Predicting the Severity of Apnea through Machine Learning

Research Question:

Can Random Forest (RF) predict the severity of apnea accurately?

Goal:

80% accuracy of RF model

Results:

Confusion Matrix

	None (PP)	Severe (PN)	Class error
None (P)	115 (TP)	49 (FN)	0.2987805
Severe (N)	38 (FP)	137 (TN)	0.2171429

Methodology:

1. Conducted demographic analysis in excel.
2. RStudio was used to filter participants to only include those with None and Severe OSA.
3. RStudio was used to run RF model.
4. The correctly predicted outcomes, true positives and negatives are divided by total participants to get prediction accuracy

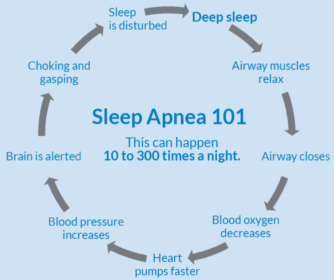
Conclusion:

- Prediction accuracy = (TP + TN)/total participants = (115 + 137)/339= 74.34%.
- This model can help decrease a patient's time spent in diagnosis and the patient's ability to receive treatment.
- Research can be expanded to more participants and moderate and mild OSA

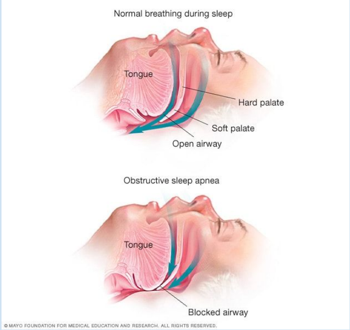
Background Information: Obstructive Sleep Apnea

Obstructive Sleep Apnea (OSA)

- Occurs when throat muscles relax and decrease airflow by 30%-50% for more than 10 seconds (Strollo & Rogers, 1996)
- Affects 5%–14% of adults aged 30–70 years (Peppard PE et al.,2013)
- Severity is measured through apnea/hypopnea index (AHI)
  - Influenced by age, sex, body mass index (BMI), neck circumference, and waist circumference



Sleep Apnea Cycle, breathediagnostics.com



No OSA vs. OSA mayoclinic.com

Problem

- Occupational accidents have a 50% increase in men with OSA and a sixfold increase in women suffering from OSA
- Documented 810,000 collisions and 1400 fatalities attributed to OSA, costing 15.9 billion dollars in 2000 (AlGhanim et al., 2007).

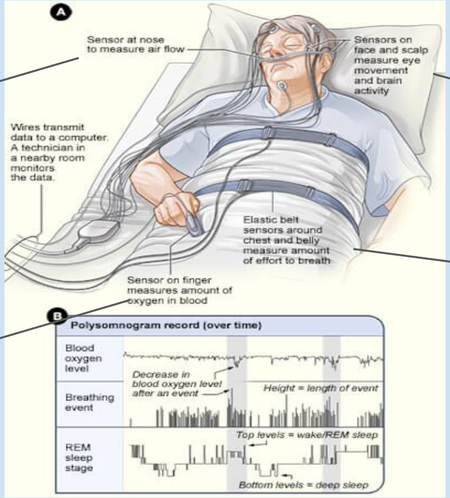
Direct health costs:	
Costs from diagnosis/treatment of sleep disorders	$146 million
Costs from associated conditions (e.g., cardiovascular disease, diabetes, depression, work-related injuries, motor vehicle crashes)	$313 million
Indirect costs:	
Work-related injuries, including production disturbance, legal, investigation, human capital, travel, funerals	$1,956 million
Motor cehicle crashes, including long-term care, workplace/labor disruption, quality of life, legal costs, repairs, towing, travel delays, administration, police, property damage	$808 million
Other costs	$1,301 million
Net cost of suffering	$2,970 million
Total	$7,494 million

Summary of costs related to sleep disorders in Australia (AlGhanim et al.)

