Multisensory Fusion and Low Latency Sleep Apnea Detection

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Overview and structure

- Motivation
- Background research
- Data collection and preprocessing
- Methodology
- Experimental results
- Future work

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Aims and Objectives

- To study and explore the issues of sleep apnoea.
- To analyse the challenges of sleep apnoea among children.
- Prepare children sleep apnoea dataset from NHS children's trust hospital sleep study data consisting raw multisensory data.
- To visualise the data in a meaningful way.
- To implement various multisensory and single sensory models with small parameter size and low latency and compare their performance.
- To prescribe a feasible low prediction latency solution for the children sleep apnoea detection problem with the NHS data.

Sleep Apnoea

What is sleep apnoea?

- Sleep apnoea is when your breathing stops and starts while you sleep. The most common type is called obstructive sleep apnoea (OSA). (NHS)

Why it happens?

- Obesity, narrow airway, sex, age, smoking, disease

How has sleep apnoea impacted us?

- Daytime fatigue
- High blood pressure, Heart disease
- Risk of death

25 million US adults have **obstructive sleep apnea** (OSA).
9-21% of US **women** have OSA.
24-31% of US **men** have **OSA.**
Post COVID, 1 in 3 UK residents (33%) have been sleeping less than before while 1 in 5 (20%) have been sleeping more than usual.
up to 4 million people have moderate or severe OSA
up to 6 million people have mild OSA

Some facts about OSA. [1,2]

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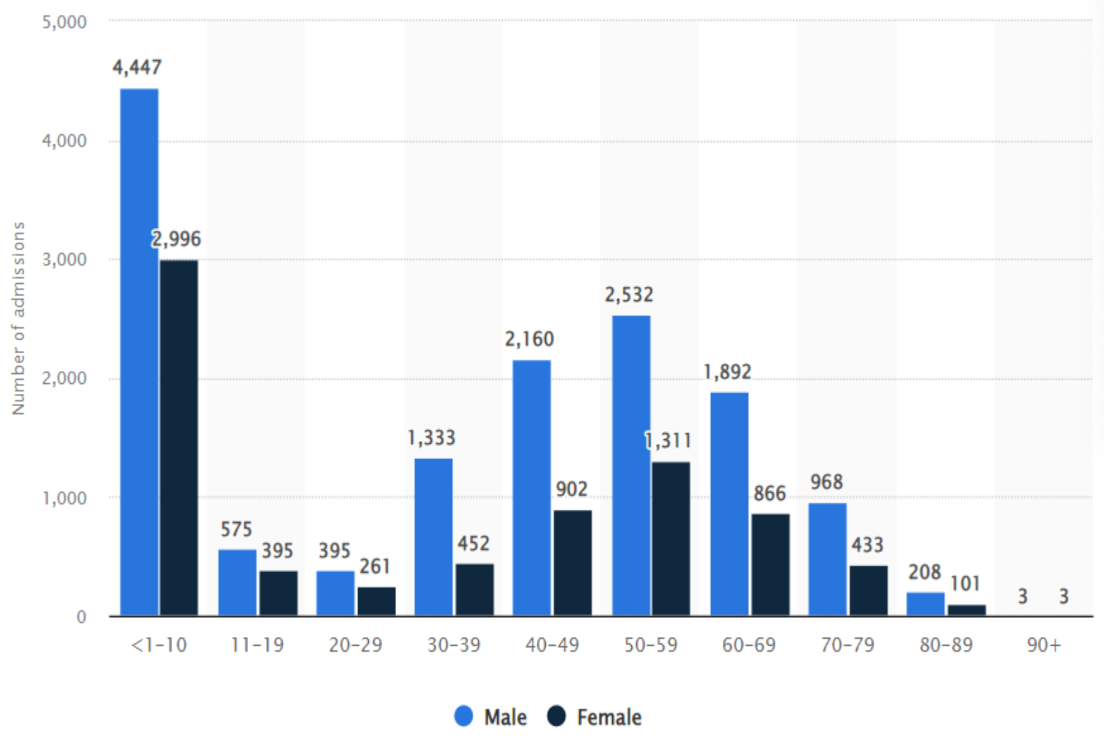
Why we need low-latency sleep apnoea detection?

