Bio - Wave - Net

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

· 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, potentially fulfilling the third sustainable development goal, where healthcare is at concern.

· Introduction ·

Bio-signals, the time-series data containing insightful vital signs, are used in a plethora of assessment and treatments, like epileptic seizures and sleep apnea. However, the tedious task to analyze the bio-signals land on the hands of extremely specialized clinicians, leading to a scarcity of personnel.

Automations attempts on bio-signal often require feature engineering to cover up the noises and lack of features from raw signals. However, development of such methodologies require deep domain knowledge, each tailor made for one specific task. The overcomplicated and resource-intensive nature deems feature engineering too rigid for bio-signal applications.

Thus, developing BioWaveNet, a generalized protocol for bio-signal applications, with the foundations from feature engineering, to create a learnable network that generates relevant features as well.

· Objectives ·

- To propose and develop M-CNN, a learnable feature extractor framework for robust bio-signal analysis.
- To test BioWaveNet's robustness on 2 bio-signal analysis tasks
  - ➢ Seizure onset detection via Electroencephalography (EEG)
  - ➢ Respiratory rate estimation via Photoplethysmography (PPG)

· Methodologies ·

· Part 1 – Data Acquisition ·

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

· Part 2 – Preprocessing ·

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

· Part 3 – Experiment Designs ·

(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

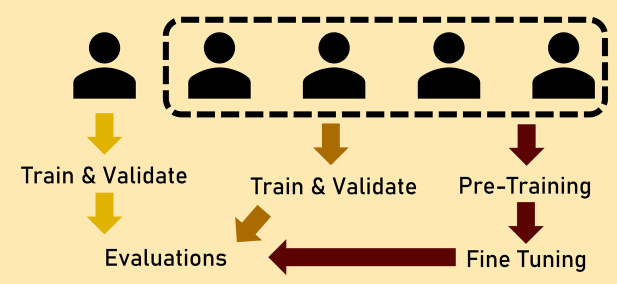


Figure 1 : Experimental Setups (all experiments used 5-fold cross validation)

· Part 4 – 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

· Part 5 – Model Architecture ·

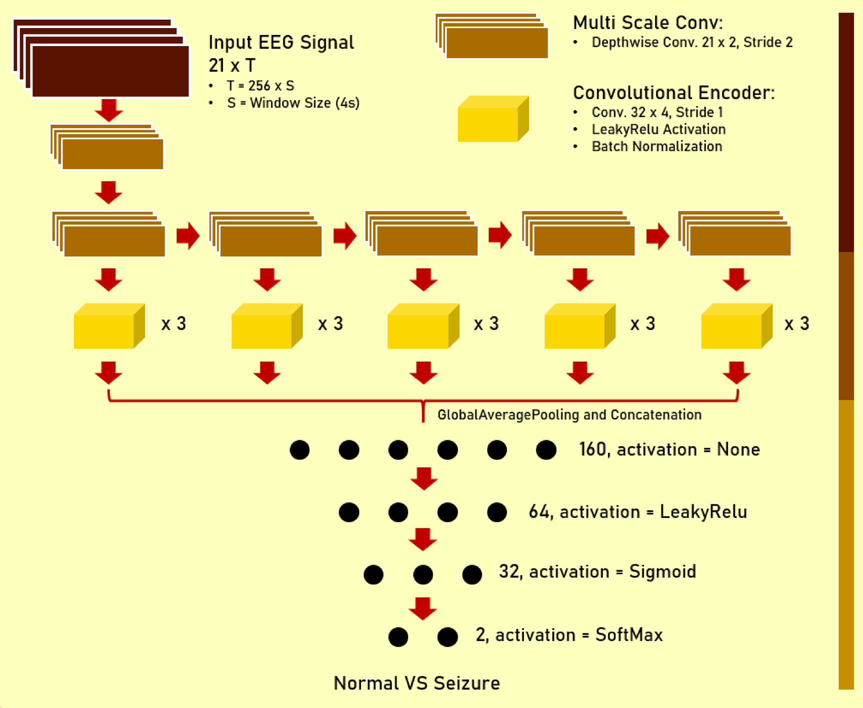


Figure 2 : EEGWaveNet Architecture (BioWaveNet for EEG)

(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

Ideas : the multi-scale module uses different sizes of convolutional filters simultaneously. The smaller filter captures sudden changes (peaks) while the larger ones view the overall propagation of the bio-signals.

