Abstract

Bio-signals have become an staple of Healthcare assessment. However, performance and robustness remains an issue on automation attempts of bio-signal analysis. Moreover, the preferred feature engineering is often overcomplicated, resource-intensive, and rigid for practical use.

In this study, we proposed to use the learn-able novel Multi-scale Convolutional Neural Network architecture called **BioWaveNet**.

Our results shows BioWaveNet's ability on two important bio-signal analysis tasks – seizure detection via Electroencephalography (brain-EEG) and respiratory rate estimation via Photoplethysmography (blood density-PPG). BioWaveNet outperforms other studies with comparable computational resources, suggesting clinical feasibility for bio-signal analysis.

Background

Bio-Signals
Signal data collected from human organs [1]

Difficulties
Require Clinical Expertise with Deep Medical Knowledge [2]

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

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

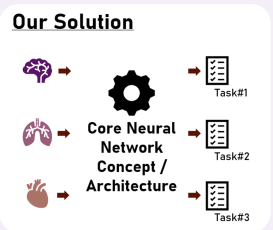
Tasks

Electroencephalography (EEG) Seizure Detection [4]

- EEG = main measure for epilepsy
- Over 100 million epilepsy patients worldwide
- Help doctors screen hours of EEG recording

Photoplethysmography (PPG) Respiratory Rate (RR) Estimation [5]

- PPG = easily collected from smartwatches (wearable devices)
- Respiratory rate can screen abnormal breathing on COVID-19



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

Methodologies

I) Data Acquisition

All open source databases

EEG Datasets :

- Bonn (N=5) 1CH EEG, normal vs pre vs seizure
- CHB-MIT (N=23) 21CH EEG, normal vs seizure
- TUSZ (N=28) 21CH EEG, normal vs seizure

PPG Datasets :

- Capnobase (N=42) clinical (intensive care unit) PPG
- BIDMC (N=52) clinical (intensive care unit) PPG
- WESAD (N=15) wearable device PPG

II) Preprocessing

EEG Preprocessing :

- Window Size: 4s with 1s overlap
- Filters: Lowpass filter at 64hz to remove noise
- Labels: Expert labels from EEG neurologists

PPG Preprocessing :

- Window Size: 16, 32, and 64s to study varying window size
- Signal Quality: Peak F1 score x Flatline ratio > 0.9
- Labels: RR obtained from respiratory belt signals

III) Experiments

- Subject Dependent : Trained & tested on the same patients
- Subject Independent : Tested on unknown patients (LOOCV)
- Transfer Learning : Pre-trained among datasets

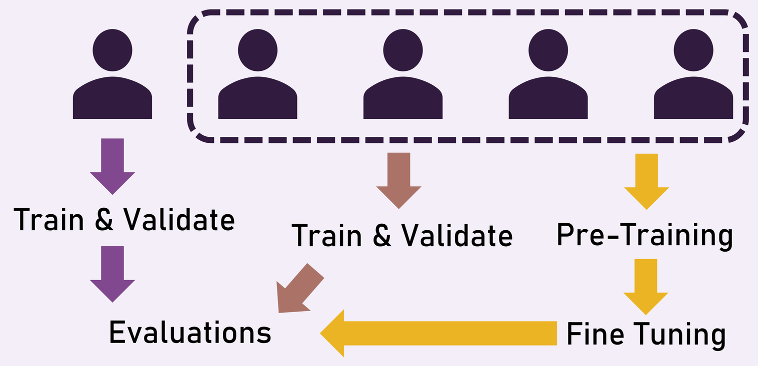


Figure 1 : Experiments Illustrations

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

IV) Training Strategies

Hyperparameters Setting – Obtaining the best setups

- Hyperparameter tuning using the hyperband algorithm
- AdaBelief optimizer with 0.001 initial learning rate

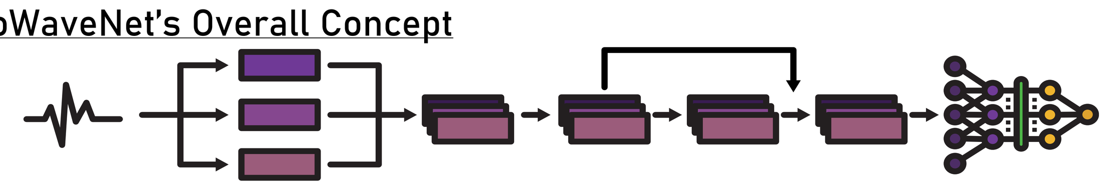
Training Callbacks – Obtaining the best model weights