- **Most of the OSA cases are undetected.[1]**
  - Approx 3 million undiagnosed OSA cases in UK alone.
  - An undiagnosed patient with moderate or severe OSA will cost the NHS twice that of a patient diagnosed and treated with CPAP.
  - Using the BLF 20146 cost estimates it reckoned 80% of 1.5 million were undiagnosed and this was costing the NHS £28 million a year.
  - Based on this, then, with 3 million still to diagnose, the current cost to the NHS is £96 million.
- **Cheaper alternatives with less computational resource**
  - Run time OSA detection and alarm.
  - Low-latency prediction for real-time execution in less computational resource devices.



People admitted to hospital for OSA in the UK in 2017/18. [3]

Related Works

- OSA detection with ECG signals.
  - EEG extracted features with SVM [4]. Reduced EEG dimension and used linear kernel for SVC.
  - Wavelet based EEG features with SVM with 125 subjects and 8 hour of avg sleep study. [5]
  - blood oxygen saturation, oronasal airflow, and ribcage and abdomen movements feature based CNN model. [6]
- OSA detection with wearable technologies
  - Devices like watches, health bands are being popular to monitor sleep cycle health parameters. [7]
  - respiratory airflow, blood oxygen saturation(SPO2), electrocardiogram(ECG) and breathing movement in real-time measuring wristwatch. [8]

Sleep apnea data

- NHS sleep study data
  - Sheffield children's' NHS foundation Trust
  - The data has been collected in 2019 between June to December
  - Eight participants totaling approximately 80 hours of multi sensory data.
- Data description
  - Multisensory data with various sampling rates (4-32).
  - Time synchronized
  - SPo2, Co2, Snore, Sum RIP sensory inputs have been used for feature preparation over 5 second backward and 5 second forward context.

Sensor name	Function measurement
SpO2	oxygen saturation levels
CO2	measures carbon dioxide levels
Snore	Snore channel that picks up the vibration of snoring
Pulse	Pulse rate of the subject.
RIP abdomen	respiratory inductance band that measure abdominal breathing - sum RIP is the sum of the two channels
RIP thorax	respiratory inductance band that measure chest breathing
sum RIP	The sum of RIP abdomen and RIP thorax channels

Data preparation

Noise removal

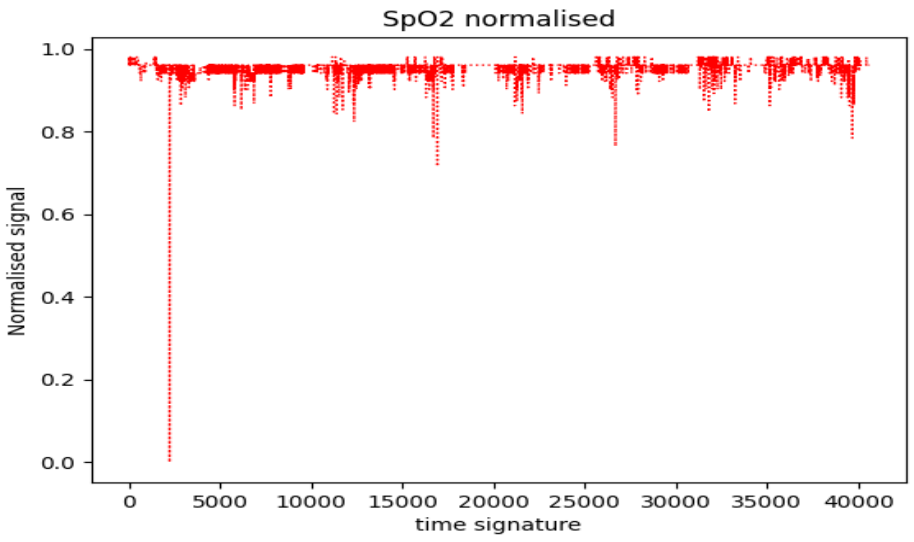
- Garbage values removal and time synchronization over the sensor timeframes.

