j.metabol.2017.10.008.
[2] Denisse Castaneda, Aibhlin Esparza, Mohammad Ghamari, Cinna Soltanpur, and H. Nazeran. 2018. A review on wearable photoplethysmography sensors and their potential future applications in health care. International journal of biosensors & bioelectronics 4 (2018), 195 – 202.
[3] Peter Charlton, Drew Birrenkott, Timothy Bonnici, Marco Pimentel, Alistair Johnson, Jordi Alastruey, L. Tarassenko, Peter Watkinson, Richard Beale, and David Clifton. 2018. Breathing Rate Estimation From the Electrocardiogram and Photoplethysmogram: A Review. IEEE Reviews in Biomedical Engineering 11 (2018), 2–20.
[4] M Melani Lyons, Jan F Kraemer, Radha Dhingra, Brendan T Keenan, Niels Wessel, Martin Glos, Thomas Penzel, and Indira Gurubhagavatula. 2019. Screening for Obstructive Sleep Apnea in Commercial Drivers Using EKG-Derived Respiratory Power Index. Journal of clinical sleep medicine : JCSM : official publication of the American Academy of Sleep Medicine 15, 1 (January 2019), 23—32. https://doi.org/10.5664/jcsm.7562.
[5] Gabriele Papini, Pedro Fonseca, Merel Gilst, Johannes van dijk, Dirk Pevernagie, Jan Bergmans, Rik Vullings, and Sebastiaan Overeem. 2019. Estimation of the apnea-hypopnea index in a heterogeneous sleep-disordered population using optimised cardiovascular features. Scientific Reports 9 (11 2019). https://doi.org/10.1038/s41598-019-53403-y.
[6] Thomas Penzel, Christoph Schöbel, and Ingo Fietze. 2018. New technology to assess sleep apnea: wearables, smartphones, and accessories. F1000Research 7 (2018), 413.