EEG : More scales to mimic clinical standard of using many frequency bands (i.e. alpha beta gamma)

PPG : Deeper network to simulate its periodic nature

EEG vs PPG

EEG	PPG
• Brain Activities	• Blood Density
• Electrical Signal	• Non-electrical Signal
• Unpredictable Waveforms	• Periodic Waveforms
• Often collected from medical-grade devices	• Often collected from commercialized wearable devices

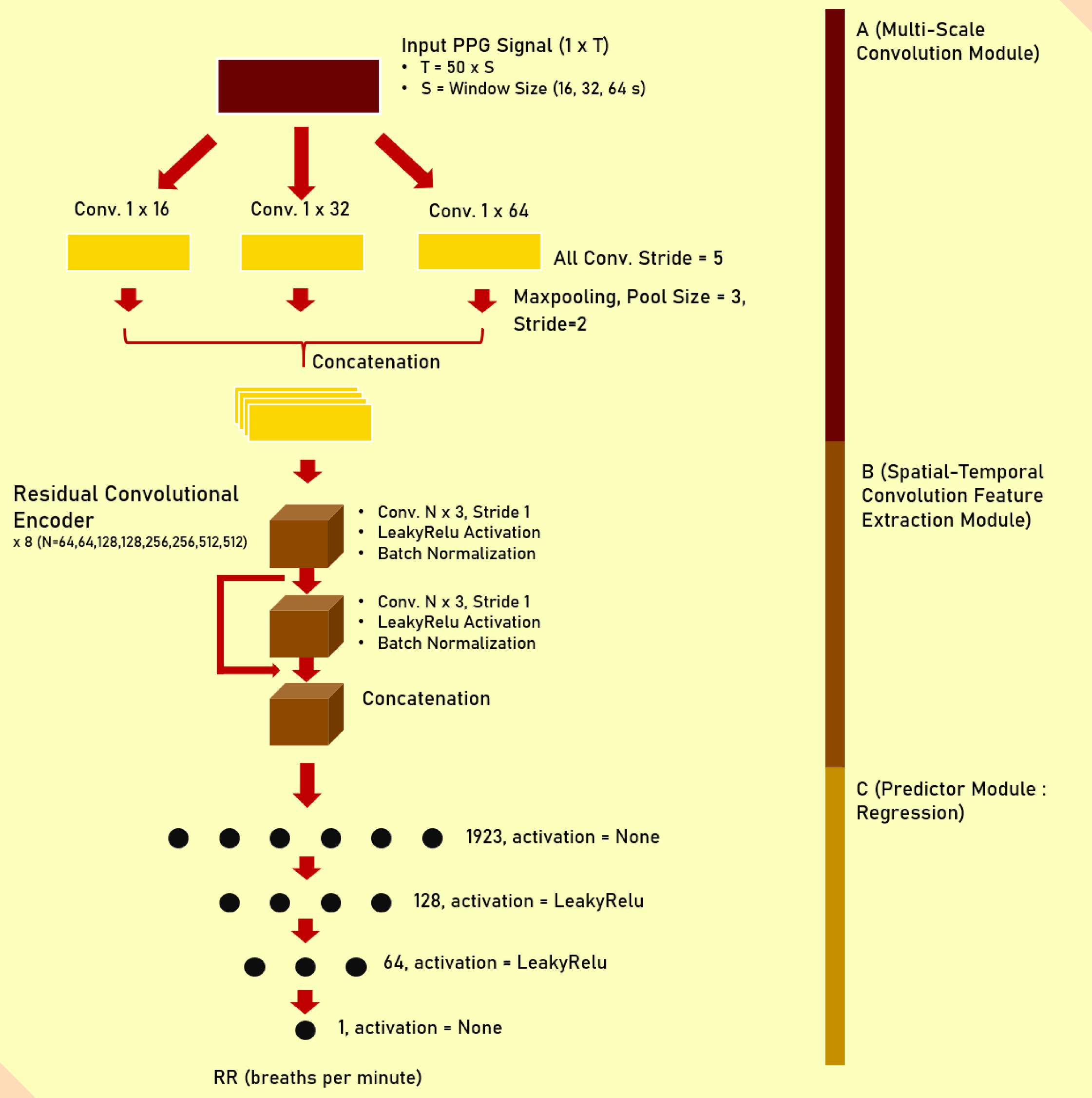
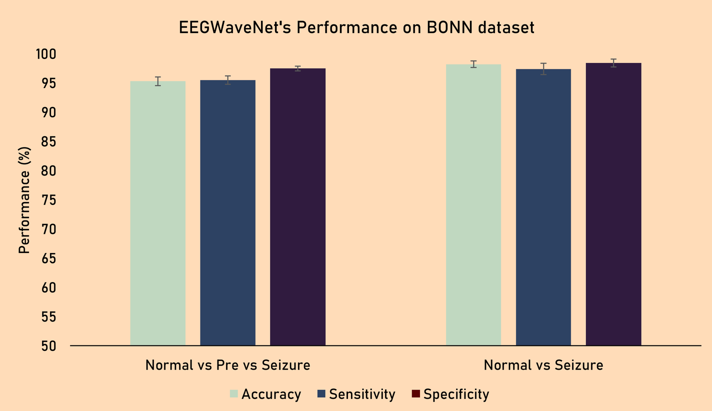
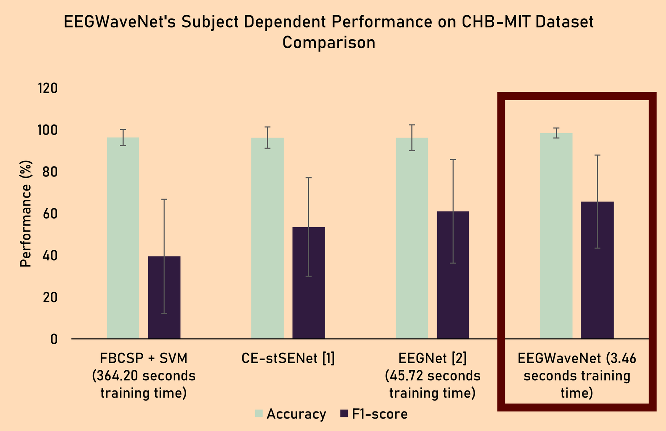