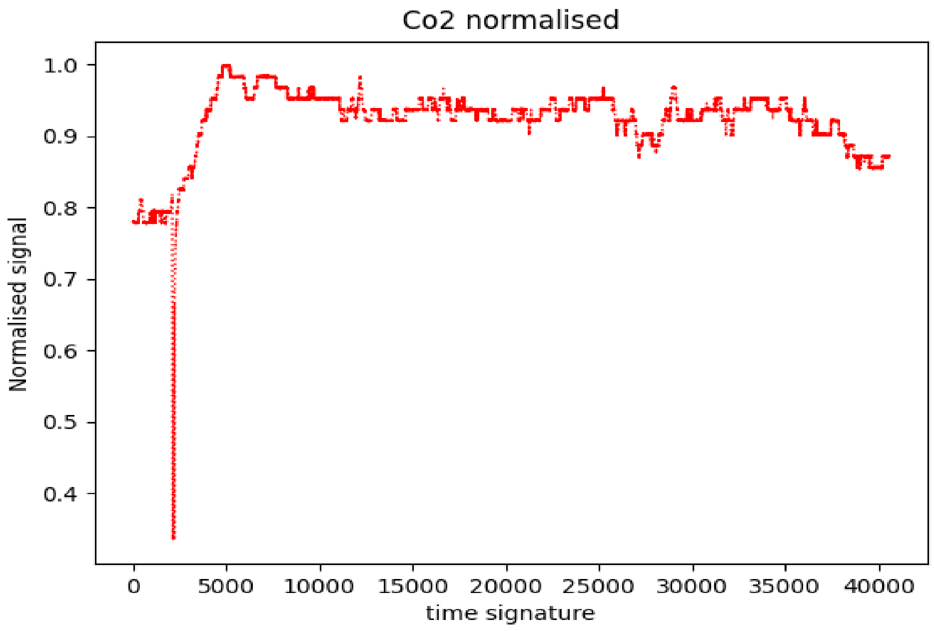
Data visualization

- Data normalization and visualization
- Wavelet feature visualization

Why multisensory

- More robustness
- Fault tolerance
- Overall study of the correlation among other health factors.

