Screening for Obstructive Sleep Apnea: Integrating Machine Learning with Physiologic Data to Improve Diagnostic Accuracy

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Team 7
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Clinical Background

- Having OSA means that the soft tissue in the back of the throat collapses and closes during sleep, causing upper airway obstruction and breathing and air movement into the lungs to cease.

- Fortunately, breathing is restarted when our bodies wake us up, often gasping for air. This cycle can happen many times, possibly hundreds of times, during the night and happens night after night, significantly reducing the quality of sleep.

- 25-30% of world population

- USA- over 20 million patients

- Most are unaware- 80% of moderate and severe OSA cases remain undiagnosed!
Figure one: The cycle of OSA during sleep

1. The person falls asleep
2. Upper airway relaxes
3. Breathing starts again, often with a gasp and body movement
4. Oxygen level falls, effort made to breathe rises
5. Airway in the throat closes or partially closes (obstructs)
6. Breathing stops (apnoea)
7. Brain makes the person partially wake up
8. The person may or may not be aware of partially waking up

Obstructive sleep apnoea cycle
Who?

- Men, overweight, age >40
- Anyone can have OSA...

Things you should know about...

Obstructive Sleep Apnea

- With sleep apnea your breathing during sleep is reduced or may stop.
- You are likely to only have breathing difficulties when asleep.
- You may have no idea this happens.
- It can be associated with other medical problems.
- It can be successfully treated.
Even children
SLEEP APNEA AFFECTS YOUR WHOLE BODY

STROKE
90%

POOR SLEEP
58% 87%

HEADACHES
- Migraines can be caused by reduced blood flow

MOOD DISTURBANCE
- Depression
- Anxiety

DAYTIME SLEEPINESS
- Affects mood, alertness, work performance

SLEEP ON THE HEART
37%

HYPERTENSION
- Also causes stroke, heart attack, and kidney disease

30%

CORONARY ARTERY DISEASE

58%

CARDIAC ARRHYTHMIAS
- May cause heart failure

48%

CONGESTIVE HEART FAILURE

76%

HEART DISEASE

38%

SUDDEN DEATH
- An 8% increase in mortality

48%

MEDICAL COSTS
- Average annual medical costs for sleep apnea: $1,100 per year

80%

GASTROESOPHAGEAL REFLUX DISEASE (GERD)

56%

SEXUAL DYSFUNCTION
- Reduced libido

80% of middle-aged men

48%

NOCTURIA
- Frequent urination at night

Inspiration Medici
www.inspirationmedici.com
**Current Screening**

**STOP Bang QUESTIONNAIRE**

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Snoring</strong> - Do you snore loudly (loud enough to be heard through closed doors or your bed-partner elbow you for snoring at night)?</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Tired</strong> - Do you often feel tired, fatigued, or sleepy during the daytime (such as falling asleep during driving)?</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Observed</strong> - Has anyone observed you stop breathing or choking/gasping during your sleep?</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Pressure</strong> - Do you have or are being treated for high blood pressure?</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Body Mass Index</strong> - More than 10% over ideal range.</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Age</strong> - Older than 50?</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Neck Size</strong> - (Measure around Adams apple) Male is your shirt collar 17” or larger? Female, is your shirt collar 16” or larger?</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Gender</strong> = Male?</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

After you have completed the STOP-BANG questionnaire, please return it to the front desk for a quick risk assessment of possible sleep apnea.
For general population
OSA - Low Risk : Yes to 0 - 2 questions
OSA - Intermediate Risk : Yes to 3 - 4 questions
OSA - High Risk : Yes to 5 - 8 questions
or Yes to 2 or more of 4 STOP questions + male gender
or Yes to 2 or more of 4 STOP questions + BMI > 35kg/m²
or Yes to 2 or more of 4 STOP questions + neck circumference 16 inches / 40cm
Diagnosis

- Given the recognized prevalence of OSA and the risk of related morbidity and mortality, **OSA screening is becoming a priority**, so that treatment may be instituted before major health issues arise due to OSA.

- **GOLD STANDARD**- formal sleep study (polysomnography): Complex, expensive, unavailable to most patients

- Physiological signals collected from different sensors (as many as 11), including electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG) and electrocardiogram (ECG), oximetry (spO2)
Apnea-Hypopnea Index

- The Apnea Hypopnea Index (AHI) is considered to be the most relevant metric to diagnose the existence and severity of the disorder, indicating the number of apnea events per hour of sleep.

