ENBM068T

BioWaveNet

A Novel Multi-Scale Convolutional Neural Network for Generalized Bio-signal Applications

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All graphics/charts/images created by finalists

Background & Inspiration

Pain Points

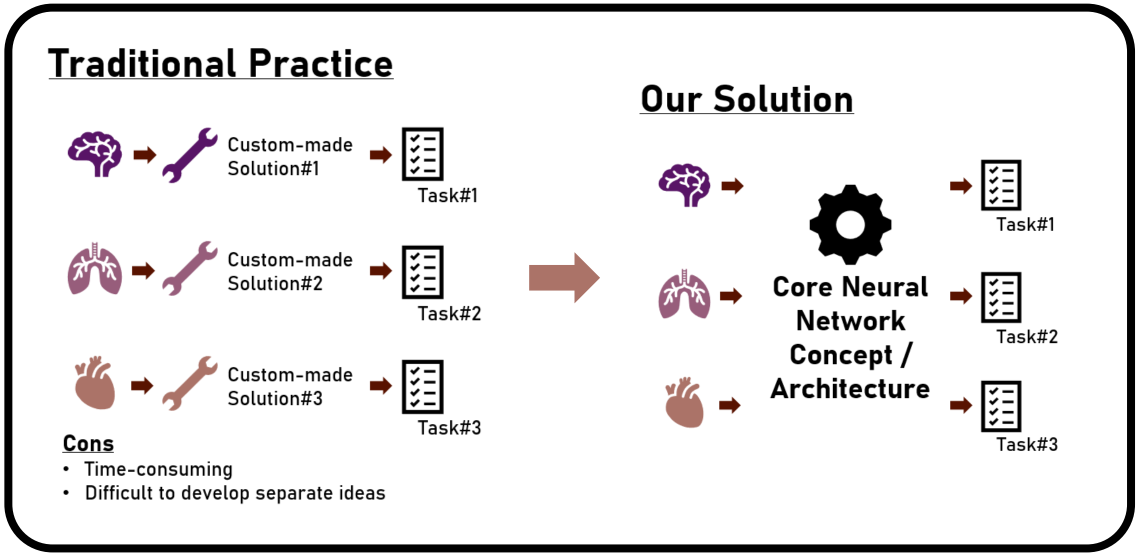
BIO-Signal
Signal data collected from human organs [1]

Difficulties
Require Clinical Expertise with Substantial Medical Knowledge [2]

Automations
Feature engineering-based machine learning algorithm to aid clinicians [1]

Limitations
Current feature engineering algorithms are too rigid and take high-domain knowledge to develop, while being too specific on a single task [3]

Goals



How can we develop a bio-signal analysis idea or prototype to generalize on many signals and tasks?

Our tasks

BIO-Signals

Choose 2 signals that cover other signal characteristics

→ Electrical Signals (electrodes)

→ Non-electrical Signals (light, kinetics)

Choose important signals and tasks

1. Electroencephalography (EEG-Brain) + Seizure Detection [4]
   - EEG = main measure for epilepsy
   - Over 100 million epilepsy patients worldwide
   - Help doctors screen hours of EEG recording
2. Photoplethysmography (PPG-Blood) + Respiratory Rate Estimation [5]
   - PPG = easily collected from smartwatches
   - Respiratory rate can screen abnormal breathing on COVID-19

EEG - Brain

- Recorded Brain Activities
- Electrical Signal
- Goal : Help Clinician Screen Hours of EEG recordings

PPG - Blood

- Recorded Circulatory Activities
- Light Sensor Signal – Wearable Devices
- Goal : Remote Report on patients' respirations

Datasets

EEG Datasets

Bonn Dataset
N = 5

Has labelled stage of pre/inter-seizure onset

CHB-MIT Dataset
N = 23

Medical cohort with long recordings of EEG per patient

TUSZ Dataset
N = 28

Contains various devices, only a few use for normal vs seizure

PPG Datasets

Capnobase Dataset
N = 42

BIDMC Dataset
N = 52

Both are ICU datasets with a large amount high-quality PPG

WESAD Dataset
N = 15

Collected from wearable devices (closest to practical use)

Experiment Protocols

Preprocess

EEG Datasets :

- Noise removal via lowpass filter at 64 Hz
- Window size 4 seconds, 1 second overlap