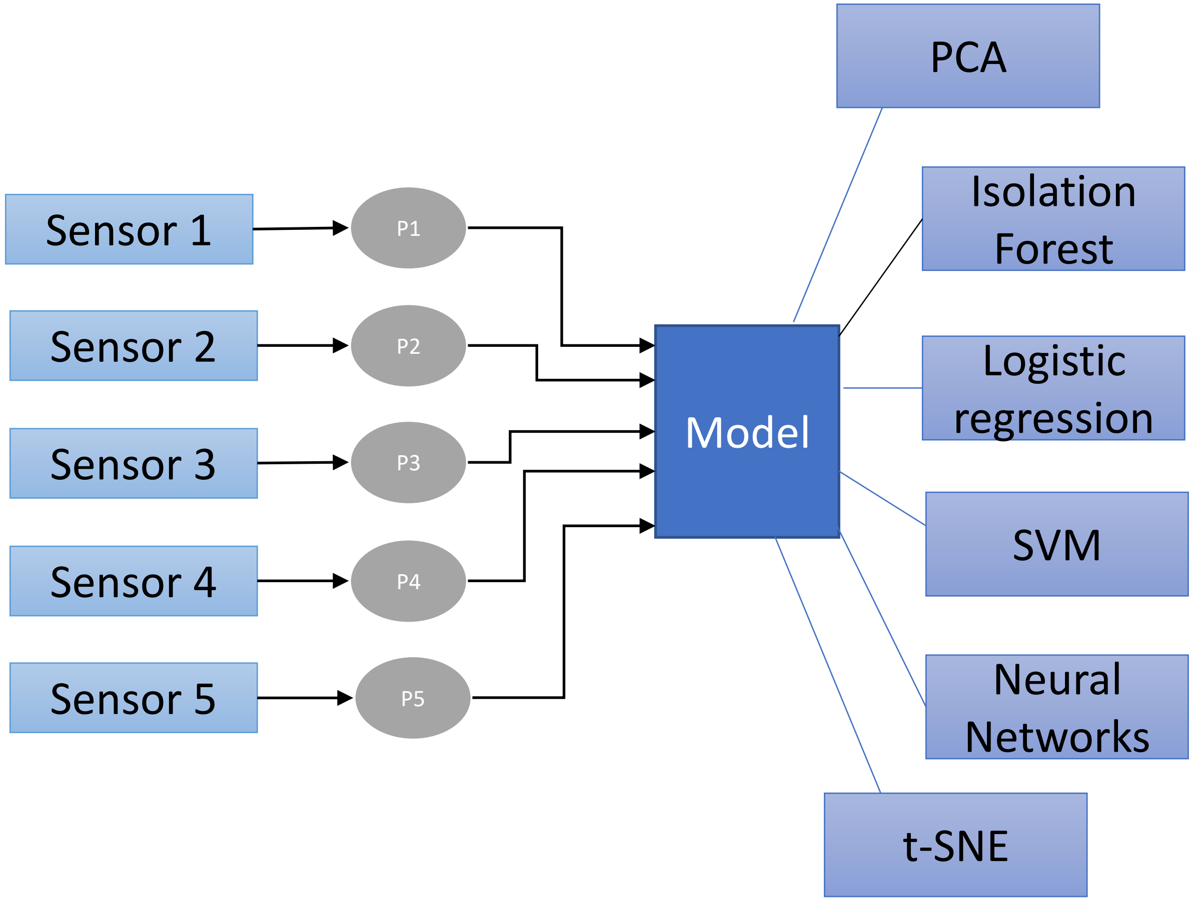




Subject 1 data: PI001 SpO2 and CO2

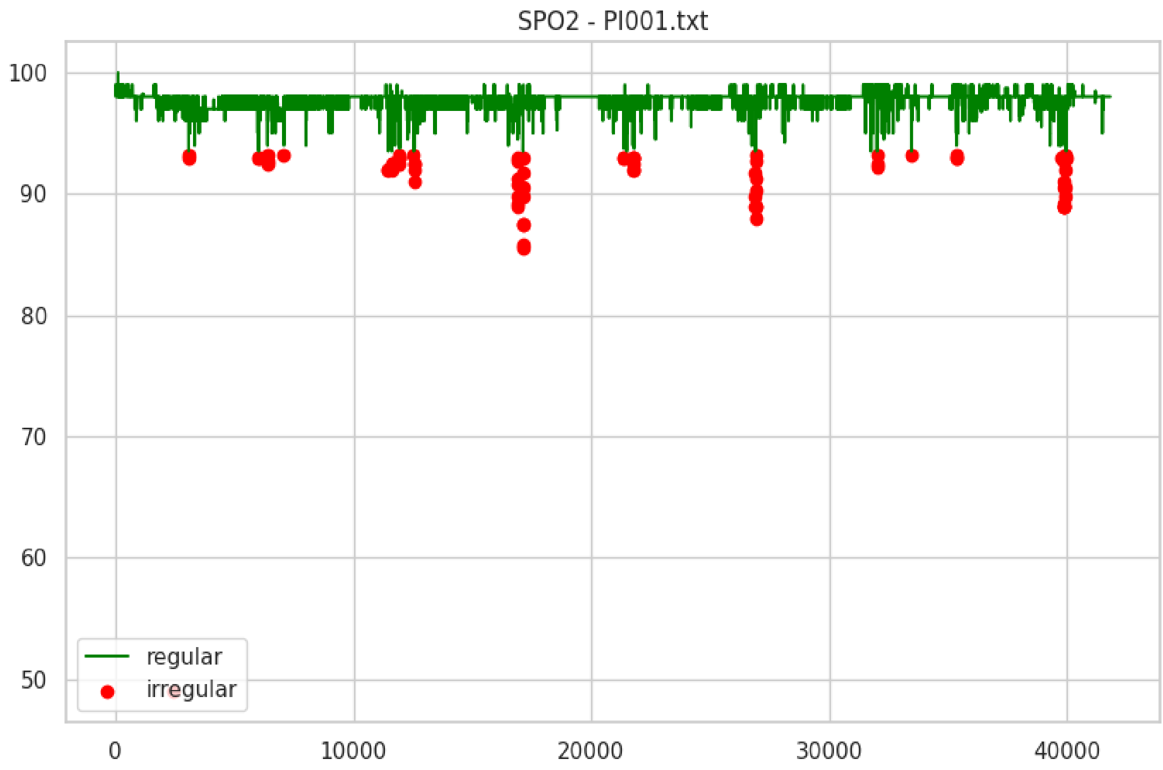
Research method

- Approach
  - Multi-sensor features
  - Flexible for weighted feature streams (P1,P2,P3,P4,P5).(11 sec context)
  - Pseudo-label data after unsupervised clustering.
  - Train the labelled data with supervised models.
  - Visualization of decision boundaries, clusters and latency.
- Models
  - Isolation forest
  - Logistic regression, SVM
  - Shallow feedforward NN, Shallow CNN-Feedforward DNN
  - Multichannel CNN



Unsupervised clustering

- **Isolation forest for anomaly detection**
  - Sleep apnoea happened in 3-4% of the overall duration of the sleep cycle according to the doctor's evaluation.
  - The outlier proportion is set according to that.
  - The hypothesis of isolation forest caters to this particular situation because sleep apnoea causes sudden drop in the SpO2 levels.
  - The number of random forest components are varied to get the optimal number.



