Multi-Modal Representation Learning and its Application in Healthcare: Applying Deep Residual Shrinkage Network in Detecting Sleep Apnea Based on BCG signals

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Introduction

➢ Problem Definition:

- **Sleep Apnea:** prevalent[1] but underrecognized[2] among population and can increase risk of cardiovascular disease[3,4]
- **Polysomnography (PSG):** golden standard for sleep disorder, but costly and inconvenient

- **Ballistocardiography (BCG):**
- Non-contact sensors embedded in the smart bed[5] to detect the vibration of human body. Cost-effective and accessible.

→ Apply machine learning to detect apnea from BCG signals

Method

➢ Overall Pipeline:

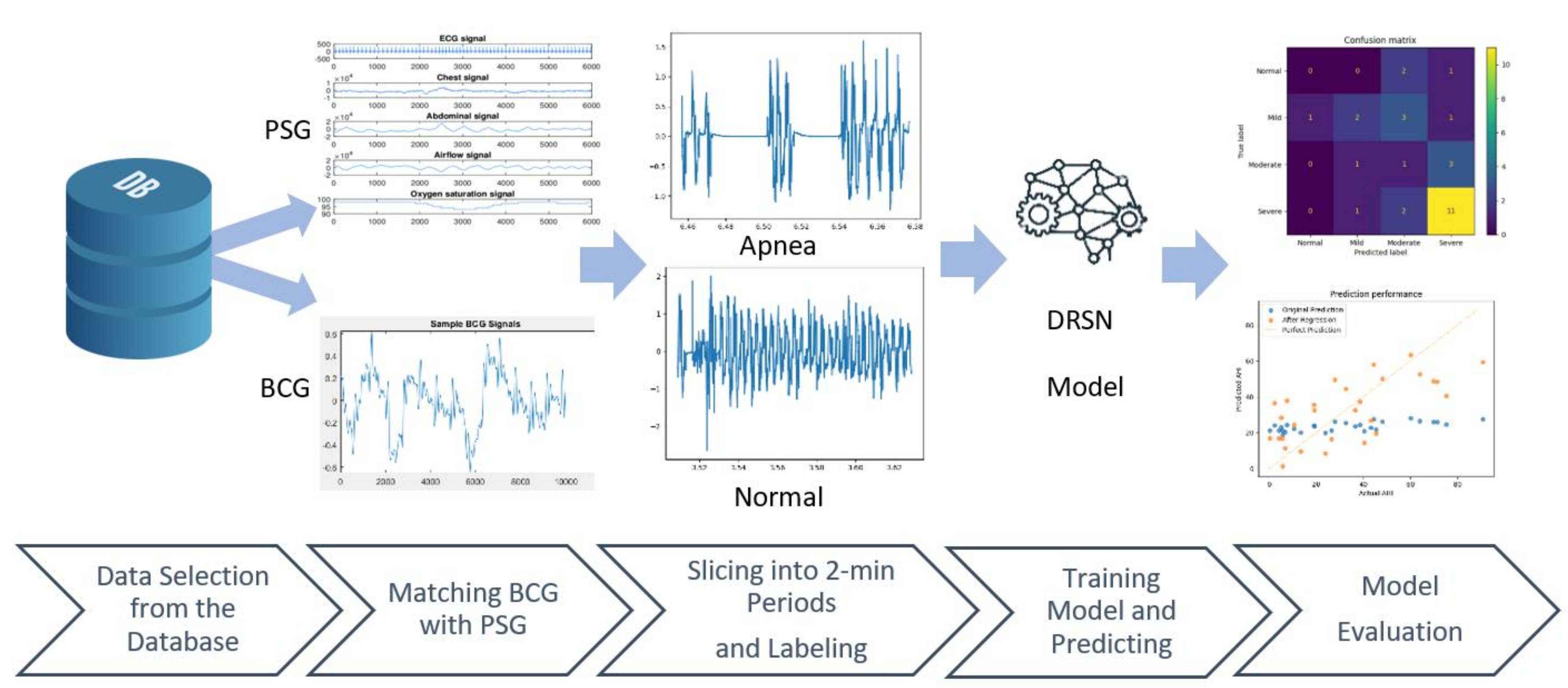

Figure 1. Overall pipeline of the study

➢ Data Collection and Processing:

- 31 pieces of BCG, PSG signals with corresponding human experts diagnosis records;
- BCG: 500/1000hz sensors, with 1.8M~3.6M data points/hour;
- PSG: Airflow, SpO_2, sound to identify and label apnea;

➢ Model Architecture and Training:

- Deep residual shrinkage network (DRSN)[6] incorporates ResNets and soft-thresholding, designed to recognize features from highly noised vibration signals
- Divide BCG signals to 2 min slices, manual labeling in contrast with PSG and train the model。

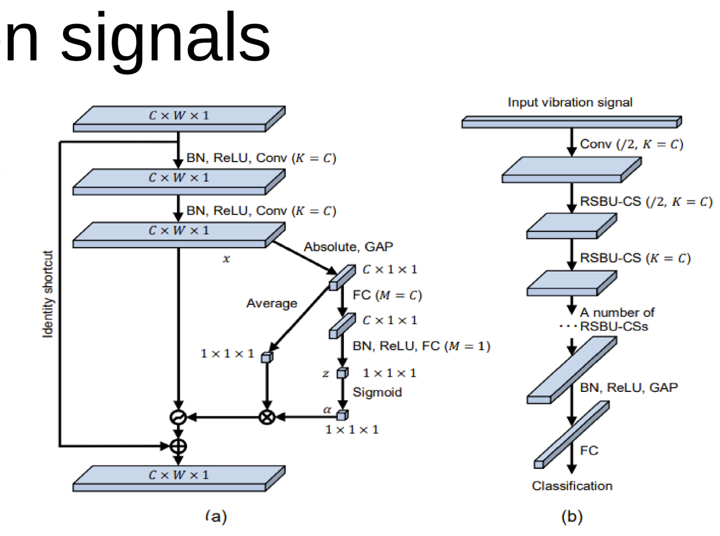

Figure 2. Model architecture

➢ Evaluation

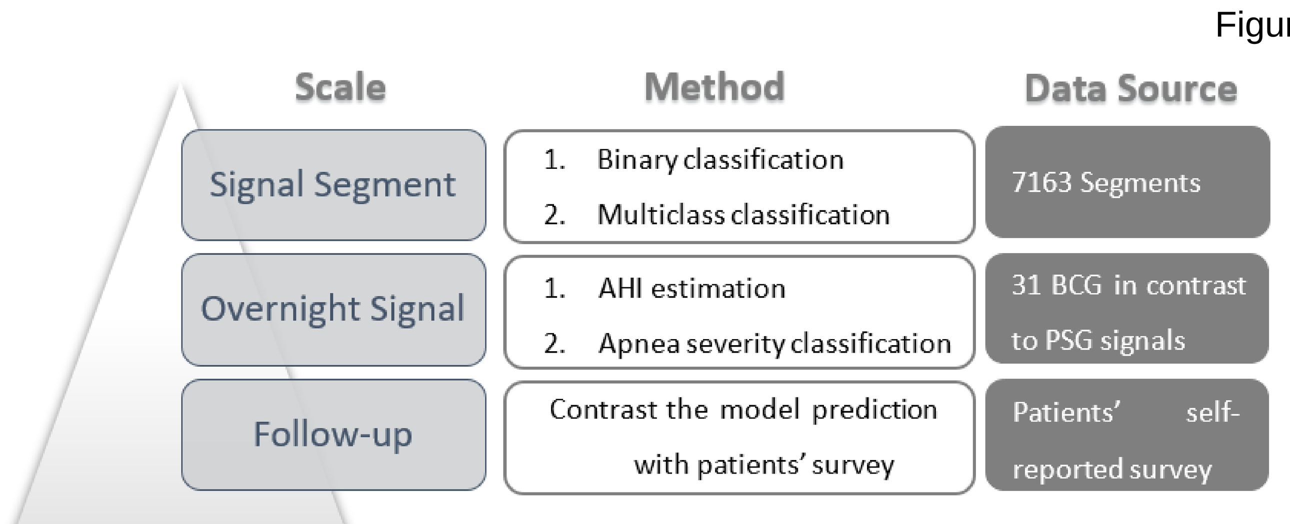

Figure 3. Three-stage evaluation scheme

Apnea Hypopnea Index

AHI	OSA Level
[0, 5]	Normal
(5, 15]	Mild
(15, 30]	Moderate
(30, +∞)	Severe

Table 1. Criteria of severity of sleep apnea according to American Academic of Sleep Medicine

Results

➢ Demographic Statistics and Survey Results:

Subject	Statistics
Sex, n (%)	