PPG Datasets :

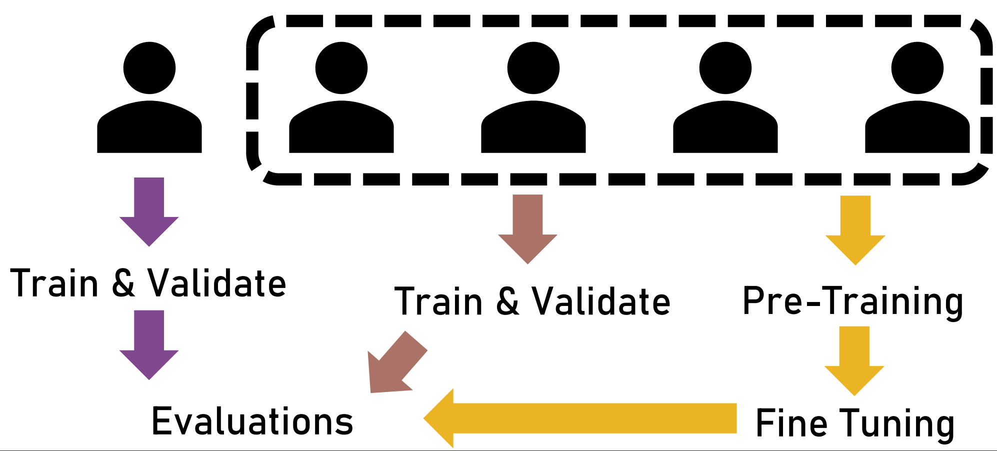
- Signal Quality Indexing (SQI) *peak F1 score x flatline ratio > 0.9*
- Window size 16, 32, and 64 seconds (test effects of window size on performance)

Experiments

(A) Subject Dependent : Trained and tested on the same patients

(B) Subject Independent : Tested on unknown patients (LOOCV)

(C) Transfer Learning : Weights are pre-trained among datasets



All training loops use 5-fold cross validation to ensure fairness

BioWaveNet – EEG and PPG

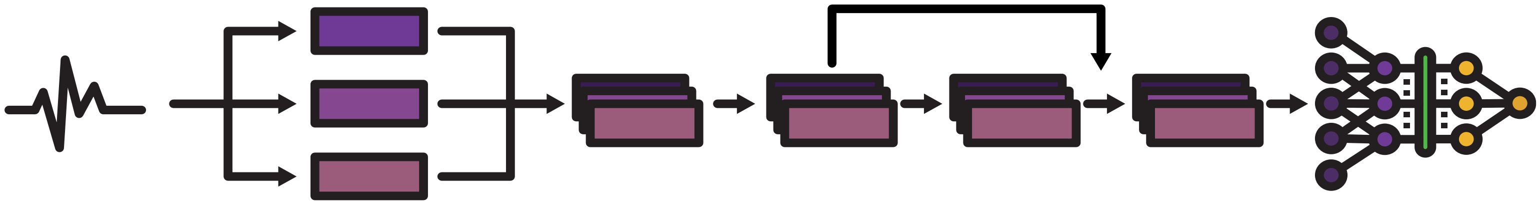


Fig 1 EEGWaveNet (BioWaveNet for EEG)