<table>
<thead>
<tr>
<th>AHI</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;5</td>
<td>Normal</td>
</tr>
<tr>
<td>5 to 15</td>
<td>Mild</td>
</tr>
<tr>
<td>15 to 30</td>
<td>Moderate</td>
</tr>
<tr>
<td>&gt;30</td>
<td>Severe</td>
</tr>
</tbody>
</table>
Application of Machine Learning

- Perhaps the most exciting and promising addition to OSA screening and diagnosis involves the application of machine-learning algorithms to better predict patients at highest risk of OSA. Previously, many studies have been limited by inadequate study population size, specific comparative study populations that may introduce bias, or selective criteria for analysis.

- In the last few years, technological advances with portable and wearable sensors have increased the availability of less expensive and more accessible, at-home sleep-study testing for OSA. Two of the more studied techniques include use of pulse oximetry and electrocardiogram (ECG) data as diagnostic indicators of OSA.
Objective

We propose a new, deep-learning model for OSA screening that combines two commonly accepted physiologic indicators of OSA; ECG and pulse oximetry, from an existing publicly available sleep study data set.

We hope to demonstrate increased diagnostic accuracy of moderate to severe OSA in an existing data set, by analyzing both ECG and oximetry together using a convolutional neural network (CNN) deep learning model.
Hypothesis

Using ECG and pulse oximetry features, our CNN will demonstrate accurate results for OSA screening, comparing favorably to the full PSG results for this data set, as well as to prior logistic regression analysis of ECG and pulse oximetry for OSA diagnosis.
Approach - Overview

- **Data Acquisition**: Our first step will be to extract the ECG and oximetry raw data from our dataset, determining what our features and labels are.
- **Data Preprocessing**: Next we will split the dataset into a training dataset and test dataset.
- **Model Development**: The train dataset will then be placed into our chosen machine learning model such as CNN, the data will be entered and the outputs will generate a trained model.
- **Model Evaluation**: This trained model will need to be evaluated via the test dataset and review performance. We will set a performance standard of 90%+ for the trained model. From there we can compare the performance of a CNN.
Data Acquisition

- Data acquired from the ISRUC-Sleep dataset
  - Contains 100 subjects
  - Age range 20-85, 56 males & 44 females
  - Each patient has an individual datafile available
- Locate and pull out ECG + pulse oximetry data for analysis
- Use ECG signals + pulse oximetry reading as features for model
- Split dataset into training dataset (70%) and test dataset (30%)
## ISRUC Dataset Example

### Table: Subgroup 1 of ISRUC Sleep dataset

<table>
<thead>
<tr>
<th>Age</th>
<th>Sex</th>
<th>Diagnosis</th>
<th>Other problems</th>
<th>Epochs</th>
<th>W%</th>
<th>N1%</th>
<th>N2%</th>
<th>N3%</th>
<th>REM%</th>
<th>Date of recording</th>
<th>W%</th>
<th>N1%</th>
<th>N2%</th>
<th>N3%</th>
<th>REM%</th>
<th>Medication</th>
<th>EEG alterations</th>
</tr>
</thead>
<tbody>
<tr>
<td>64</td>
<td>M</td>
<td>SAOS</td>
<td>Depression</td>
<td>880</td>
<td>30</td>
<td>8.3</td>
<td>22.05</td>
<td>26.25</td>
<td>13.41</td>
<td>18/5/2009</td>
<td>30.91</td>
<td>4.77</td>
<td>24.09</td>
<td>26.25</td>
<td>13.98</td>
<td>SSRI, mirtazapine</td>
<td></td>
</tr>
<tr>
<td>52</td>
<td>M</td>
<td>SAOS</td>
<td>Restless leg syndrome</td>
<td>964</td>
<td>25.41</td>
<td>11.93</td>
<td>35.79</td>
<td>16.29</td>
<td>10.58</td>
<td>8/6/2009</td>
<td>21.99</td>
<td>11.93</td>
<td>44.4</td>
<td>11.1</td>
<td>10.58</td>
<td></td>
<td></td>
</tr>
<tr>
<td>38</td>
<td>M</td>
<td>REM Sleep Behaviour Disorder</td>
<td>PLMS</td>
<td>943</td>
<td>14</td>
<td>17.5</td>
<td>26.09</td>
<td>18.35</td>
<td>24.07</td>
<td>21/5/2009</td>
<td>12.73</td>
<td>4.45</td>
<td>30.24</td>
<td>15.69</td>
<td>27.89</td>
<td>Risperidone, Tegretol</td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>M</td>
<td>SIVAS</td>
<td>Sleep apnea</td>
<td>963</td>
<td>29.1</td>
<td>6.75</td>
<td>41.24</td>
<td>22.22</td>
<td>23.88</td>
<td>18/6/2009</td>
<td>2.7</td>
<td>3.43</td>
<td>43.61</td>
<td>25.65</td>
<td>24.61</td>
<td></td>
<td>Paroxysmal activity left fronto-parietal</td>
</tr>
<tr>
<td>58</td>
<td>F</td>
<td>SAOS</td>
<td>Insomnia</td>
<td>875</td>
<td>33.33</td>
<td>12.34</td>
<td>30.29</td>
<td>18.74</td>
<td>4.8</td>
<td>25/5/2009</td>
<td>35.66</td>
<td>4.69</td>
<td>35.66</td>
<td>18.86</td>
<td>5.14</td>
<td>BZD</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>M</td>
<td>PLMS</td>
<td>Epilepsy; brain tumour</td>
<td>997</td>
<td>80.49</td>
<td>1.78</td>
<td>6.69</td>
<td>11.04</td>
<td>0</td>
<td>18/5/2009</td>
<td>80.27</td>
<td>2.67</td>
<td>5.24</td>
<td>12.82</td>
<td>0</td>
<td>Valproate</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>M</td>
<td>SAOS</td>
<td>Clavus-stitches</td>
<td>953</td>
<td>14.36</td>
<td>18.33</td>
<td>21.97</td>
<td>25.08</td>
<td>20.26</td>
<td>1/6/2009</td>
<td>15.43</td>
<td>11.04</td>
<td>29.9</td>
<td>25.08</td>
<td>18.54</td>
<td>Slower amplitude alfa; electrode instability</td>
<td></td>
</tr>
</tbody>
</table>
Data Processing