- Early-stopping after 10 consecutive epochs
- Reduce learning rate by 0.25x after 5 consecutive epochs

Both used when validation loss ceases to improve

V) BioWaveNet's Rationale and Architecture

BioWaveNet's Overall Concept



Why these signals and tasks

Both signals covers electrical and non-electrical signals in both classification and regression tasks

Components

(A) Multi-scale Convolution : Our novelty – utilizes various convolutional filters sizes parallelly for learnable "feature engineering"

(B) Spatial-temporal Feature Extraction : Normal or residual convolutional neural network to analyze signal patterns in each scale from (A)

(C) Multilayer Perceptron : Fully-connected network leading to either a classifier or regressive predictor

EEGWaveNet's Architecture

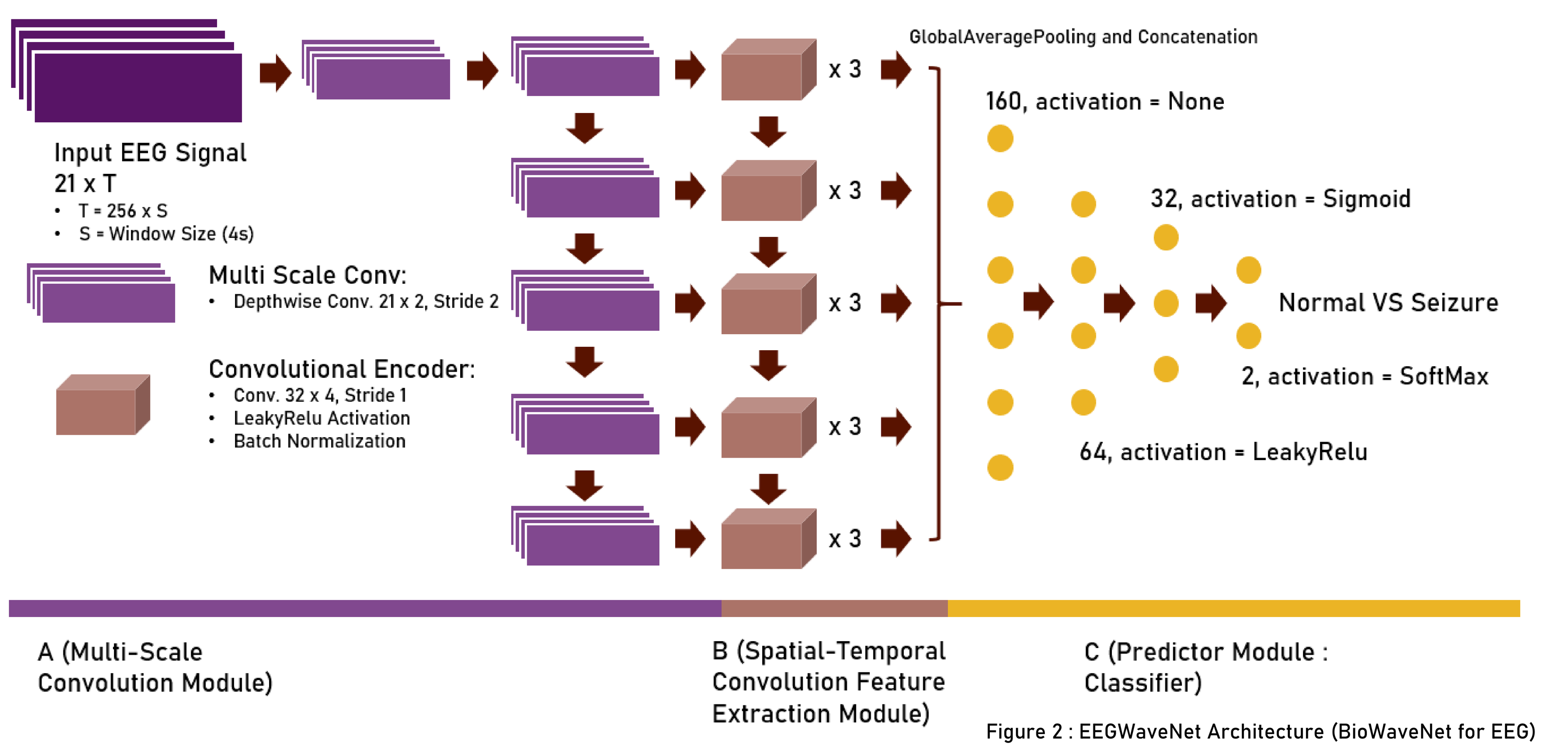


Figure 2 : EEGWaveNet Architecture (BioWaveNet for EEG)