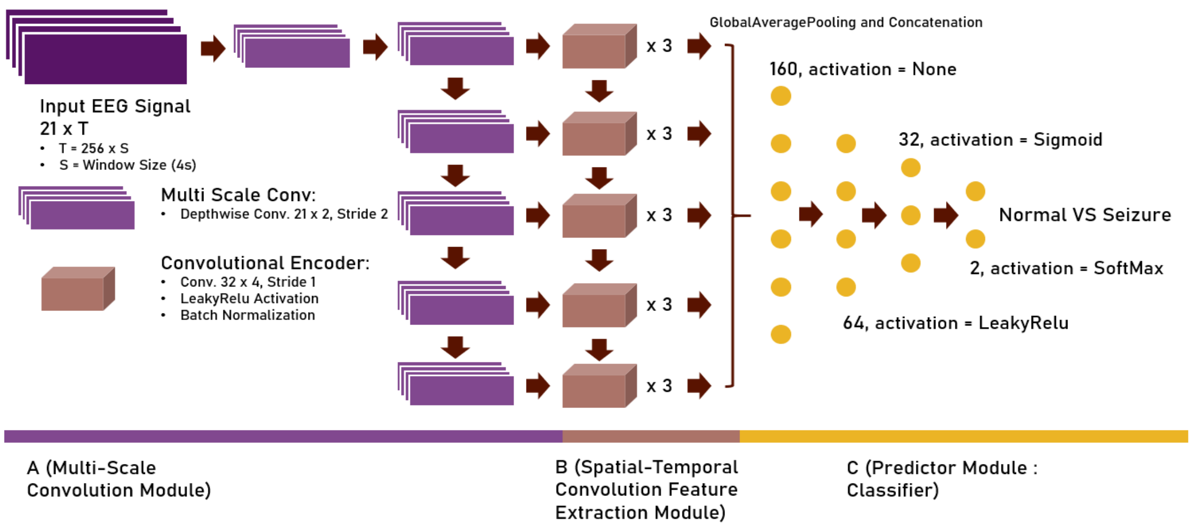
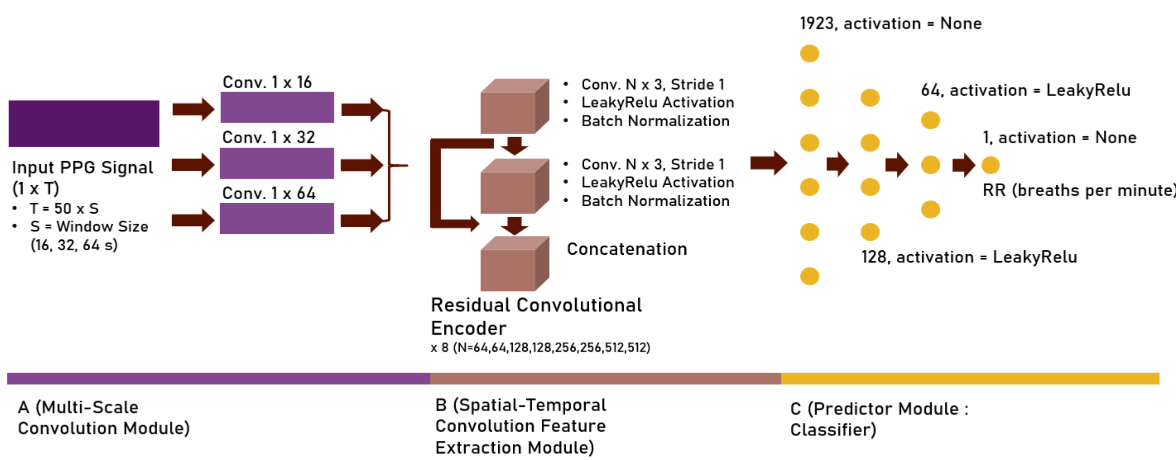


Fig 2 PPGWaveNet (BioWaveNet for PPG)



BioWaveNet Concepts

(A) Multi-scale Convolution (NOVELTY)

: various convolutional filters connected parallelly for learnable scaling

Small filter size for sudden/sharp bio-signal peaks

Larger filter size for gradual changes

(B) Spatial-temporal Feature Extraction

: CNN to analyze signal patterns from (A)