Male	23 (74.19)
Female	3(9.68)
Undefined	5(16.13)
Age ($\bar{x} \pm s$)	41.47(12.04)
BMI ($\bar{x} \pm s$)	27.32(4.62)
AHI ($\bar{x} \pm s$)	33.91(25.51)
Sleep hours, minutes ($\bar{x} \pm s$)	449.48(124.27)

Top 5 most prevalent symptoms reported, n(%)	
Mouth breathing	12(100)
Snoring	11(91.67)
Sleep apnea	11(91.67)
Morning xerostomia	9(75)
Rhinitis	6(50)

(Left) Table 2. Demographics of selected participants
(Right) Table 3. Frequent self-reported symptoms in the survey among patients

➢ Segment Prediction:

Metrics	Score (95% C.I.)
Accuracy	0.962 (0.951, 0.971)
Precision	0.961 (0.946,0.975)
Recall	0.958 (0.940,0.972)
F1 score	0.959 (0.947,0.968)
AUC	0.9915

Table 4. Results of binary classification: with or without apnea

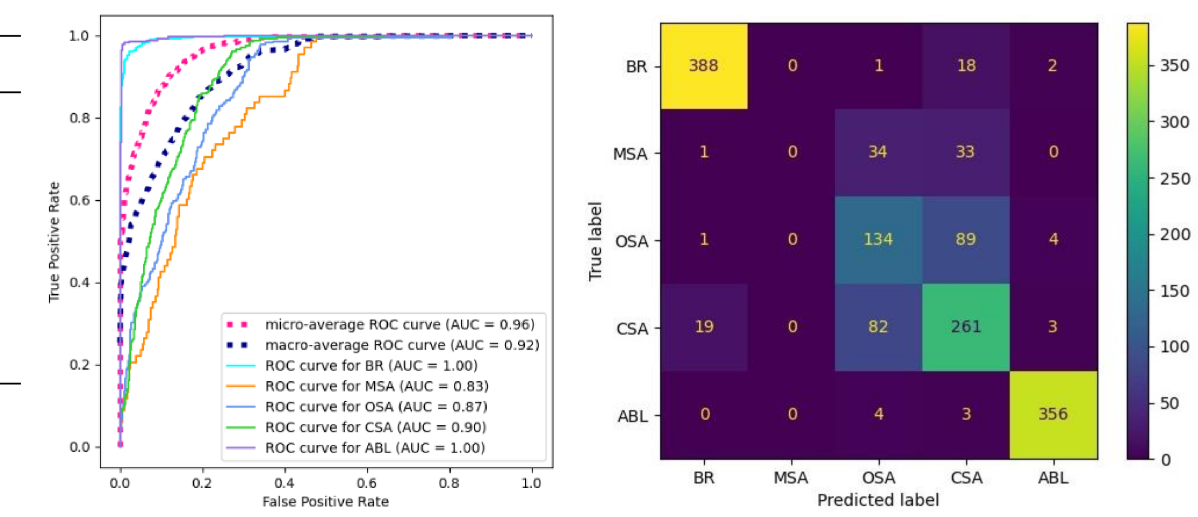

Figure 4. Results of 5-class classification. Left: ROC curve for individual classes and overall AUC score. Right: Confusion matrix

➢ AHI and Severity Prediction:

- AHI prediction: correlation with actual AHI is 0.81; regression, $R^2 = 0.656$, 95% C.I. is [1.001,1.861], p < .0001
- With demographic variables BMI Age, F/M: correlation 0.849, $R^2 = 0.722$, BMI is significant variable

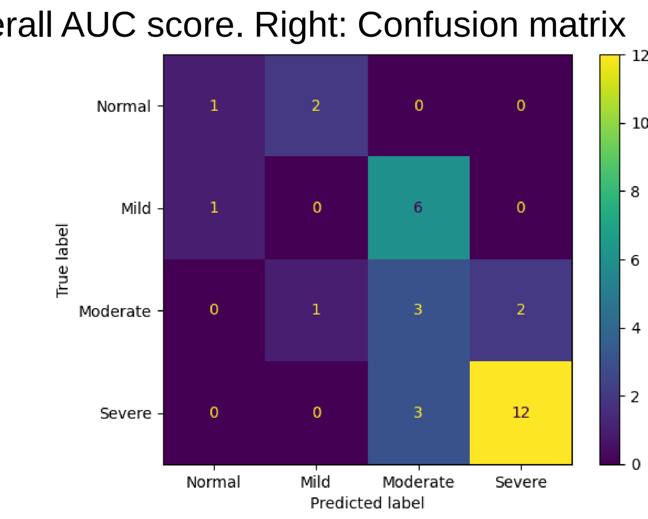

Figure 5. Confusion matrix of severity prediction

Severity	Precision	Recall	f1 Score	Support
Normal	0.50	0.33	0.40	3
Mild	0	0	0	7
Moderate	0.25	0.50	0.33	6
Severe	**0.86**	**0.80**	**0.83**	**15**

Table 5. Severity classification results based on predicted AHI

Discussion

➢ Intrinsic challenges in BCG Signals:

- Heterogeneous vibration
- Instability, due to signal saturation, external disturbance
- Non uniform presentation of apnea

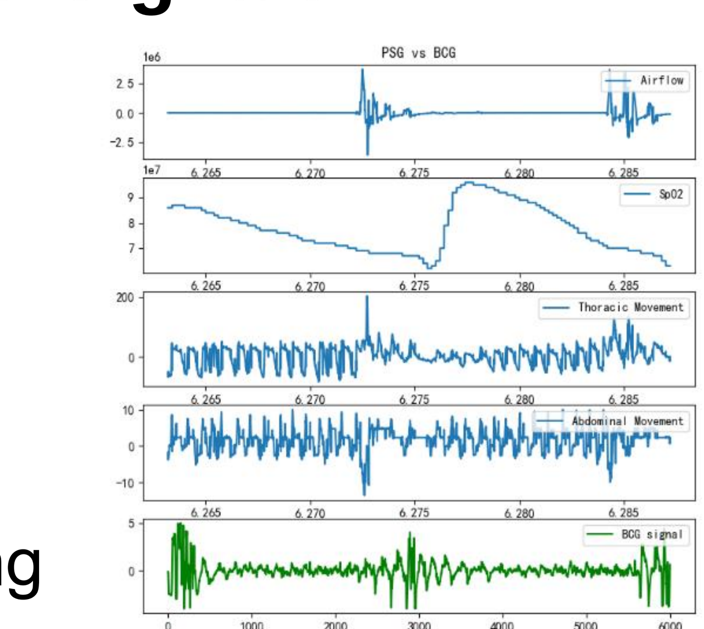

Figure 6. BCG signals in comparison with PSG channels

➢ Potential Implications:

- Deep learning's potential in learning patterns of non-contact BCG signals
→ Various sleep disorders detection
- BCG sensors embedded in bed - higher user compliance, less influence to sleep quality compared to in-lab test

→ Long-term at-home monitoring of sleep disorders
→ Contribute to a comprehensive health management system

➢ Future Directions:

- Collect patient's survey and complete follow-up evaluation
- Tackle instability and enhance model's interpretability;
- Integrate with more functional modules related to sleep medicine, including sleep staging insomnia detector etc.

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