PPGWaveNet's Architecture

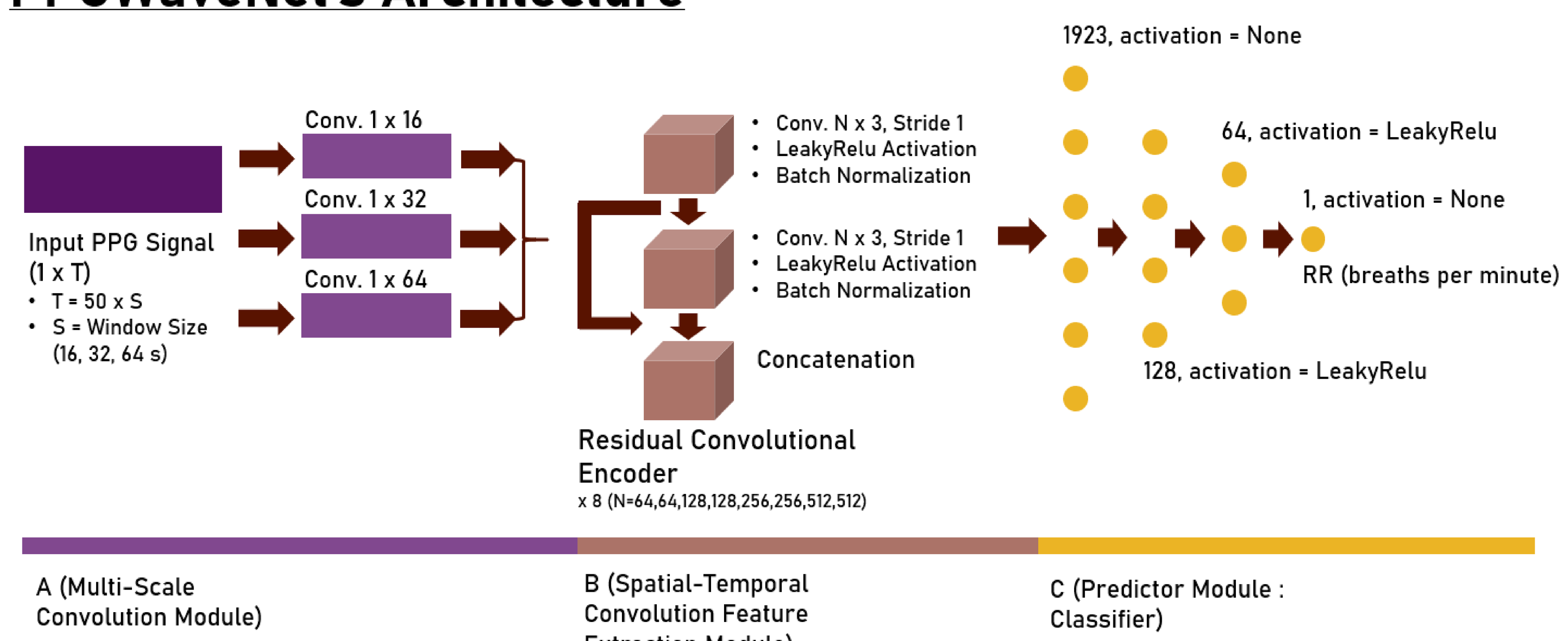


Figure 3 : PPGWaveNet Architecture (BioWaveNet for PPG)

Ideas

Overall Concept

- Small Scale/Filter size (capture sudden changes)
- Bigger scale/filter size (capture gradual changes)

EEG Model

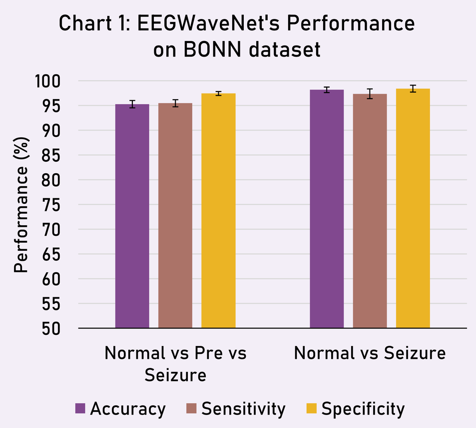
- More scales (simulate variations in epileptic spikes)
- Less deep network (to avoid gradient vanishing)
- Loss – Cross Entropy