Regular vs Irregular SpO2 levels in timeframes with Isolation Forest (Subject PI001)

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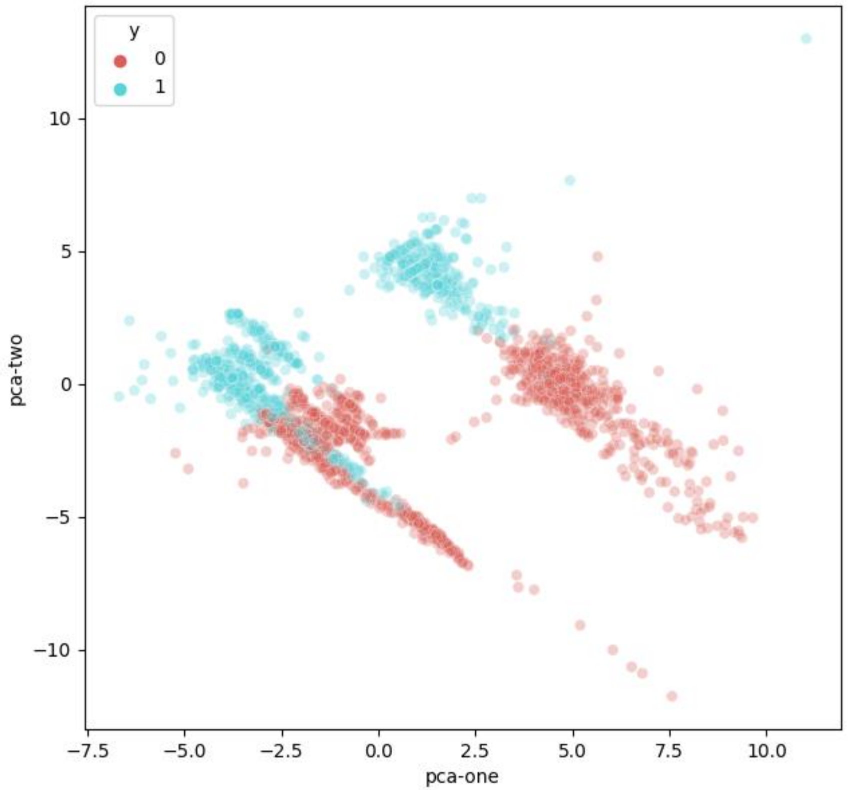
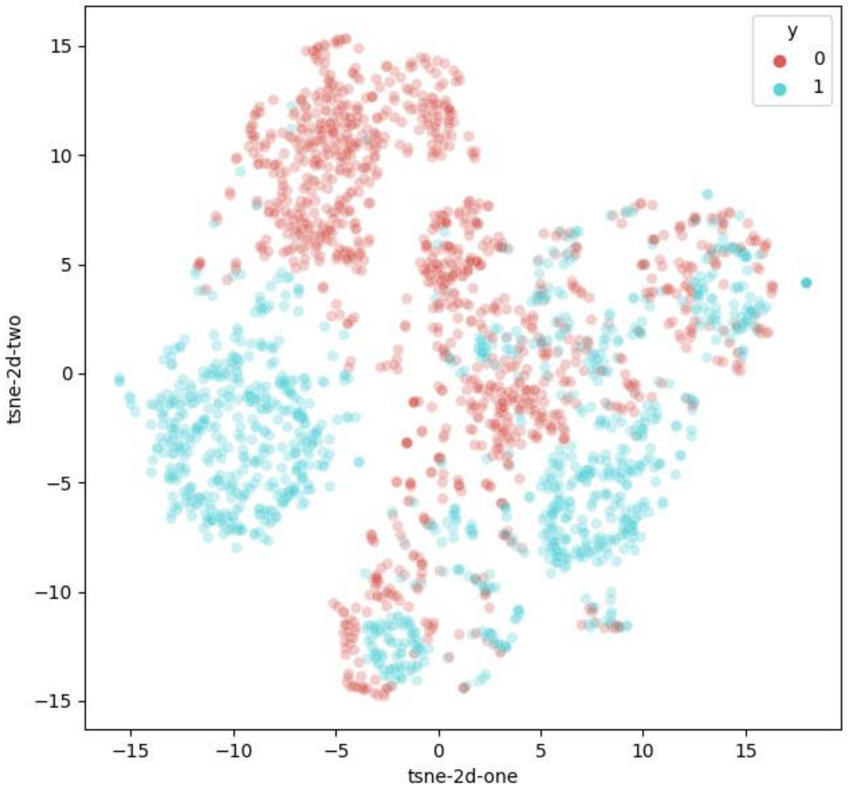
Dimension reduction and clustering