(C) Multilayer Perceptron

: Output - Regression or Classification

Training Strategies

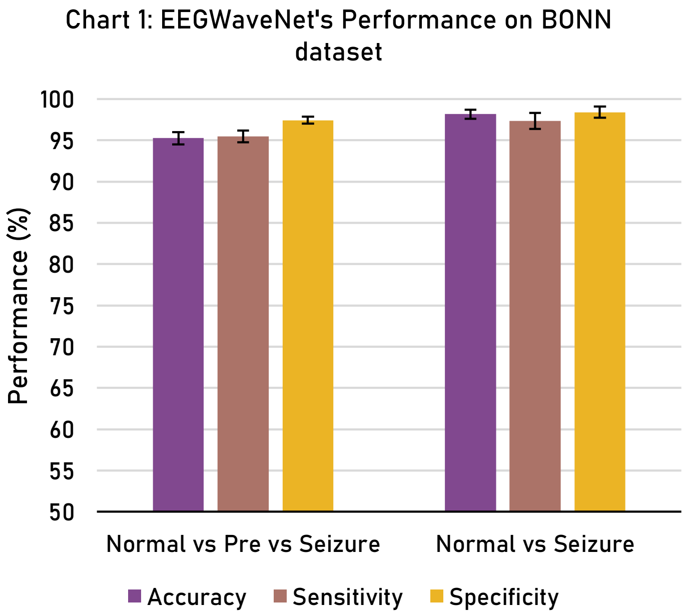
(i) Hyperband for hyperparameter tuning

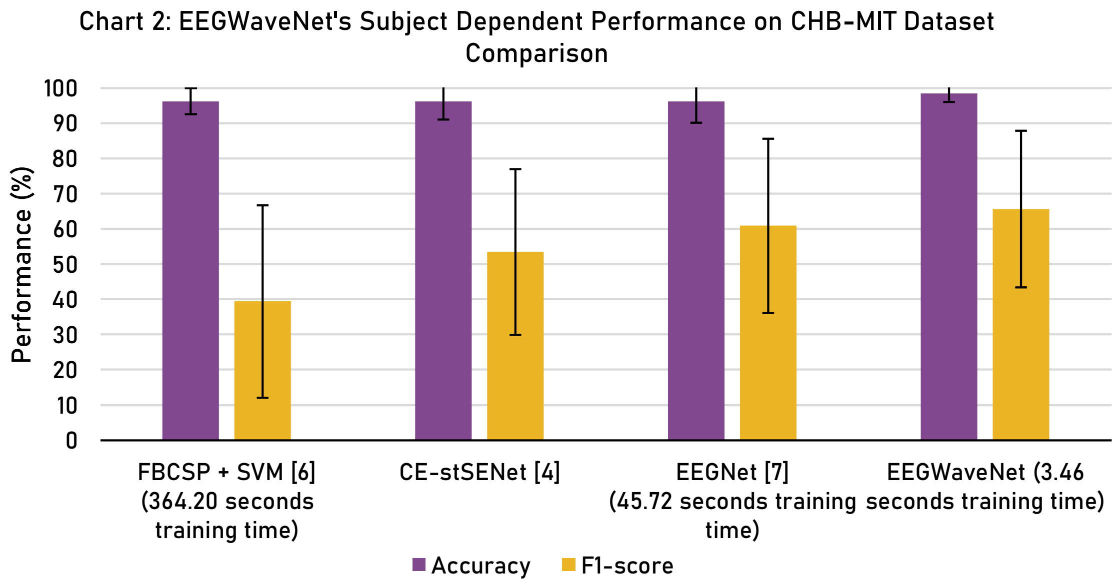
(ii) AdaBelief optimizer with 0.001 learning rate (0.25 decay – 5 patience)

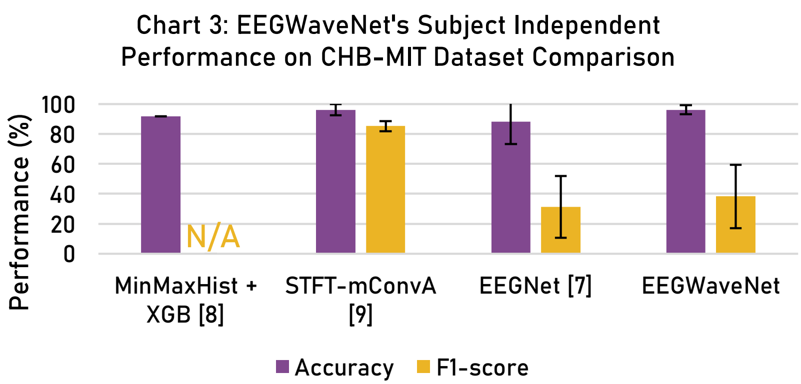
(iii) Earlystopping after 10 consecutive epochs