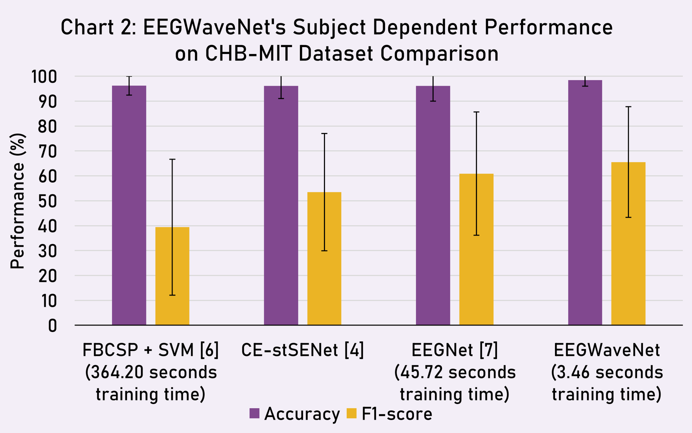
PPG Model

- Deeper network (to capture periodic nature of PPG)
- Residual Network (to avoid gradient vanishing)
- Loss – Mean Squared Error

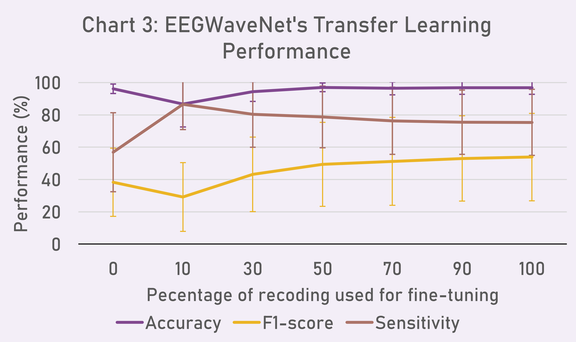
Results

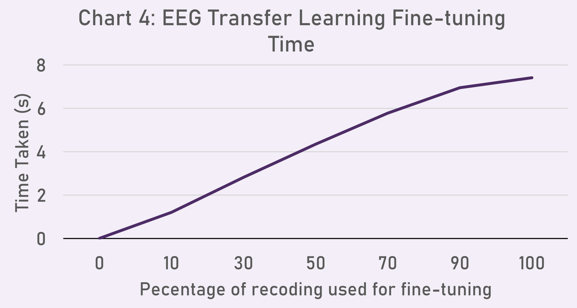
EEG Results





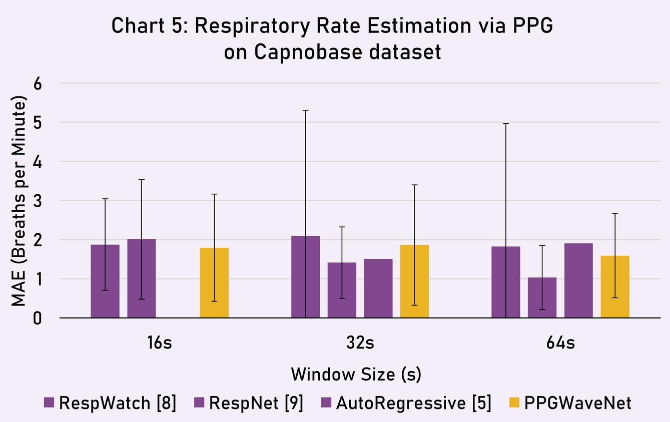
- Bonn of seizure: Model can differentiate 3 stages
- CHB-MIT: Model achieves the highest performance along with the fastest training time per patient

