## Abstract

To be written…

## Introduction

Obstructive Sleeping Apnea (OSA) is a common breathing disorder during sleep. It is characterized by recurrent episodes of complete or partial obstruction of the upper airway leading to reduced or absent breathing during sleep. OSA presents in 5% of adults and 1% of children in developed countries and it is an independent risk factor for diabetes, hypertension, myocardial infarction, and stroke. In addition, OSA in infants has been associated with failure to thrive, behavioural deficits, and sudden infant death.[[1]](#endnote-1)

In clinical diagnosis, the severity of OSA is indicated by Apnea–Hypopnoea Index (AHI). It is represented by the number of apnea and hypopnea events per hour of sleep where the apnea must last for at least 10 seconds and be associated with a decrease in blood oxygenation. For children, an AHI larger than one will be considered abnormal. Typically, polysomnography (PSG) is the most commonly used way for collecting data to detect the AHI and help for diagnosis. It records variant signals, including EEG, ECG, and SaO2[[2]](#endnote-2). There have been previous studies about auto-diagnosing the OSA from PSG signals such as [[[3]](#endnote-3)], from single-lead ECG like the research in [[[4]](#endnote-4)], or from SaO2 and other parameters like the research in [[[5]](#endnote-5)].

Beyond that, Electrical impedance tomography (EIT) is widely used for disease diagnosis, especially lung cancer and adenocarcinoma. There are many studies building models from EIT data of lung, like [[[6]](#endnote-6)] and [[[7]](#endnote-7)]. Since EIT performs well in building images for lung, it can also be used to monitor the OSA.

Machine learning in 3D image analysis is a popular topic in the past few years. Segmentation of the images and auto-diagnosis of the diseases are the main topics. Many useful algorithms are studied, such as convolutional neural networks (CNN) reviewed in [xii] and the use of decision tree in [[[8]](#endnote-8)]. Based on previous researches, in this project, 3D images from EIT are used in machine learning to build the model.

## Aims and Objectives

The project aims to build a model to predict the apnea of neonates, based on analysing the 3D image of lungs. OSA is a harmful respiratory disorder which is one of the main reasons of developmental and functional impairment of the central nervous system and the brain for neonates. Thus, an accurate prediction could warn the physicians in advance and eliminate the effect for the neonates.

### 1.Pre-processing the Data

In this project, a machine learning technique is used to build the models. Before build the algorithms and the different models, the data should be pre-processed. Pre-processing steps include data cleaning, transformation, feature selection and sampling for modelling and validation.

Since there are uninterpretable points, some filter will be found to eliminate the underlying abnormal values, which will be the data cleaning part. For transformation, the 3D images from EIT will be segmented on a minute-by-minute basis. Then they may be cut into 2D pieces for analysis. The segmentation of image should be done, using the existing models such as 3D U-Net[[9]](#endnote-9) [[10]](#endnote-10) which is popular in medical image segmentation, fully convolutional network (FCN)[[11]](#endnote-11) and CNN[[12]](#endnote-12). In addition, there is also a technique FAIM for image registration[[13]](#endnote-13) and FCM segmentation for both 2D and 3D images[[14]](#endnote-14). There are also deep learning methods such as. Feature selection will be the most important job in data pre-processing. Different features should be extracted for further training. It is mentioned in the previous job that some control point could be defined in the 3D images as the feature[[15]](#endnote-15).

After all the pre-processing, the data will be divided into two sets. One is the training set, taking up to 80% of the total data, which will be used to train the model, and the remaining part will be the testing set for evaluating the performance.

### 2. Build Different Models

In machine learning, data with selected features will be input to different algorithms to learn and train the models. Typically, Naïve Bayesian classification and k-NN classification are wildly used as simple models. Besides, support vector machine (SVM), hidden Markov model (HMM), and decision tree are also popular and performance well. Thus, several models will be built using different numbers of features. Furthermore, the opinion of ensemble learning allows us to unite multiple models to obtain higher performance. Typically, ensemble learning includes bagging, boosting, stacking and blending, and random forests is one way which has good performance which will be used in this project.

### 3. Evaluate the Performance

When the models are successfully built, their performance should be evaluated, as a vital representation of the result. The testing set will be input into the model without their labels, and the result will be compared to the known labels. Several index will be calculated, including accuracy, sensitivity, specificity, ROC and area under the ROC curve (AUC). Having these index, the performance of our model can be compared with other’s researches. The meaning and calculation of the indexes are explained in detail below.

1. Accuracy is the number of correctly predicted data points out of all the data points. More formally, it is defined as the number of true positives and true negatives divided by the number of true positives, true negatives, false positives, and false negatives.
2. Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or true positive). Sensitivity is also termed as Recall. This implies that there will be another proportion of actual positive cases, which would get predicted incorrectly as negative (and, thus, could also be termed as the false negative).
3. Specificity is defined as the proportion of actual negatives, which got predicted as the negative (or true negative). This implies that there will be another proportion of actual negative, which got predicted as positive and could be termed as false positives. This proportion could also be called a false positive rate. Specificity = (True Negative)/(True Negative + False Positive)
4. An ROC curve (receiver operating characteristic curve) is a graph of true positive rate (TPR) verses false positive rate (FPR) TPR= (True Positive)/(True Positive + False Negative) FPR =(False Positive)/(False Positive + True Negative)
5. AUC measures the entire two-dimensional area underneath the entire ROC curve (think integral calculus) from (0,0) to (1,1).

If the performance seems to be bad, different ways of building the model should be implement, to obtain a better result. In addition, the k-folder cross-validation method can be used to train the model, rather than simply dividing the data in to training set and testing set.

### Timing

Eight weeks for data preparation

5 Oct- 18 Oct (2 weeks): data cleaning and transformation

19 Oct – 8 Nov (3 weeks): image segmentation

9 Nov – 29 Nov (3 weeks): feature extraction/selection

Eight weeks for building the models

30 Nov – 13 Dec (2 weeks): building Naïve Bayesian and k-NN

14 Dec – 27 Dec (2 weeks): for building SVM

28 Dec – 10 Jan (2 weeks): HMM model

11 Jan – 24 Jan (2 weeks): decision tree and random forests

Five weeks for evaluate the models

25 Jan – 7 Feb (2 week): verify and fix the models

8 Feb – 28 Feb (3 weeks): evaluate the models, and improve the performance

Four weeks for build the models

1 Mar – 11 Mar (3 weeks): build the models targeting higher performance

12 Mar – 28 Mar (4 weeks): combine the models

Four weeks for verify the models

29 Mar – 11 Apr (2 week): verify and fix the models

12 Apr – 25 Apr (2 weeks): evaluate the models, and improve the performance using cross validation

Rest time are retained for buffering and the failure risk

## Preliminary Assessment of Risks (Failure Risks)

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| **Risk** | **Detail** | **Risk Level** |
| Bias | Bias can be introduced in many ways and can cause models to be wildly inaccurate. Lack of consideration in pre-processing the data may cause a bias. | Medium |
| Data | Since machine learning requires a large amount of dataset, not having enough data can bring enormous risk to the modeling process. Bad data will also lead to failure, so we need to implement data cleaning. | Medium |
| Over-Optimization | When building models, we may over-estimate the performance. We may be failed when building models and the accuracy may be low. The model may be lack of variability so it may performance well in one dataset and bad in another. | High |
| Output interpretation | How to use and interpret the model can be a huge risk. A bad evaluation way may lead to a failure. | Low |

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