- PCA (overlapping clusters with two principal components)
- t-SNE (unsupervised clustering of the samples with fifty-five length feature vector)
- 2634 samples of 55 feature length

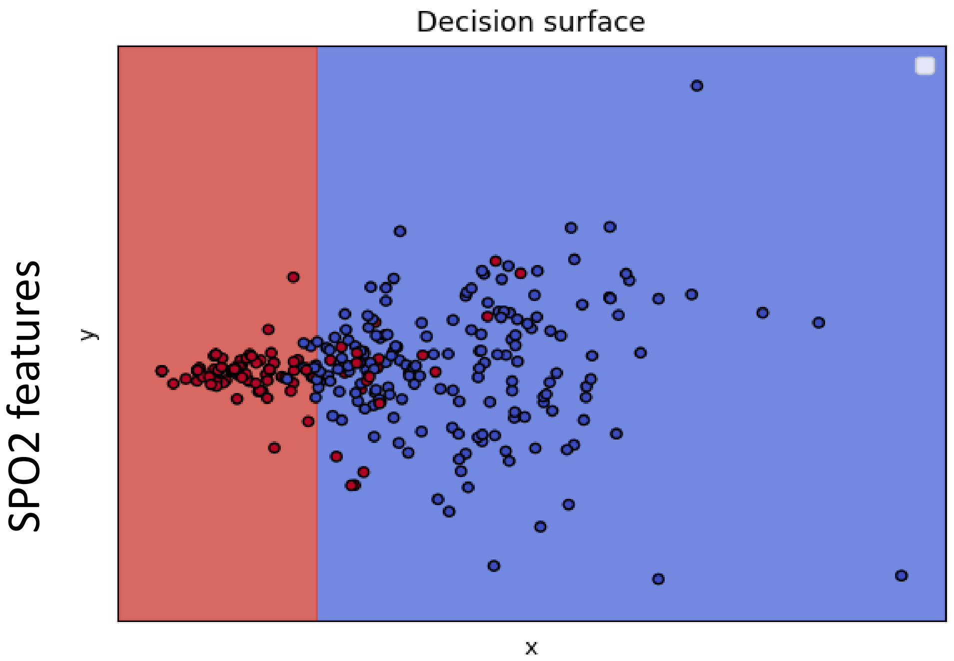


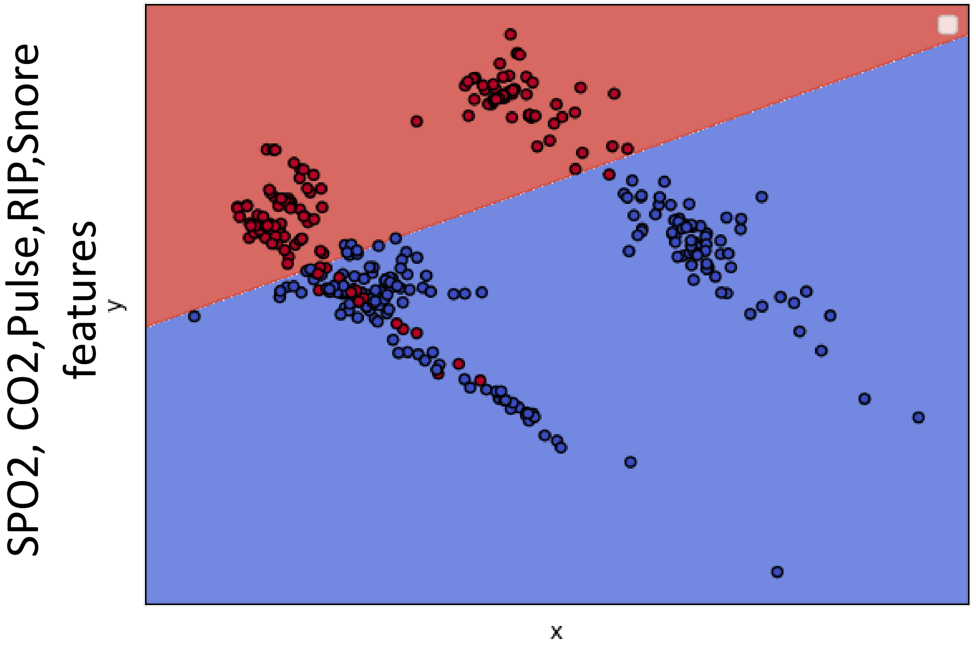


Support Vector Machine