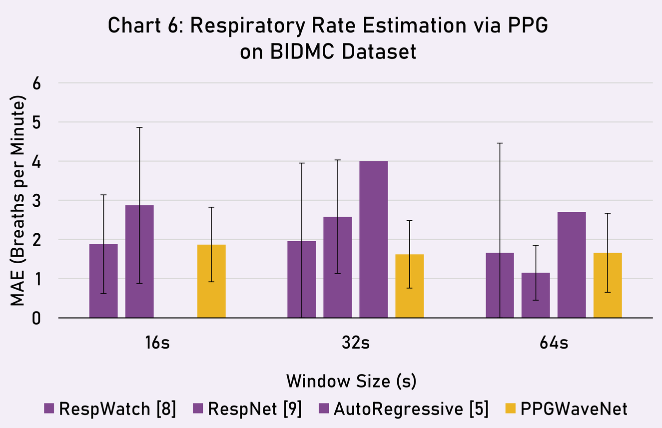


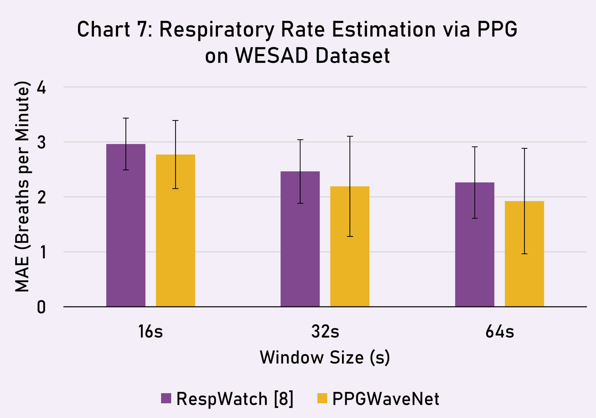


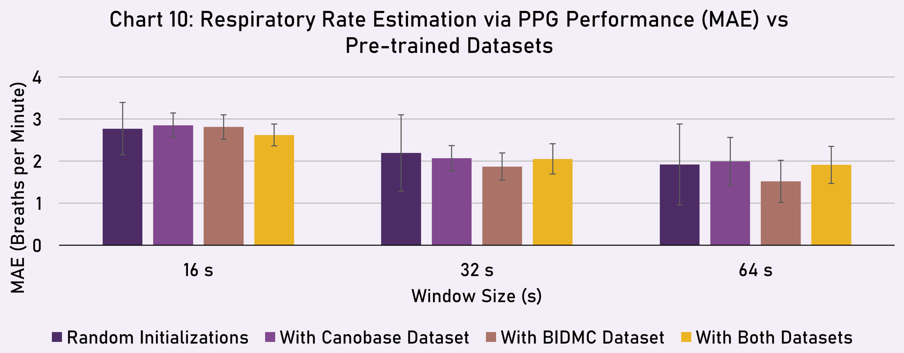
- Small percentages: increase in sensitivity
- Large percentages: lower sensitivity for more precision and F1-score
- Training time: all within 10 seconds

PPG Results









Subject Independent: PPGWaveNet's performs best on small window size, albeit not statistically significant to other studies

Transfer Learning datasets: Performance boost is varied between

BIDMC yields the best results while Capnobase ended with lower performance

Discussions

I) Robustness

EEG Seizure Detection

Higher accuracy and F1-score from lower false positive rate

Fine tuning with 1 hour recording can increase the sensitivity or F1-score based on fine-tuning percentage

PPG RR Estimation

Higher accuracy and F1-score from lower false positive rate

Fine tuning with 1 hour recording can increase the sensitivity or F1-score based on fine-tuning percentage

II) Training Capabilities

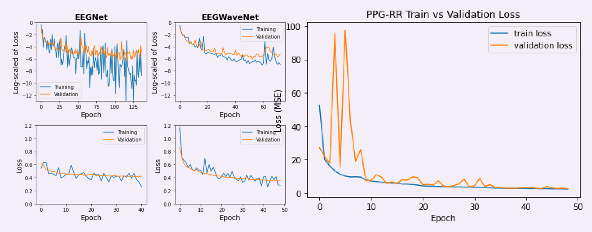


Figure 4 : Training and Validation Loss

EEGWaveNet reached its local minima earlier with a lower loss.

PPGWaveNet is smaller and reaches the minima faster.

Overall Loss Curve – The model does not overfit.

III) Explainable AI – Kernel Plot

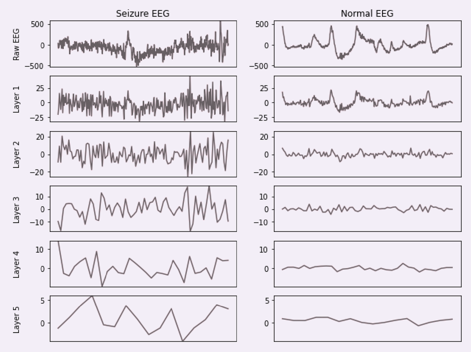


Figure 5 : EEGWaveNet's Generated Scales

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.

IV) Explainable AI – SHAP Plot

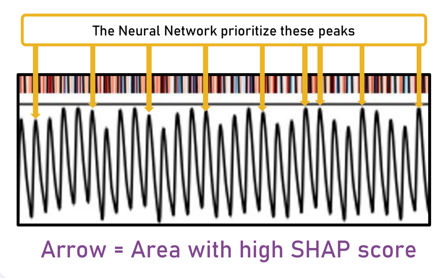


Figure 6 : PPGWaveNet's SHAP Explanation

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].

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 in hospitals.

EEG Seizure Detection
Our model can be developed into a screening application for seizure diagnosis.

PPG Respiratory Rate Estimation
Our model can screen abnormal breathing remotely, especially in COVID pandemic.

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