- The ECG recordings and pulse oximetry data will need to be extracted from the datasets, cleaned, and validated.
- The ECG recordings and pulse oximetry data will both originate as signal data and need to be passed through a filter to reduce noise.
- The distribution of sleep apnea epochs (events) will then be classified and divided into three subgroups to create the test and train dataset:
  - Normal
  - Hypopnea - less severe apnea, shallow breathing
  - Apnea – cessation of breathing
Model Development

- A CNN consists of three main parts: convolution layer, pooling layer, and classification layer. In the convolution layer, the feature map was extracted by applying a filter kernel to produce the convolution integral of the input data activation function, thereby enhancing discrimination. In the pooling layer, the feature map has reduced and restricted the dimensions of input data. Finally, the classification layer is performed the final discrimination of the input data by using the fully-connected network. At this stage, and the learning process is performed through feed-forward and back-propagation algorithms.

- Python, Keras Library, and TensorFlow background
Figure 2: Hypothetical 1D vs 2D CNN model that uses ECG as inputs

- **ReLU** = rectified linear unit. Linear identity for all positive values, and zero for all negative values. All values greater than 0 are not transformed, values less than 0 transformed to 0.

- **Softmax** is in the Sigmoid family, turns numbers known as logits into probabilities that sum to one. Probability distributions.

- Large neural nets trained on relatively small datasets can overfit the training data. This can produce noise, one approach to reduce this is to fit all possible neural networks on the same dataset and average predictions. Dropout is a regularization method that approximates training a large number of neural networks with different architectures.

- The FC layer is the last layer, the “Fully Connected” layer. It's job is to classify features extracted during the convolution and pooling layers.
Similarly, we would employ convolution, pooling, and activation layers for the design of our architecture.

These three activation layers would represent three sublayers, with the convolutional layer using one-dimensional (1-D) convolution to extract feature maps via the input signal.

Following the convolutional layer, there would be the pooling and then activation layer or “activation function”. The pooling layer would then be used to reduce dimensions of the feature maps and network parameters.

To help avoid overfitting and preserve the network’s ability to generalize, we would next perform a final step known as drop-out. During dropout, randomly selected neurons are temporarily removed from the network, along with all its incoming and outgoing connections during training.

Lastly, in the classification section, the model is a fully connected neural network that can judge whether an input event is normal, hypopnea or apnea.
True positive (TP), true negative (TN), false positive (FP), and false negative (FN) are all metrics to be considered for classification of performance. Furthermore, these values can then be taken to calculate accuracy (Acc), specificity (Spc), positive predictive value (PPV) and sensitivity (Sen).

Training a neural network is typically done in two phases: a forward and backward phase. The forward phase is where the input(s) are passed through the network and the backward phase is where backpropagation occurs, and weights are updated.

One key insight we will be looking for is will the model correctly identify and classify AHI events given the features and labels used from the ECG and pulse oximetry signal data.
Next Steps

- Deep learning, wearable biosensors ➔ remote monitoring and management ➔ improved screening (think Apple Watch)
- Use CNN model – tested and trained on sleep study cohort (ECG and oximetry data) to evaluate accuracy of home-based ECG / pulse oximetry sensor for diagnosis of OSA
- Available to the masses: more effective screening
- As processing power scales up, the size of devices scale down
Thank you!

◊ Sweet dreams of neural networks & easy breathing...

-Team 7

One does not simply sleep in grad school