Figure 3 : PPGWaveNet Architecture (BioWaveNet for PPG)

· Part 1 – EEG Seizure Detection ·

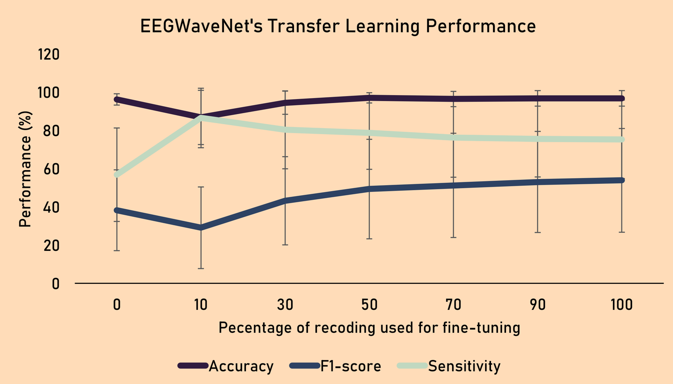
Subject Dependent – Able to differentiate seizure states, all higher performances are statistically significant

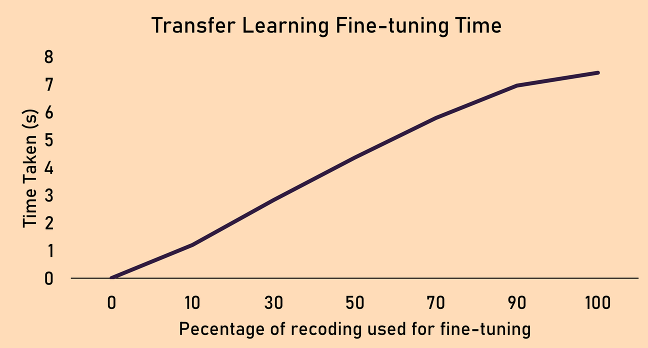




- Bonn Model can differentiate 3 stages of seizure
- CHB-MIT Model achieves the highest performance along with the fastest training time per patient

Transfer Learning – Performance increases with one-hour recording worth of fine-tuning





- Small percentages increase in sensitivity
- Large percentages lower sensitivity for more precision
- Training time all short, within 10 seconds

· Part 2 – PPG Respiratory Rate Estimation ·

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

	Capnobase Dataset (MAE Mean±SD)			BIDMC Dataset (MAE Mean±SD)			WESAD Dataset (MAE Mean±SD)		
	16 s	32 s	64 s	16 s	32 s	64 s	16 s	32 s	64 s
Autoregressive [3]	N/A	1.50	1.90	N/A	4.00	2.70	N/A	N/A	N/A
RespNet [4] (Raw signal)	3.62 ± 1.37	1.41 ± 0.91	1.03 ± 0.82	2.87 ± 1.99	2.58 ± 1.45	1.15 ± 0.70	Dataset Limitations (Lack of CO_2 signals)		
RespWatch [5] (Raw signal)	1.87 ± 1.17	2.09 ± 3.21	1.82 ± 3.15	1.88 ± 1.26	1.96 ± 1.99	1.66 ± 2.80	2.96 ± 0.47	2.46 ± 0.58	2.26 ± 0.65
PPGWaveNet	1.79 ± 1.37	1.86 ± 1.54	1.59 ± 1.08	1.87 ± 0.95	1.62 ± 0.86	1.66 ± 1.01	2.77 ± 0.62	2.19 ± 0.91	1.92 ± 0.96

Transfer Learning – Performance increases with one-hour recording worth of fine-tuning