Background Information: Polysomnography

- Method for diagnosing OSA and the degree of sleep fragmentation
  - Records brain waves, blood oxygen level, heart rate, breathing, respiratory rates (RR), eye, and leg movements during hours of monitored sleep (Rodrigues et al., 2020).
- Assessment requires 3 studies
  - Electroencephalography (EEG)
  - Electrooculography (EOG)
  - Surface electromyography (EMG)
  - Extra assessment to study: Electrocardiography (ECG), channels are used for monitoring airflow, & pulse oximetry

Thermistor channel &
Pressure transducer



Electroencephalography (EEG) & Electrooculography (EOG)

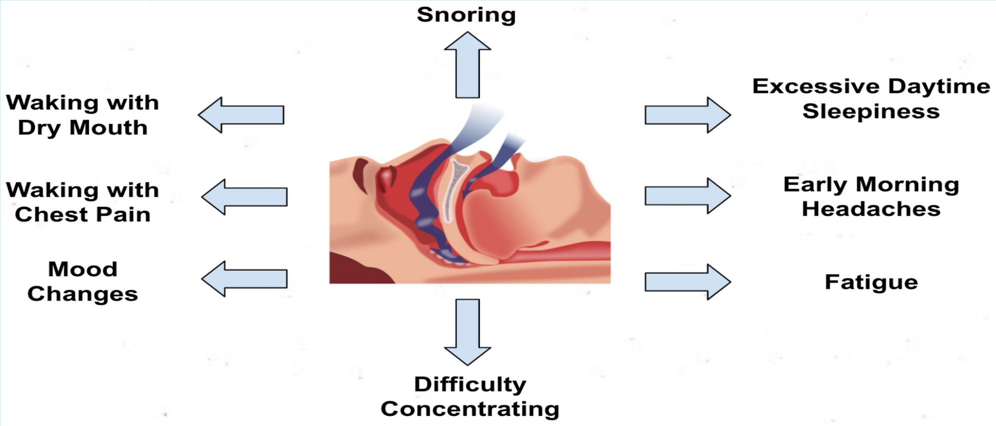
Surface electromyography (EMG)

Pulse oximetry

Polysomnography set up,
Disabled-world.com

Background Information: Polysomnography

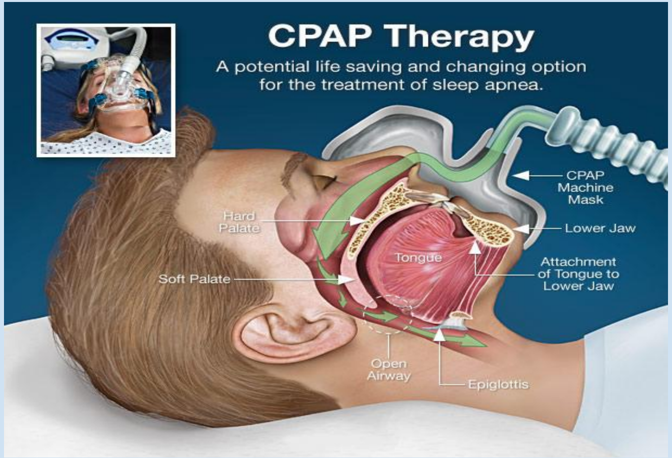
- Data was collected by a Type II PSG device
  - Has a minimum of 7 channels (eg, EEG, EOG, EMG, ECG-heart rate, airflow, respiratory effort, oxygen saturation).
    - monitors sleep staging → apnea-plus-hypopnea index (AHI) can be calculated
    - Gave us the respiratory rates and QT interval
- Use data to test severity by apnea/hypopnea index (AHI)
  - Severities are listed as follows: no apnea (AHI,5), mild apnea (5 ≤AHI<15), moderate (15≤AHI<30), and severe (AHI≥30).