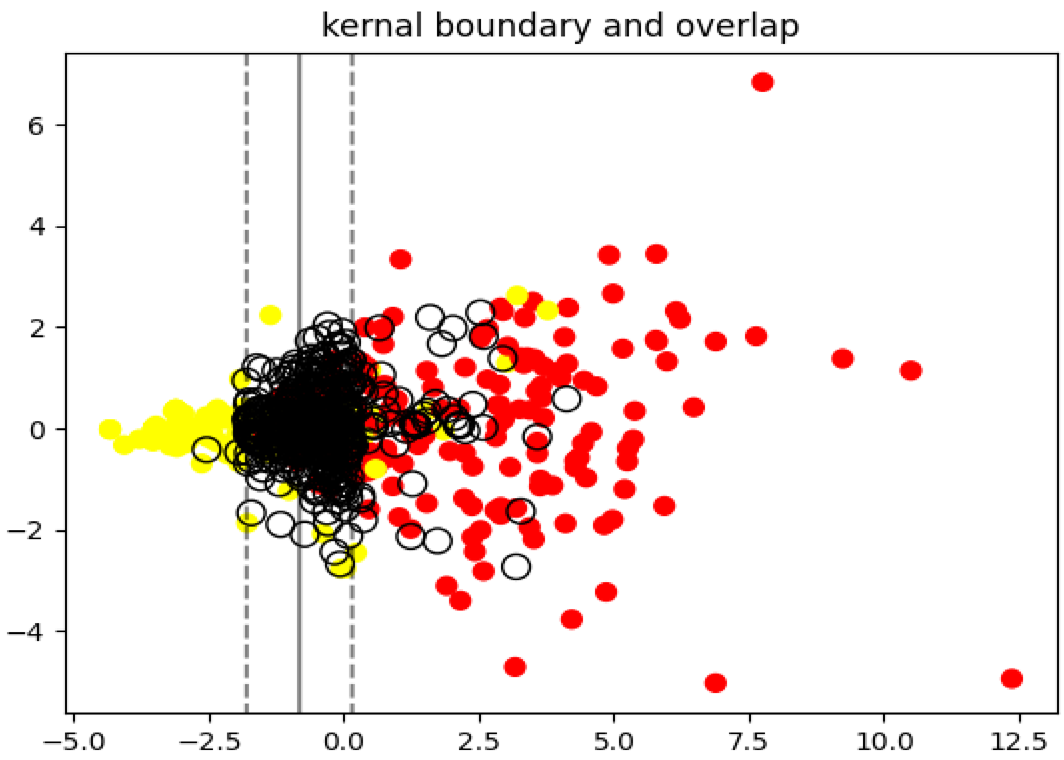
Sensory Features	Model	Accuracy (%)	Prediction Latency (millis)
SPO2 (11)	SVC linear	94.8	1.6
SPO2, CO2,Pulse, RIP,Snore (55)	SVC linear	94.2	2.3
SPO2 (11)	Logistic regression	94.5	0.15
SPO2, CO2,Pulse, RIP,Snore (55)	Logistic regression	94.2	0.16