Pretrained Weights	Performance (MAE Mean±SD)		
	16 s	32 s	64 s
Random Initializations	2.77 ± 0.62	2.19 ± 0.91	1.92 ± 0.96
With Canobase Dataset	2.85 ± 0.29	2.07 ± 0.30	1.99 ± 0.57
With BIDMC Dataset	2.81 ± 0.29	1.87 ± 0.32	1.52 ± 0.50
With Both Datasets	2.62 ± 0.26	2.05 ± 0.36	1.91 ± 0.44

- BIDMC dataset gives the highest performance after fine-tuning
- Capnobase dataset lower the performance
- Both dataset givers and overall performance increase
- ICU datasets can improve performance when trained
- on wearable device datasets

· Discussions ·

· Part 1 – BioWaveNet's Robustness ·

Seizure EEG – EEGWaveNet's highest F1-Score was from a lower false positive rate, leading to less false alarms. Transfer learning can mitigate the lower sensitivity/recall score at lower fine-tuning percentage.

Respiratory PPG – PPGWaveNet is best used on small (16s) window and does not have any restrictions. This translate to a faster inference time, as PPGWaveNet can infer a minute worth of breathing within 16 seconds.

· Part 2 – Training Capabilities ·

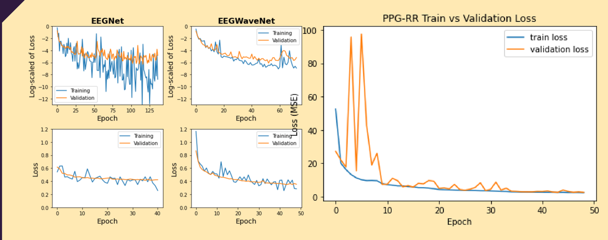


Figure 4 : Training and Validation Loss

Seizure EEG – EEGWaveNet reached its local minima earlier with a lower loss.

Respiratory PPG – PPGWaveNet is smaller and reaches the minima faster.

Overall Loss Curve – The model does not overfit.

· Part 3 – Multi-scale Module ·

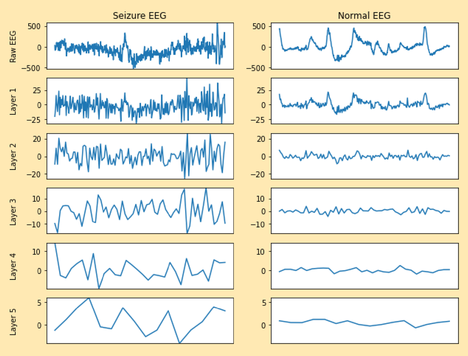


Figure 5 : EEGWaveNet's Generated Scales

In the case of EEG signals in epileptic seizure detection, M-CNN scales show differentiation from seizure and normal EEG, where the discrimination is amplified through each scale.

This proves our hypothesis of the multi-scale module's capability as a robust and learnable feature engineering tool.

· Part 4 – Further Explainable AI ·

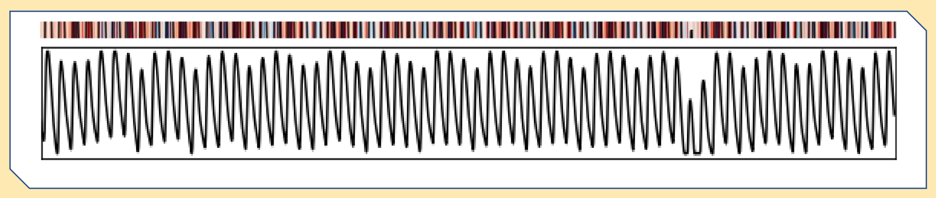


Figure 6 : PPGWaveNet's SHAP plots on raw PPG signals
Red = Important Peaks

In a regressive task like respiratory PPG, we employed the SHAP technique to assess PPGWaveNet's ability. Red heatmaps corresponds to highly relevant features, in which the model is able to detect the change in PPG amplitude, which is scientifically proven as the RIIV measure that correlates with the respiratory rate.

· Conclusion ·

This study proposes BioWaveNet using the concept of multi-scale CNN, which utilizes convolution layers as learn-able feature instead of mathematical feature extraction techniques. The scales are then analyzed by a spatial-temporal convolutional encoder.

The BioWaveNet models showed their robustness on two signals – EEG and PPG. The model shows low-false-positive rate on seizure EEG with possibility to tune and improve the performance, all within less than 10 seconds. The PPG model works the best on short-length signals, translating to a shorter prediction time.

Explanations attempts shows relevance features being selected from the BioWaveNet networks. The multi-scale module is able to discriminate the input EEG signals, while the model as a whole is able to correctly analyze the peaks of the PPG signals.

· References ·

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