Results from Apnea, cureus.com

Background Information: Treatment of OSA

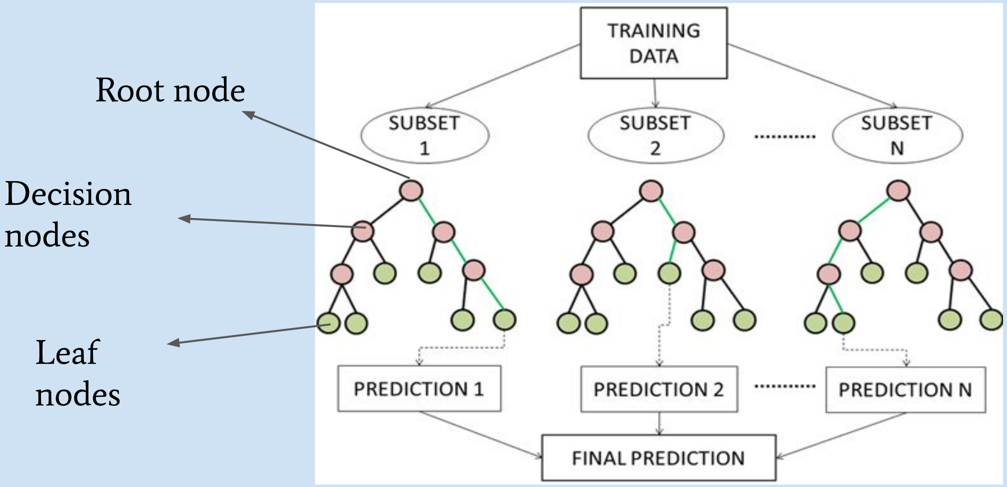
- Average time to receive medical therapy after PSG diagnosis is 11.6 months (Rotenberg et al., 2010)
- Continuous positive airway pressure (CPAP)
  - Machine delivers constant air pressure
  - Other types of positive airway pressure include: varied (autotitrating) pressure (APAP) and Bilevel positive airway pressure (BPAP)
- Surgeries
  - Surgical removal of tissue from the back of the mouth and top of the throat



CPAP Therapy, carlossantosmdpa.com

Background information: Machine Learning

- Machine learning: application of artificial intelligence (AI), the study and development of systems that can learn from and make AI-based diagnoses from the data
- Algorithms:
  - Random forest (RF)
  - Deep Learning (DL) & Long short-term memory (LSTM)



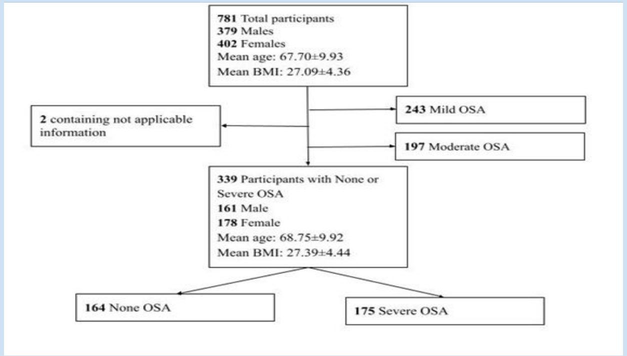
Example of RF workflow (Laudato et al., 2020)

Procedure

Demographic analysis of the 781 participants

Machine parameters: RR, QT, QTc, and QTbc

Age, eduction, ethnicity, gender, race, BMI, smoking status, waist & neck circumference



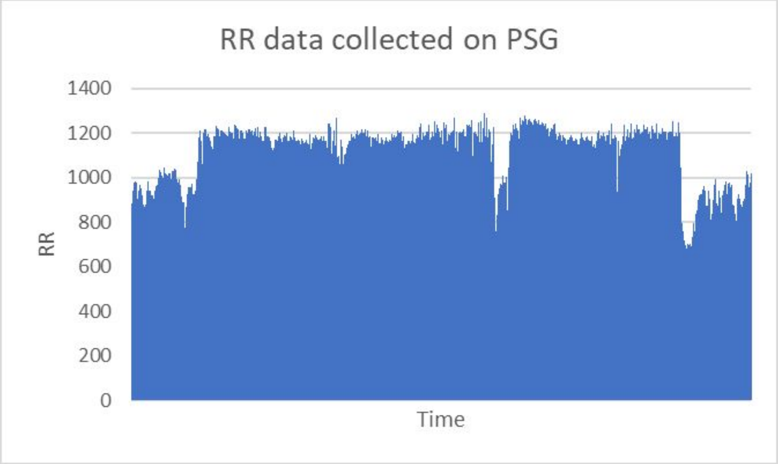
Filtering of participants

```r
## 1. Load the data
dat <- read.csv("sleep_study_table_data_210220.csv", head=T, stringsAsFactors = F)

## 2. Load the required packages. If you haven't installed the randomForest package, please use
## install.package("randomForest") to install this package.
library(randomForest)

## 3. Data cleaning. We will use some predictors in data modeling
model_dat <- data.frame(Age=dat$Age, Education=as.factor(dat$Education), Ethnicity=as.factor(dat$Ethnicity), Gender=as.factor(dat$Gender),
                        Race=as.factor(dat$Race), BMI=dat$BMI, Smoke=dat$Smoking.Status, Waist=dat$Waist.Circumference..cm.,
                        Neck=dat$Neck.Circumference..cm., dat[, 19:48], HeartR=dat$Heart.Rate,
                        AHIc=dat$AHI)
## Remove missing values
model_dat <- model_dat[!(is.na(model_dat$BMI)|is.na(model_dat$STVQT_sd_STVQT)), ]

## Consider None vs Severe
model_dat1 <- model_dat[model_dat$AHIc %in% c("None", "Severe"), ]

rf_model <- randomForest(as.factor(AHIc)~., data=model_dat1)
```