Result Comparison for different sensory inputs

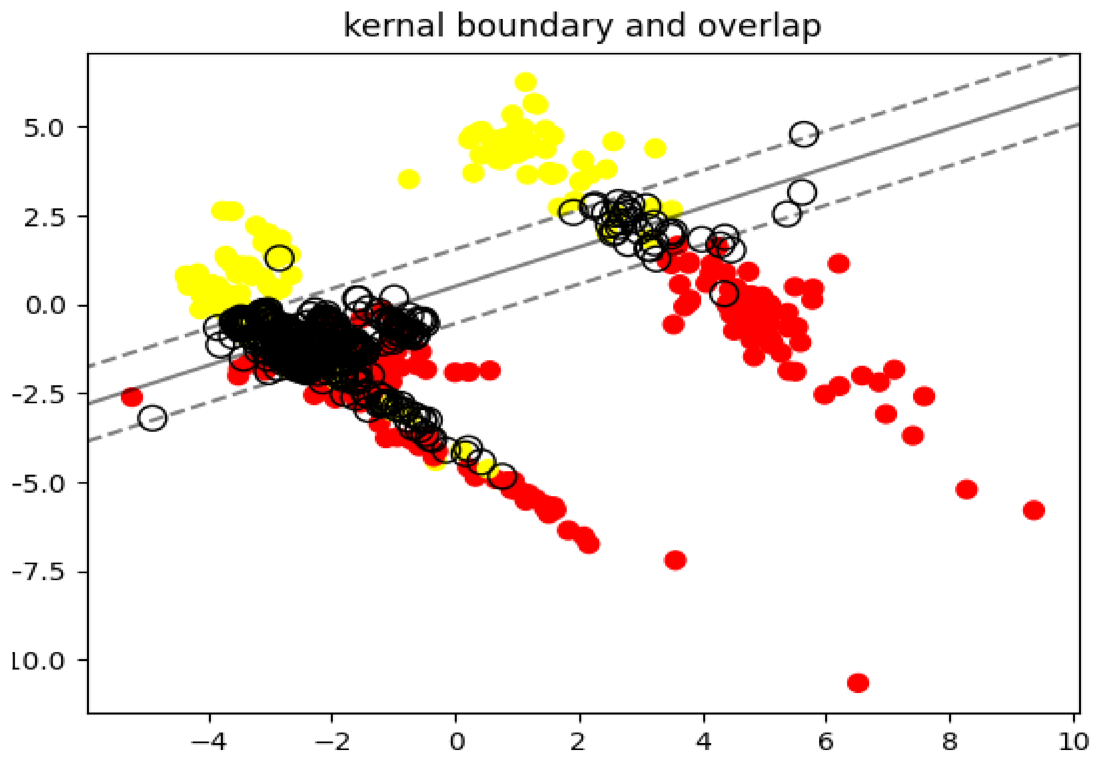




Support Vector Machine (contd.)



SPO2 features



SPO2, CO2,Pulse,RIP,Snore features

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Low latency neural networks

Features	Model	Layer description	Num of Parameters	Latency (ms)	Accuracy (%)
SPO2, CO2,Pulse, RIP, Snore	Multichannel CNN + feedforward	5x parallel conv1d(1,64,5),1x Conv1d(64,128,5) 1x Conv1d(128,64,5), 1x Conv1d(64,64,5),1x Linear(64,128), 1x Linear(64,64), 1x Linear(64,1)	121222	9.46	98.1
SPO2, CO2,Pulse, RIP, Snore	CNN + feedforward	1x Conv1d(64,128,5) 1x Conv1d(128,64,5), 1x Conv1d(64,64,5),1x Linear(64,128), 1x Linear(64,64), 1x Linear(64,1)	115713	5.68	97.0
SPO2, CO2,Pulse, RIP, Snore	Feedforward	1x Linear(55,128), 1x Linear(128,128), 1x Linear(128,1)	23809	2.03	96.7

Low latency neural networks

Features	Model	Layer description	Num of Parameters	Latency (ms)	Accuracy (%)
SPO2	CNN + feedforward	1x Conv1d(64,64,5),1x Conv1d(64,64,3), 1x Linear(64,128), 1x Linear(128,64), 1x Linear(64,1)	45761	3.7	95.1
SPO2	Feedforward	1x Linear(55,128), 1x Linear(128,128), 1x Linear(128,1)	23809	2.03	94.8

Discussion and Future work

- It has observed that with single sensory data SVMs performed better compared to multisensory data. This can be linked to the sparseness of SVM's solution classifier. It samples a subset of training examples for the support vectors for learning boundary. Therefore, feature selection is important for SVM.
- However, for NNs the scenario is quite different. They perform quite similarly with single sensory and multi sensory data (if not better with multisensory data). The reason is NNs process the whole feature vector over all the training samples. Thus, learning the covariate shift in the data and better generalization.
- The multichannel CNN network performs better with increased latency. The essential reason is the parallel CNN blocks learn different representation from 5 different sensors and then they are fused together with learnable weighted parameters. This acts like a mixture model which cause better learning and prediction.
- Although it can be argued that the number of parameters are significantly high in the NN models. The effect of the number of parameters in similar architecture can be analysed as a future work. The children OSA dataset used here is small and the parameter number vs dataset size tradeoff analysis may give helpful direction for optimizing the OSA detection systems.
- Another possible future direction could be to explore the temporal feature selection for reducing uncertainty in these small low resource models.


Thank you..Questions?

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