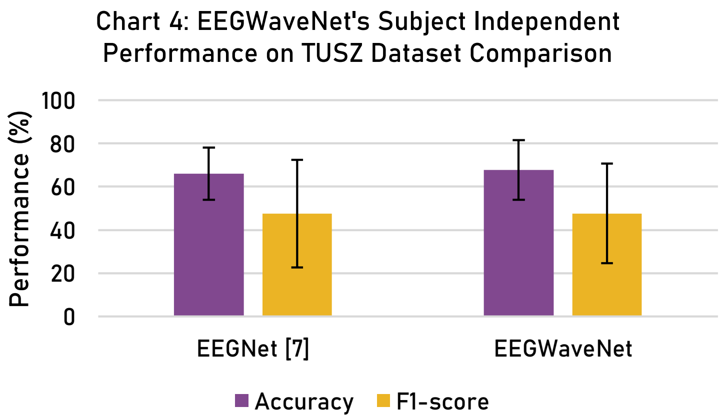
(iv) Cross Entropy (classification) and MSE (regression) loss

EEG Seizure Results









Findings (Dependent) : EEGWaveNet achieves the best performance while trains the fastest, due to faster fitting to minimal loss. Further exploration shows the high F1-score from the lowest false-positive rate.

Findings (Independent) : EEGWaveNet outperforms the SOTA (EEGNet) while achieving a reasonable starting performance before transfer learning.

Chart 5: Respiratory Rate Estimation via PPG on Capnobase dataset

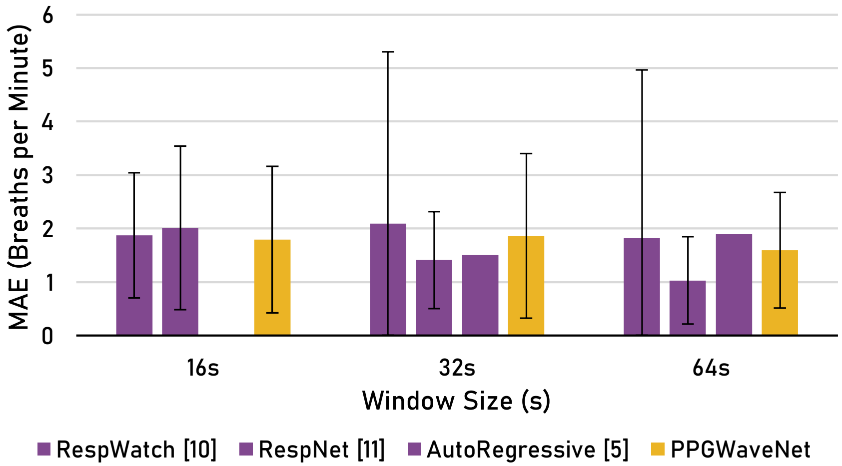


Chart 6: Respiratory Rate Estimation via PPG on BIDMC Dataset

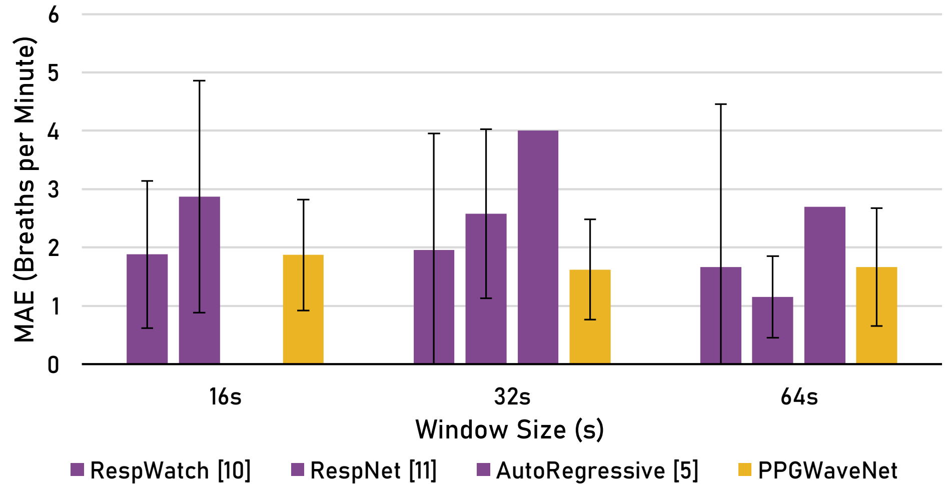
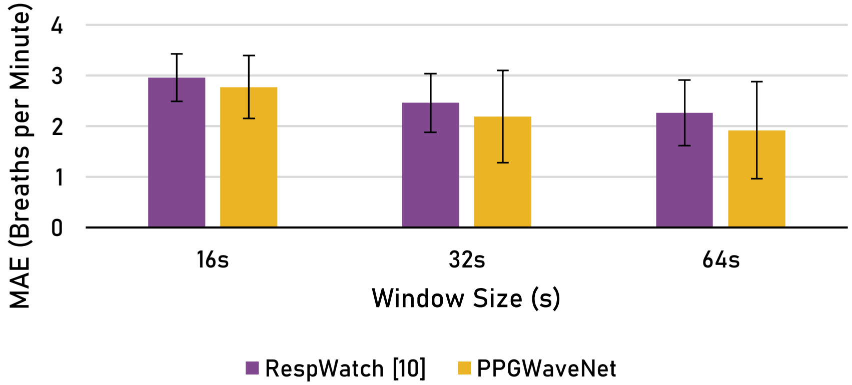