Create RF code using RStudio

Run model and study confusion matrix

Procedure: Descriptive Analysis



RR, breaths per minutes, data taken over time (every 9 seconds) by PSG; Subject ID: 200059; OSA: Severe; Date collected: 1/1/1985.

Name	**Description**	**P-value in association with AHI**
Body Mass Index (BMI)	Person's weight divided by the square of height. Correlates with waist circumference and hypertension	$p<0.01$
Age	A continuous variable ranging from 39 years to 90 years	$p>0.05$
Gender	Categorical variable with female and male.	$p<0.01$
Diabetes	Disease that occurs when your blood glucose, also called blood sugar, is too high. Categories include yes or no.	$p>0.05$
Waist Circumference	Measurement taken around the abdomen at the level of the umbilicus	$p<0.01$
Hypertension	Blood pressure reading of 130/80 mm Hg or higher. Categories include yes or no.	$p<0.01$
Cardiovascular Disease (CVDs)	A group of disorders of the heart and blood vessels like heart attack, stroke, etc. Categories include yes or no.	$p>0.05$
Smoking	Inhalation of the smoke of burning tobacco encased in between cigarettes, pipes, and cigars. Categories include never, or former, or current.	$p<0.05$

Different variables used in prediction with description and p-value association with AHI.

Results

	None (PP)	Severe (PN)	Class error
None (P)	115 (TP)	49 (FN)	0.2987805
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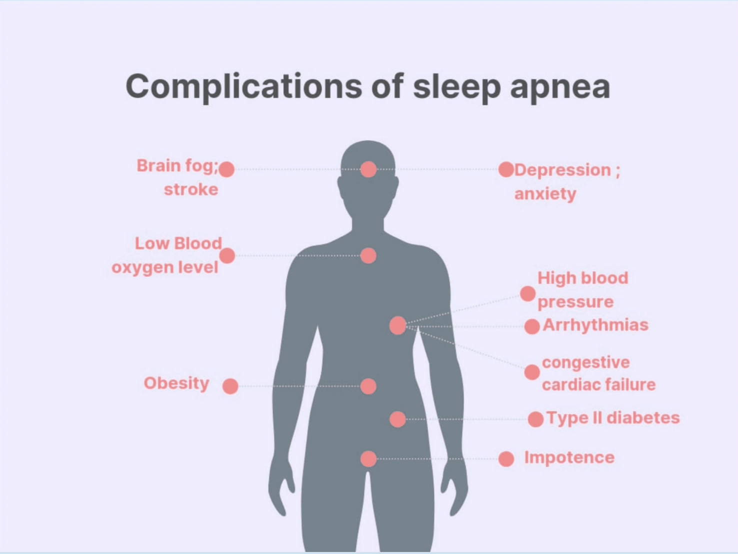
Confusion matrix of prediction model. PP=predicted positive, PN=predicted negative, P=actual positive, N=actual negative, TP=true positive, FN=false negative, FP=false positive, TN=true negative

- Each row represents the actual case, and the columns represent the predicted case
- Prediction accuracy = (TP + TN)/total participants = (115 + 137)/339= **74.34%**.

Significance



Complications of Sleep Apnea, cureus.com

IMPORTANCE

- Model includes both females and males in the study whereas others only include males
- Decrease a patient’s time spent in diagnosis and the patient’s ability to receive treatment.
    - Only needs questionnaire and overnight polysomnography

Discussion

FUTURE PLANS

- Parameters include Epworth Sleepiness Scale (ESS), PaO2 (mmHg), and PaCO2 (mmHg) to diversify data set.
- Recognize mild and moderate OSA so doctors can provide more personalized treatment.
- Participants can be expanded to > 1000 for greater accuracy.

LIMITATIONS

- Usable data only 339 could be the reason for lower accuracy.
- Data was from 1980s and 1990s could have caused some of the machine data to not be correct.

References

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