Chart 7: Respiratory Rate Estimation via PPG on WESAD Dataset



Findings (1) : PPGWaveNet achieves the best performance on 16 seconds – the smallest window size (model can infer up to 60 seconds after!).

Findings (2) : When compared the model size, PPGWaveNet is the smallest and works on all datasets. Some other models require more than 1 signal, which isn't always present.

Transfer Learning Results

Chart 8: EEGWaveNet's Transfer Learning Performance

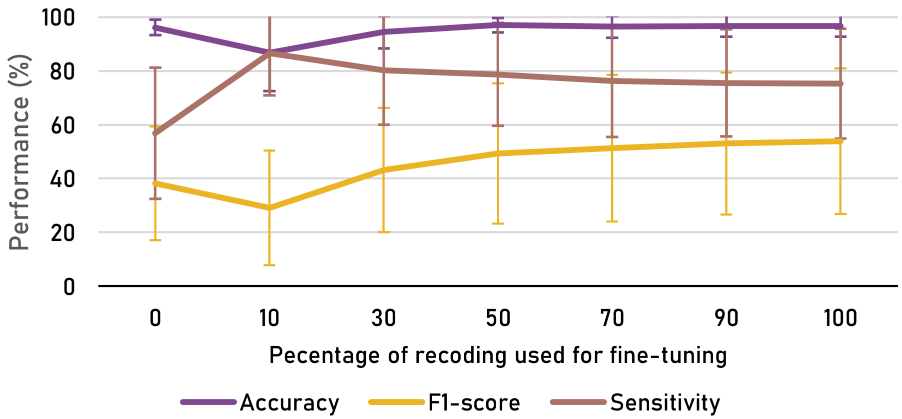


Chart 9: EEG Transfer Learning Fine-tuning Time

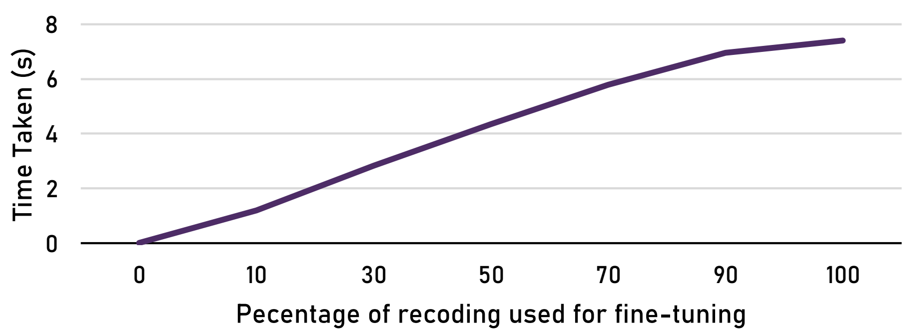
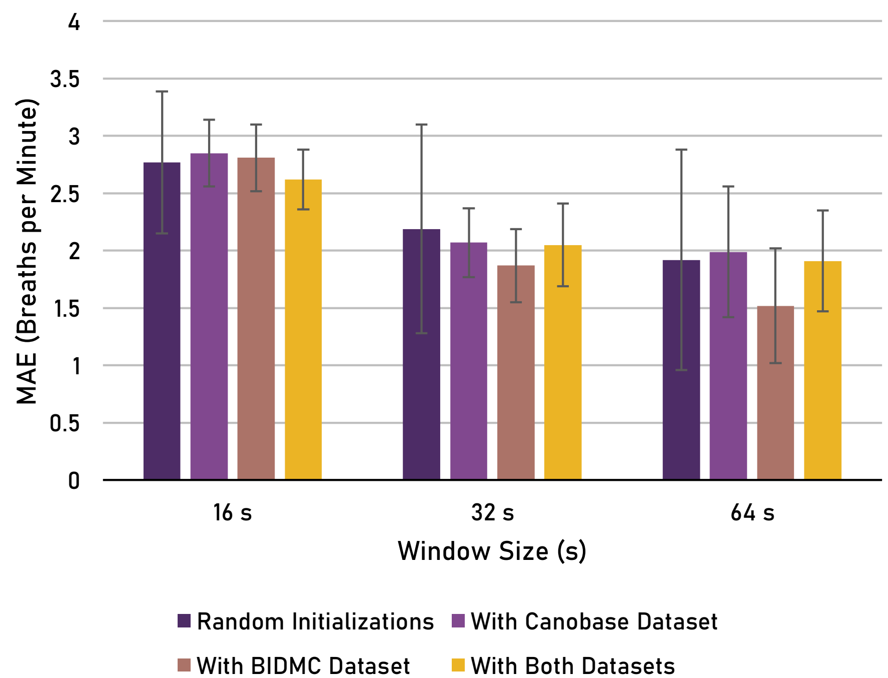


Chart 10: Respiratory Rate Estimation via PPG Performance (MAE) vs Pre-trained Datasets

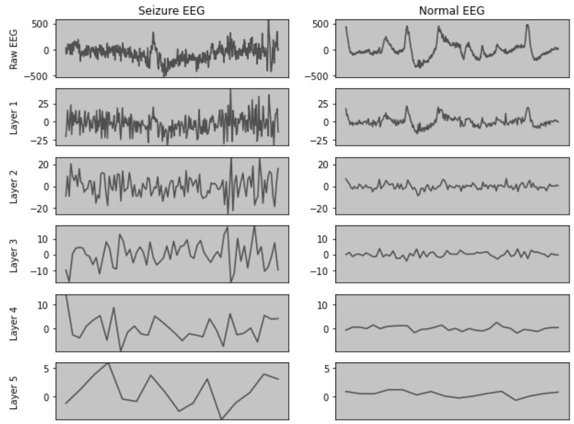


Findings (EEG) : Transfer learning with 1-hour fine-tuning data can increase our performances, all within 10 seconds of fine-tuning.

Findings (PPG) : Transfer learning from an ICU dataset can reduce the error when trained again on the WESAD (wearable device) dataset.

Discussions

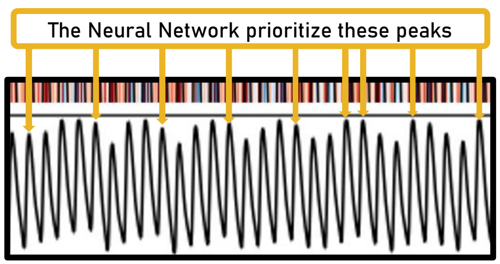
Fig 3 EEGWaveNet's Generated Scales



Findings (EEG) : Seizure (left) and normal (right) EEG are further discriminated when passed through the multi-scale module.

This seizure event results in a noisy EEG even after filtering. The model amplified the hidden noises through the scales.

Fig 4 PPGWaveNet's SHAP Explanation



Arrow = Area with high SHAP score

Findings (PPG) : SHAP values are shown in peaks that corresponds medically to respiratory rate.

The amplitude change in PPG corresponds to the RIIV measure, which was proven to be connected to how fast a person breathes [5].

Findings (Overall) : Our multi-scale module allows for a smaller and more effective model, while transfer learning strategies boost our performances.

Conclusions and Impacts

Conclusions

Generalized Bio-signal Model

We successfully created a generalized system for bio-signal applications, and showcased on 2 tasks.

Transfer Learning Experimental Protocol

We proposed transfer learning protocols that deal with the lack of data, which could be applied in hospitals.

Impacts

EEG Seizure Detection

Our model can be developed into a screening application for seizure diagnosis, potentially saving millions of epilepsy patients.

PPG Respiratory Rate Estimation

Our model can screen abnormal breathing remotely, potentially allowing telemedicine on COVID-19 patients through smartwatches.

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